2016

NATIONAL INSTITUTE OF TECHNOLOGY, ROURKELA

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[ASSESSING THE IMPACT OF CLIMATE CHANGE ONTHE HYDROLOGICAL PARAMETERS USING STATISTICAL DOWNSCALING METHODS]

Under the guidance of
Prof. K C Patra,
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Assessment of the impact of climate change on the hydrological parameters using statistical downscaling

Thesis submitted to the
National Institute of Technology, Rourkela
in partial fulfillment of the requirements
for the dual degree of

Bachelor and Master of Technology
in
Civil Engineering
(*PG Specialization: Water Resources Engineering*)

by

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SUPERVISOR'S CERTIFICATE

This is to certify that this thesis entitled "**Assessment of the impact of climate change on hydrological parameters using statistical downscaling**", put together by **Mr. Prayas Rath,** bearing the roll number **711CE4092**, a B. Tech and M. Tech Dual Degree scholar in the Civil Engineering Department, National Institute of Technology, Rourkela, in partial fulfilment for the award of the dual degree of **Bachelor of Technology** in **Civil Engineering** and **Master of Technology** in **Water Resources Engineering**, is a bona fide record of a genuine research work completed by him under my guidance and supervision. This thesis has satisfied all the necessities according to the regulations of the Institute and has, in my opinion, come to the standard required for submission. The results included in this thesis have not been uploaded/submitted to any other institute or university for any academic award, degree or diploma.

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ACKNOWLEDGEMENTS

My most recent five years venture at **National Institute of Technology, Rourkela** has added significant and valuable experiences to my life. I have utmost regard and adoration for this institute and I will always remember the individuals who have made this environment so exceptional and extraordinary. Now it is time to proceed onward to my future. Before I go any further, I like to express my sincere gratitude to those who have assisted me along the way.

First and foremost, praise and heartfelt thanks go to the Almighty for the blessing that has been showered upon me in all my endeavours.

I would like to thank my project supervisor, **Dr. Kanhu Charan Patra** for furnishing me with a stage to chip away at an incredibly energizing and testing field of **Assessment of the impact of climate change on hydrological parameters using statistical downscaling**. His untiring exertion, commitment and way of supervision is highly brain stimulating and extracts the best from a student. I also want thank **Dr K.K. Khatua** who has regularly given me the opportunity to envision, execute and analyse, but has coincidently guided me sharply to keep on track throughout the project work. It has helped me a lot for self-development for which I am obliged the most.

I want to express profound gratitude to my father who has been my constant source of inspiration. Without whom I am nothing. It is his effort and love which has made me. I also

I am very appreciative to my classmate **Prasang Singh Parihar (711CE4010)** of Department of Civil Engineering who was sufficiently kind to help me in my project work.

Most importantly, this would not have been possible without the affection and support of my friends and family. They have been a constant source of love, concern, support and strength all these years. I would like to express my heart-felt appreciation to them.

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ABSTRACT

Water resources in India are already under tremendous strain due to population explosion and urbanization. But the problem is compounded by the climate change due to global warming. Proper evaluation of this climate change is a must for planning and mitigation of water resources. This work is aimed to assess the impact of climate change in the Indian subcontinent using statistical downscaling methods from GCMs which are derived from HADCM2 and HADCM3 ensembles using IPCC AR4 (SRES) and CANESM2 using IPCC AR5 (RCP). This study tries to investigate the relationships between the various atmospheric and surface variables. The 26 predictor variables of all the GCMS were considered for selected regions for the temperature and precipitation predictands.The temporal stability of the key predictor-predictand relationships was also checked for the GCMs using different decades and comparing them. Two regions were selected Rourkela and Mumbai. One is an urban area another the largest metro The CanESM2 was not found suitable for analysis of Rourkela region. Then the future trends in rainfall and temperature are discussed. The trend analysis was performed using Mann-Kendall test and Sen-slope estimator.

Keywords: *Statistical downscaling; GCM; IPCC AR4 & AR5; predictor, predictand*

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ABBREVIATIONS

GCM : General circulation models

RCP : Representative concentration pathway

SDSM : Statistical Downscaling Model

CHAPTER 1: INTRODUCTION

1.1 General

India is facing a grim situation. Out of the 20 major river basins, 14 are being considered over stressed due to the population explosion and economic strain. The problem of global warming has made the problem dire. Water availability has decreased from 1816 cubic meters per capita to 1545 cubic meters in a span of ten years from 2001 to2011. And the temperature of the Indian subcontinent is expected to rise by 2.5^{o}C to 4.5^{o}C by 2100. It will have serious repercussion on the region.

The recent events of climate extremes can be attributed to this climate change. The flood of Rishikesh in 2013 comes into everyone's minds. The carnage was caused due to the loose snow pack and instability of glaciers due to the increased temperatures. The glacial dams broke and a tsunami was triggered. Also underlying this obvious reason was a subliminal cause- the changing pattern of monsoons. The rains have been coming earlier, and snows are forming very late. The snow formation which was starting from October now takes place in January. So when the summer comes, the snow pack is not dense enough to resist melting. Thus, the melt water has increased dramatically. Also due to the temperature rise extreme events like cloud bursts have become more frequent. The heavy downpour which used to take place once in 5-6 years now occurs every year. The dangerous combination of the snow melt and the downpour caused one of the worst floods.

Another example of the impact of climate change was seen in the mega flood of Chennai. Urban flooding has always been a huge challenge, but extreme events like heavy retreating monsoons which are due to the increased temperatures worsened the problem in Chennai.

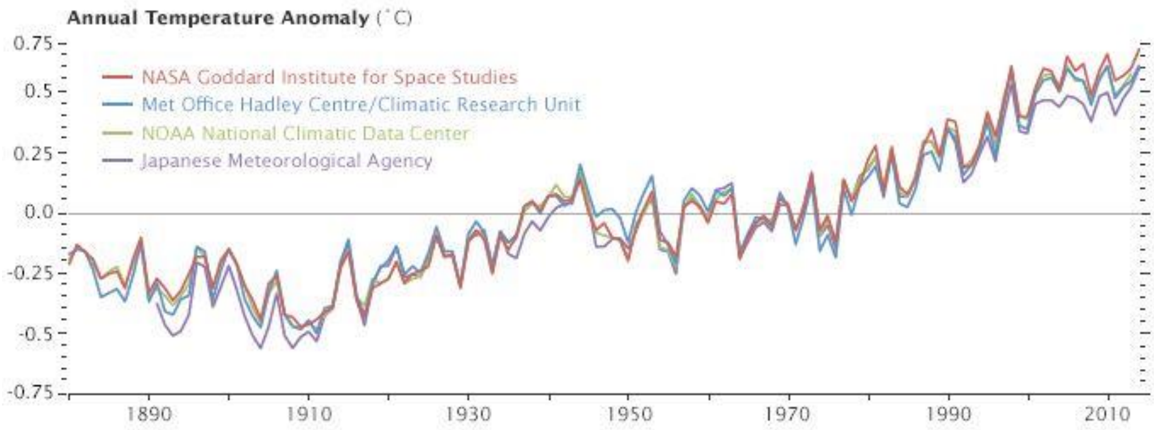


Figure 1.1: Depicting the recorded annual temperature anomalies from1880 to 2014.

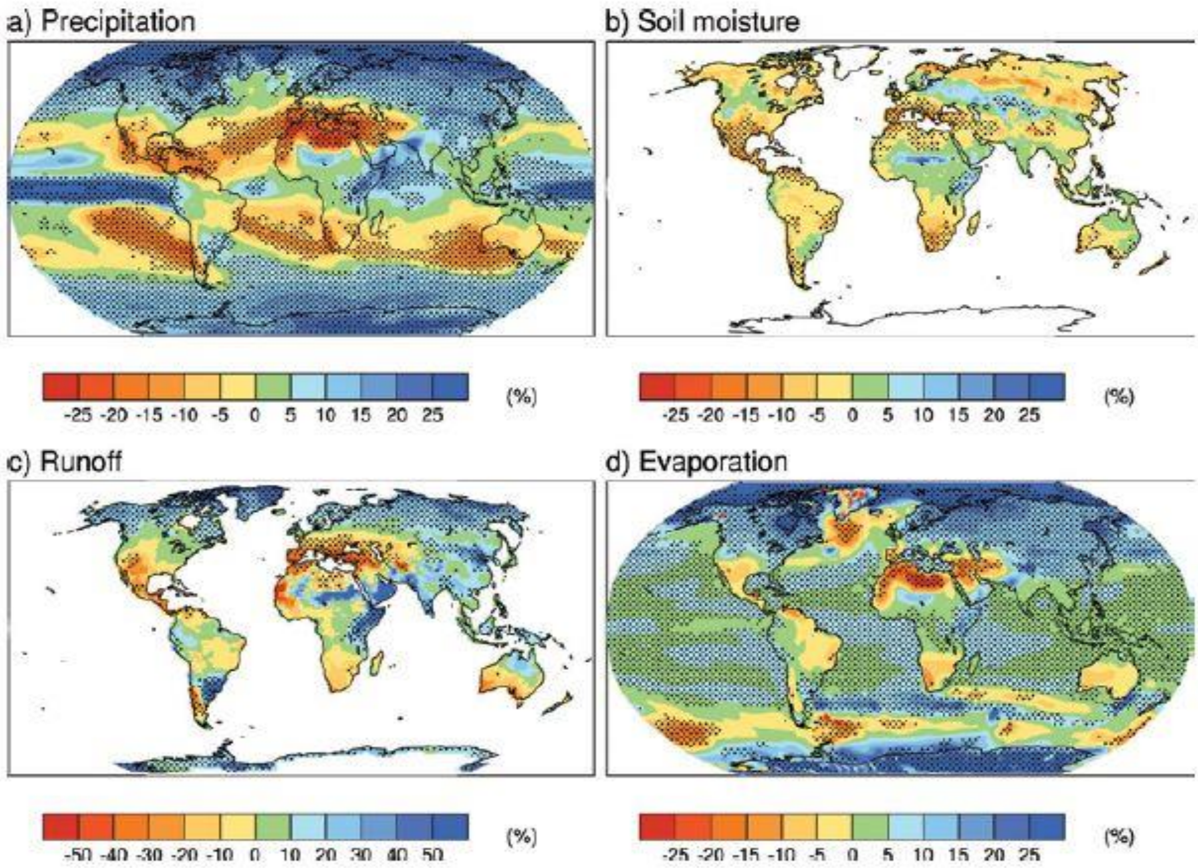


Figure 1.2: Depicting changes in annual mean percentages predicted in the decade 2080-89.

Basically it is an accepted fact that climate change is real .The main problem arises in the quantification and measuring the extent of this change. Without knowing the magnitude of the change and the impacts due to it, policymakers will not be able to do much. The solution lies in a model-based approach which can replicate the real world scenarios and give us a hint of what can be expected in the future.

General circulation models are the most used models in depicting the changes of climate. The GCMs are the most comprehensive and exhaustive models. It is basically a mathematical model based on the general circulation of the earth's atmosphere and ocean. Many complex equations of fluid dynamics like Navier-Stokes equation, thermodynamic principles, Coriolis force and many more complex phenomena are employed. GCMs are the best tools available to us which help us to determine the global distribution of the important factors of climate change. (Maraun et.al 2010)

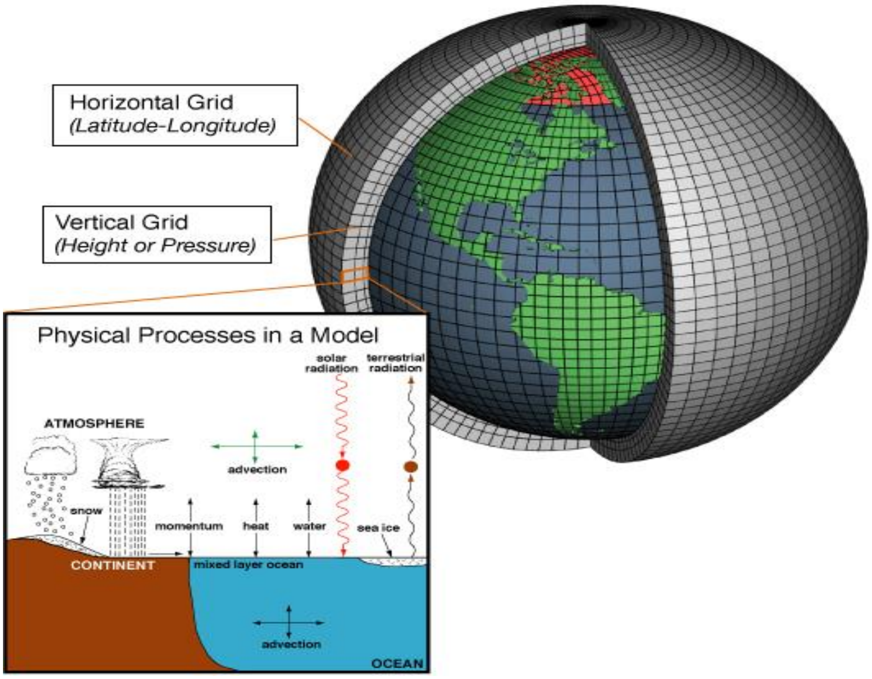


Figure 1.3: Depicts the process in a GCM (Source: Wikipedia)

GCMs work on very coarse regions. To make them useful for emancipating useful information for hydrological impact they have to be downscaled. As all the hydrological impacts which are needed for study are at much finer resolutions, downscaling plays a very important role. (Wilby et.al 2000). Downscaling aims to bridge the scale mismatch between the coarser GCMs and the information deemed useful by hydrologists to assess the impact of climate change.

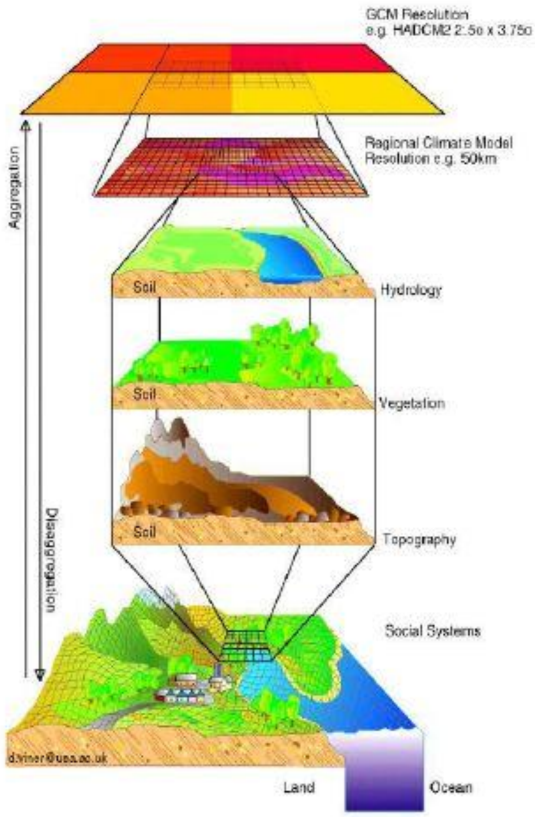


Figure 1.4: Depicting the downscaling of GCM (Source: HADCM)

Basically, downscaling is of two types- dynamic and statistical downscaling. Both the methods have their advantages and disadvantages. And one method cannot be singled out to be better.(Wilby 2000)

Table 1.1: Comparison of the main strengths and weakness of statistical and dynamical downscaling

	Statistical downscaling	Dynamical downscaling
Strengths	Station-scale climate information from GCM-scale output	10– 50 km resolution climate information from GCM-scale output
	Cheap, computationally undemanding and readily transferable	Respond in physically consistent ways to different external forcings
	Ensembles of climate scenarios permit risk/uncertainty analyses	Resolve atmospheric processes such as orographic precipitation
	Flexibility	Consistency with GCM
Weaknesses	Dependent on the realism of GCM boundary forcing	Dependent on the realism of GCM boundary forcing
	Choice of domain size and location affects results	Choice of domain size and location affects results
	Requires high quality data for model calibration	Requires signifi cant computing resources
	Predictor– predictand relationships are often non-stationary	Ensembles of climate scenarios seldom produced
	Choice of predictor variables affects results	Initial boundary conditions affect results
	Choice of empirical transfer scheme affects results	Choice of cloud/convection scheme affects (precipitation) results
	Low-frequency climate variability problematic	Not readily transferred to new regions

In the present work statistical downscaling method is used.

Also GCMs used are from AR4 and AR5 in this project. The important difference in both these reports is the emission scenarios. In AR4 SRES was used but in AR5 more comprehensive RCP is being used. RCP is the representative concentration pathways. RCP is better approach as it employs parallel approach.

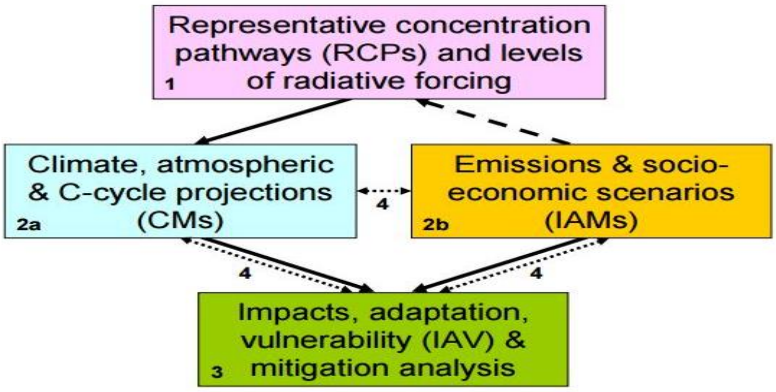


Figure 1.5: Parallel approach of RCP

Table 1.2: Scenarios of AR4

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 economic development

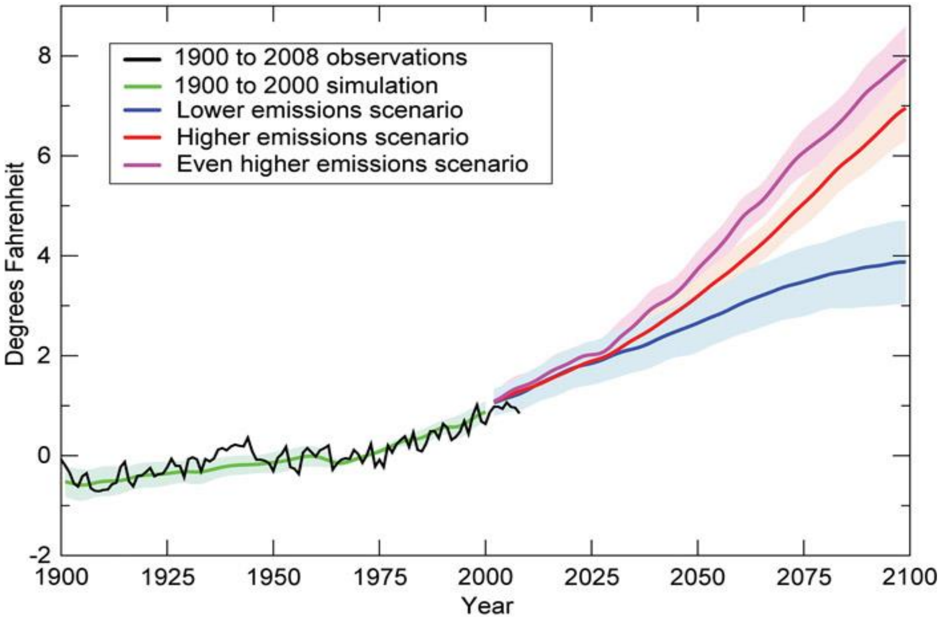


Figure 1.6: RCPs of AR5

1.2 Objectives:

This project aims to evaluate the climate change impact. This goal can be substantiated with the following aims

-To study the various GCMs and equations used in the models.

-To study the various statistical downscaling methods.

-To establish the relationship between various predictands and predictor variables.

-To test the temporal stability of these relationships

-To predict future temperature and precipitation trends.

CHAPTER 2: LITERATURE REVIEW

2.1 Climate and Water Resources

Rao P G and Kumar (1992) studied 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 analogies for the assessment of climate change impacts. The gaps between the GCMs ability and requirements of the hydrological models for assessment were analysed. 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) reviewed the existing gap and the methodologies for narrowing the gap between GCMs' ability and the need of hydrological modelling.

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 groundwater 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.

Mujumdar and 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.

2.2 Downscaling

Winkler et al., (1997) advised that enough data should be available for both model calibration and validation. As 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: stochastic weather generators; regression methods; weather pattern-based approaches; 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 the derivation of detailed regional 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 mesoscale atmospheric variables to grid and subgrid-scale surface variables using downscaling technique.

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).

Hessami et al (2008) used autoregressive models for 10 years data. Using different GCMs and ensembling data results in better output.

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

Duhan Pandey et al(2014) used MLR ,RBF, LS-SVM methods to downscale temperature in Tons river basin. LS-SVM was found to be the best fit. And using LS-SVM method it was observed that minimum temperatures increase at greater rate than the maximum temperature.

Ghosh et al 2014 used statistical downscaling using Bayesian learning and RVM methods. A decreasing trend was observed for Monsoon streamflow in Mahanadi basin because of high surface warming in the future scenarios.

Table 2.1: Various downscaling methods

Method	Advantages	Limitations
Transfer function	• Straightforward to apply • Employs full range of available predictor variables • Availability of software and solutions	• Poor representation of observed variance • May assume linearity and/or normality of data
Weather typing	• Provides physically interpretable link to the surface climate • Versatility • Composite for analysis of extreme events	• Requires additional task of weather classification • Circulation-based schemes can be insensitive to future climate forcing • May not capture intra-type variations in surface climate
Weather generator	• Production of large ensembles for uncertainty analysis or long simulations for extremes • Spatial interpolation of model parameters using landscape in regions with sparse data • Capability of generating sub-daily information • Ability to alter the parameters in accordance with scenarios of future climate changes- changes in variability as well as mean changes	• Arbitrary adjustment of parameters for future climate • Unanticipated effects to secondary variables of changing precipitation parameters • Most are designed for use independently at individual locations and few of them account for the spatial correlation of climate

2.3 Reanalysis Hydro-climate Data

Reanalysis data from different sources have shown promising potential in global climate research studies. In this section literature relevant to the National Center for EnvironmentPrediction and National Center for Atmospheric Research (NCEP/NCAR) global reanalysis - NNGR (Kalnay et al., 1996) and the North American Regional Reanalysis - NARR (Mesinger et al., 2006) data is discussed. Several studies have compared the global reanalysis precipitation and temperature data with other available databases at different locations. Neito et al. (2004) compared the NNGR data with ECHAM4/OPYC3 and HadCAM3 models to analyze the correspondences and or the discrepancies within the observed winter precipitation data during 1949-2000 for the Iberian Peninsula. NNGR precipitation data effectively captured the spatial and temporal variability and showed a good agreement with the observed precipitation.

Ruiz-Barradas and Nigam (2006) found a correlation coefficient of 0.99 when the NNGR data were compared with the observed summer precipitation to analyze the interannual precipitation variability over the Great Plains, United States. However, while Tolika et al. (2006) found an inferior agreement between NNGR and observations, they also found a closer inter-annual variability when NNGR was compared with the GCMHadAM3P data for examining the suitability of the averaged distributions and the spatial and temporal variability of the winter precipitation in Greece.

In many applications, the NNGR resolution appeared to be less satisfactory than the observed temperature and precipitation, especially in regions with complex topographies, (Choi et al 2009; Tolika et al, 2006; Rusticucci and Kousky, 2002; Haberlandt and Kite, 1998) due to coarse resolution (250 km X 250 km) and physical parameterizations (Castro et al 2007).

The recently released North American Regional Reanalysis (NARR) dataset, developed by Mesinger et al. (2006), designed to be “a long term, dynamically consistent, high resolution, high frequency, atmospheric and land surface hydrology dataset for the North American domain”, is a major improvement upon the global reanalysis datasets in both regions.

Castro et al. (2007) applied 53 years of NNGR data with dynamic downscaling using the Regional Atmospheric Modeling System (RAMS) to generate regional climate model (RCM) climatology of the contiguous US and Mexico. They compared the RAMS simulated data with that of the NARR, the observed precipitation and temperature data, and found a good agreement of the NARR data in some parts of the Great Plains. The literature cited above clearly indicates the potential of the reanalysis dataset for use in hydrologic modeling and/or climate change for studies to replicate the current climate regime.

CHAPTER 3: Data collection

3.1 GCM Data

The GCM used was the UK Meteorological Office, Hadley Centre's coupled ocean:atmosphere model(HadCM2) forced by combined CO2 and albedo (as a proxy for sulphate aerosol, SUL) changes (Johns et al., 1997; Mitchell and Johns, 1997). In this 'SUL' experiment, the model run begins in 1861 and is forced with an estimate of historical forcing to 1990 and a projected future forcing scenario over 1990–2100. The historical forcing is only an approximation of the 'true' forcing, with the result that the GCM results for model years 1980–1999, for example, would not be expected to represent present-day conditions exactly (see Appendix A in Wilby et al., 1998b). Nonetheless, HadCM2 output for 1980–1999 has been employed as a proxy of the present climate for downscaling daily precipitation, temperature, humidity, sunshine totals and wind speeds in selected regions of the USA (Wilby et al., 1998b), Europe (Conway et al., 1996) and Japan (Wilby et al., 1998a).

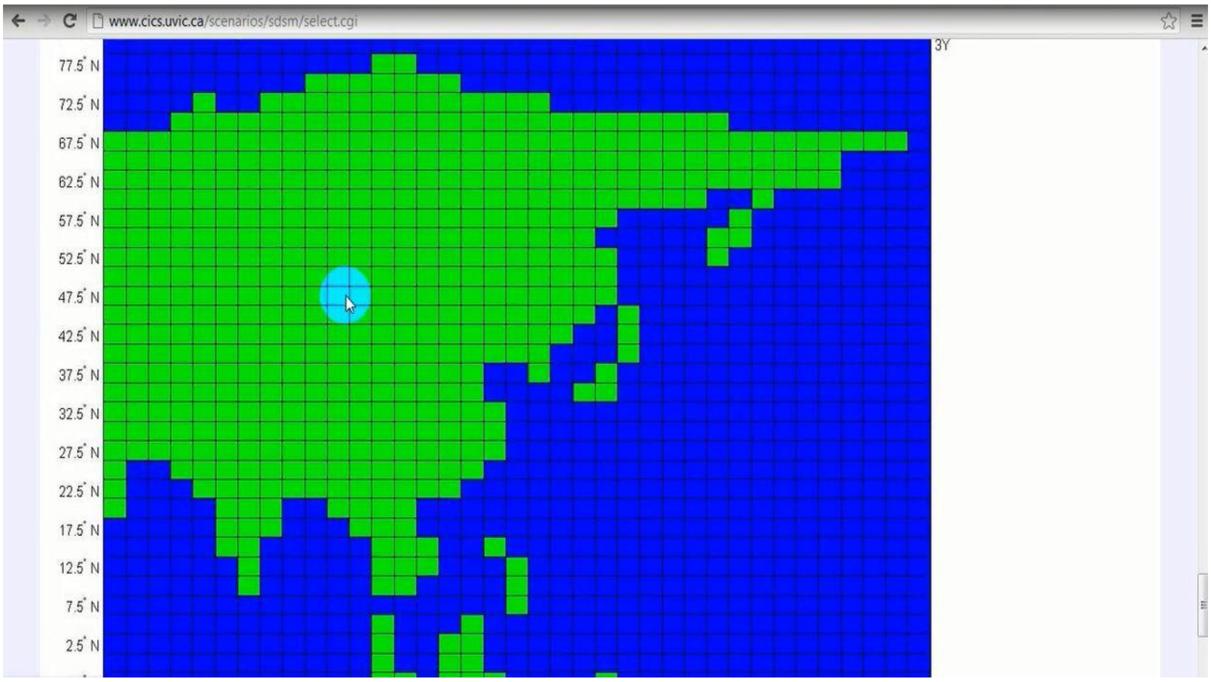


Figure 3.1: Site of GCM data collection

Daily maximum (Tmax), minimum (Tmin) and mean temperatures were obtained for the six target regions from HadCM2 output (using the 1980–1999 means of daily Tmax and Tmin). (Note that, for the observations, station temperature data were employed rather than re-analysis data, since these were considered to be more reliable. However, the daily station means and re-analysis data are highly correlated). In addition, daily mean surface relative humidity and 0.995 sigma level relative humidity were obtained for all regions using both HadCM2 (1980–1999) and re-analysis (1979–1995) output. In both cases, because specific humidity (q) has been shown to be a valuable downscaling predictor (Crane and Hewitson, 1998), daily mean temperatures and relative humidities were used to estimate daily mean specific humidities using Richards' (1971) non-linear approximation. This estimation procedure was necessary because only relative humidity had been archived at daily time-steps for the HadCM2 experiment. 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

As HADCM2 and HADCM3 are based on AR 4, for AR5 CanESM2 data was used. CanESM is developed by Canadian Climate Society to inculcate and contribute to the AR5 www.cccsn.ec.gc.ca/?page=sdi-cmip5intro

PREDICTORS (Atmospheric Variables)	ORIGIN (i.e. NCEP or GCM)	TIME WINDOW
Mean Sea Level Pressure	CanESM2	1961-1990 (baseline climate) 2000-2099
1000hPa Wind Speed		
1000hPa Zonal Velocity		
1000hPa Meridional Velocity		
1000hPa Vorticity		
1000hPa Wind Direction		
1000hPa Divergence		
500hPa Wind Speed	CanESM2	1961-1990 (baseline climate) 2000-2099
500hPa Zonal Velocity		
500hPa Meridional Velocity		
500hPa Vorticity		
500hPa Geopotential		
500hPa Wind Direction		
500hPa Divergence		
850hPa Wind Speed	CanESM2	1961-1990 (baseline climate) 2000-2099
850hPa Zonal Velocity		
850hPa Meridional Velocity		
850hPa Vorticity		

3.2 Collection Of AR5 scenario data

3.2.1 Data and processing

This dataset comprises 29/29/29 scenario experiments for RCP2.6/4.5/8.5 from 29 climate models (Figure 4.1) (CCCma). Only concentration-driven experiments are used (i.e., those in which concentrations rather than emissions of greenhouse gases are prescribed) and only one ensemble member from each model is selected, even if multiple realizations exist with different initial conditions and different realizations of natural variability. Hence each model is given equal weight. Maps and time series are provided for three RCPs.

Table 3.1: Depicting the models used in CMIP5

#	CMIP5 Model Name	Historical	RCP2.6	RCP4.5	RCP8.5
1	BNU-ESM	1	1	1	1
2	CCSM4	1	1	1	1
3	CESM1-CAM5	1	1	1	1
4	CESM1-WACCM	1	1	1	1
5	CNRM-CM5	1	1	1	1
6	CSIRO-Mk3-6-0	1	1	1	1
7	CanESM2	1	1	1	1
8	EC-EARTH	1	1	1	1
9	FGOALS-g2	1	1	1	1
10	FIO-ESM	1	1	1	1
11	GFDL-CM3	1	1	1	1
12	GFDL-ESM2G	1	1	1	1
13	GFDL-ESM2M	1	1	1	1
14	GISS-E2-H	1	1	1	1
15	GISS-E2-R	1	1	1	1
16	HadGEM2-AO	1	1	1	1
17	HadGEM2-ES	1	1	1	1
18	IPSL-CM5A-LR	1	1	1	1
19	IPSL-CM5A-MR	1	1	1	1
20	MIROC-ESM	1	1	1	1
21	MIROC-ESM-CHEM	1	1	1	1
22	MIROC5	1	1	1	1
23	MPI-ESM-LR	1	1	1	1
24	MPI-ESM-MR	1	1	1	1
25	MRI-CGCM3	1	1	1	1
26	NorESM1-M	1	1	1	1
27	NorESM1-ME	1	1	1	1
28	bcc-csm1-1	1	1	1	1
29	bcc-csm1-1-m	1	1	1	1
	Number of models	29	29	29	29

3.2.2 Reference Period

Projections are expressed as anomalies with respect to the reference period of 1986-2005 for both time series and spatial maps (i.e., differences between the future period and the reference period)

3.2.3 Equal Model Weighting

The different CMIP5 models used for the projections in the plots are all considered to give equally likely projections in the sense of 'one model, one vote'. Models with variations in physical parameterization schemes are treated as distinct models.

3.2.4 Seasons

The standard meteorological seasons, March to May, June to August, September to October, and December to February, are used.

3.2.5 Variables for graphics and tables

Six variables are provided for CMIP5 graphics and tables: surface air temperature change, relative precipitation change, sea ice thickness change, sea ice concentration change, snow depth change, and near-surface wind speed change. The relative precipitation change is defined as the percentage change from the 1986-2005 reference period in each ensemble member.

For the time series, the variables are first averaged over the domain and then the changes from the reference period are computed.

3.2.6 Time series

The areal mean is computed on the common 1x1 degree grid using land points. As an indication of the model uncertainty and natural variability, the time series of each model and scenario over the common period 1900-2100 are shown on the top of the page as anomalies relative to 1986-2005. The multi-model ensemble means are also shown. Finally, for the period 2081-2100, the 20-year means are computed and the box-and-whisker plots show the

25th, 50th (median) and 75th percentiles sampled over the distribution of the 20-year means of the model time series, including both natural variability and model spread.

3.2.7 Spatial maps

Maps shown on CCDS show the difference between the periods, 2016-2035, 2046-2065 and 2081-2100, and the reference period, 1986-2005. The colour scale is kept constant for all maps.

As local projections of climate change are uncertain, a measure of the range of model projections is shown in addition to the median response of the model ensemble interpolated to a common 1x1 degree grid. It should again be emphasized that this range does not represent the full uncertainty in the projection. The distribution combines the effects of natural variability and model spread

3.3 Observed 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). The data used are maximum temperature, minimum temperature, mean temperature, precipitation. Data was collected from six distinct geographical regions of India so that spatial stability could also be tested. The regions included Rourkela and Mumbai

India is a land of diverse climate. So to get an idea of climate change impact on the water resources, data was collected from distinct geographical and climatic locations.

In India, an increase in the surface air temperature has been observed in the past century.A warming trend is visible along the west coast, central India, interior peninsula and the North-Eastern India, but some cooling trends are also visible in the North-West India and parts of South-India. (NAPCC, 2008). To analyze the comparative change in the Indian peninsula, both sea level temperature and land surface temperature are required to be recorded on long term basis at different climatic zones of the country.

Indian monsoon rains are the backbone of Indian economy as most of our agricultural activities, rivers and replenishment of ground water sources have a direct dependence on monsoon rains. Monsoon rains are a manifestation of the complex interactions between land, ocean and atmosphere. Rainfall data are collected by the India Meteorological Department (IMD) in respect of the meteorological subdivisions of the country on day-to-day basis. A significantly long series of rainfall data are therefore available to analyze patterns of change in distribution, intensity and duration of rainfall.

The framework for statistics related to climate change included the following variables/indicators .

Temperature /Precipitation

(i) Rain Fall Max/Min./Avg

(ii) Snowfall

(iii) Temperature Max/Min/Avg

(iv) Relative Humidity

Table 3.3.2: Rainfall Data

Year	Annual		Jan-Feb		Mar-May		June-Sept		Oct-Dec	
	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
1940	19.24	28.88	13.57	24.46	20.31	30.66	23.25	30.93	16.62	27.24
1941	19.85	29.46	14.25	24.37	21.53	32.12	23.52	31.37	17.00	27.62
1942	19.45	28.98	14.10	24.03	21.19	31.80	23.37	30.99	16.20	27.23
1943	19.06	28.80	13.75	24.03	20.33	30.80	23.10	30.83	16.02	27.33
1944	19.18	28.89	13.45	23.62	20.39	31.03	23.29	31.25	16.38	27.16
1945	18.89	28.97	12.93	23.86	20.26	31.19	23.36	31.48	15.52	26.82
1946	19.38	29.37	13.55	25.49	20.73	31.50	23.25	31.23	16.76	27.30
1947	19.23	28.84	13.57	23.99	21.05	31.78	23.46	31.20	16.08	26.70
1948	19.49	28.73	14.03	23.62	20.81	31.27	23.32	30.84	16.70	26.77
1949	19.28	28.89	13.87	24.49	21.01	31.27	23.29	30.88	15.80	26.79
1950	18.95	28.47	13.39	24.02	20.28	30.72	23.25	30.48	15.72	26.58
1951	19.36	29.09	13.20	24.16	20.27	30.67	23.24	31.13	17.16	27.77
1952	19.51	29.16	14.53	25.17	20.91	31.13	23.39	31.11	16.27	27.26
1953	19.71	29.43	14.22	24.71	21.55	32.19	23.52	31.12	16.46	27.56
1954	19.33	28.92	14.02	24.20	21.11	31.89	23.28	30.90	15.84	26.46
1955	19.19	28.76	14.02	24.90	20.29	30.88	23.23	30.72	16.13	26.59
1956	19.29	28.63	13.25	24.40	21.09	31.53	23.07	30.25	16.46	26.37
1957	19.30	28.64	13.60	23.87	20.09	30.42	23.23	31.07	17.06	26.82
1958	19.92	29.34	14.58	25.43	21.18	31.74	23.64	31.23	17.26	27.01
1959	19.60	29.02	13.82	24.05	20.93	31.71	23.48	30.99	16.96	27.03
1960	19.27	29.31	13.99	25.49	20.25	31.17	23.40	31.29	16.32	27.36
1961	19.27	28.72	13.79	24.18	20.76	31.47	23.38	30.75	15.96	26.30
1962	19.20	28.89	13.52	24.24	20.53	31.31	23.21	31.08	16.32	26.65
1963	19.28	29.04	13.39	24.73	20.24	30.94	23.14	31.28	17.08	27.00
1964	19.11	29.09	13.38	24.29	20.87	31.89	23.01	30.82	15.96	27.20
1965	18.98	29.16	13.76	24.67	19.76	30.73	22.80	31.37	16.57	27.61
1966	19.31	29.41	14.32	25.54	20.46	31.69	23.12	31.24	16.40	27.26
1967	19.08	29.14	13.57	25.31	20.07	31.04	23.07	31.32	16.43	26.90
1968	18.83	29.07	12.82	23.68	20.02	31.24	22.94	31.55	16.18	27.19
1969	19.32	29.61	13.40	24.99	20.76	32.02	23.17	31.55	16.69	27.71
1970	19.16	29.47	13.92	25.19	20.77	32.03	23.11	31.16	15.76	27.50
1971	18.77	29.15	13.18	24.99	20.16	31.58	22.72	30.91	15.84	27.17
1972	18.91	29.31	12.70	24.49	20.10	31.49	22.91	31.67	16.53	27.21
1973	19.38	29.44	14.12	25.35	20.88	32.19	23.34	31.28	16.09	26.97
1974	18.76	29.26	12.77	24.34	20.57	31.92	22.67	31.39	15.73	27.03
1975	18.62	28.89	13.26	24.12	20.03	31.62	22.51	30.66	15.58	26.99
1976	18.90	29.27	13.18	24.61	19.83	31.45	22.66	31.09	16.76	27.76
1977	19.31	29.41	13.51	25.15	20.42	31.65	23.09	31.22	17.01	27.59
1978	19.25	29.23	13.50	24.36	20.41	31.57	23.09	31.11	16.79	27.64
1979	19.55	29.63	13.94	24.99	20.30	31.70	23.27	31.87	17.56	27.67

Table 3.3.3: Rainfall Data

Year	Annual		Jan-Feb		Mar-May		June-Sept		Oct-Dec	
	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
1901	19.51	28.96	14.16	23.27	20.67	31.46	23.38	31.27	16.59	27.25
1902	19.44	29.22	13.64	25.75	21.12	31.76	23.28	31.09	16.50	26.49
1903	19.25	28.47	13.87	24.24	20.25	30.71	23.40	30.92	16.29	26.26
1904	19.22	28.49	13.72	23.62	20.72	30.95	22.96	30.66	16.44	26.40
1905	19.03	28.30	12.81	22.25	19.97	30.00	23.43	31.33	16.39	26.57
1906	19.51	28.73	13.72	23.03	20.76	31.11	23.45	30.86	16.88	27.29
1907	19.08	28.65	14.46	24.23	19.87	29.92	22.98	30.80	16.14	27.36
1908	19.09	28.83	13.68	24.42	20.61	31.43	23.19	30.72	15.70	26.64
1909	19.13	28.38	13.33	23.52	20.40	31.02	22.97	30.33	16.61	26.88
1910	19.01	28.53	13.68	24.20	20.35	31.14	23.15	30.48	15.72	26.20
1911	19.31	28.62	13.81	23.90	20.41	30.70	23.26	31.14	16.66	26.31
1912	19.27	28.95	14.56	24.88	20.54	31.10	23.12	31.15	16.02	26.57
1913	19.09	28.67	13.91	24.25	20.24	30.89	22.96	30.92	16.24	26.42
1914	19.41	28.66	14.03	24.59	20.33	30.73	23.47	30.84	16.66	26.40
1915	19.64	28.94	13.73	23.22	21.00	31.06	23.72	31.51	16.79	27.19
1916	19.34	28.82	13.64	24.57	20.95	31.88	23.31	30.52	16.23	26.31
1917	19.02	28.11	13.60	24.52	19.72	30.06	23.29	30.24	16.25	25.74
1918	19.02	28.66	13.24	23.57	20.15	30.68	23.06	31.10	16.33	26.78
1919	19.37	28.66	14.22	23.71	20.53	31.17	23.33	30.80	16.36	26.60
1920	19.07	28.76	13.79	23.64	20.15	30.40	23.01	31.08	16.26	27.45
1921	19.54	28.86	13.85	23.91	21.16	32.05	23.18	30.81	16.34	26.43
1922	19.32	28.80	14.31	24.43	20.56	31.21	23.27	30.90	16.03	26.38
1923	19.36	28.74	13.88	23.73	20.83	31.40	23.24	30.98	16.37	26.43
1924	19.52	28.80	14.11	23.94	20.86	31.44	23.42	30.96	16.56	26.49
1925	19.24	28.67	13.05	23.57	20.90	31.47	23.18	30.67	16.43	26.59
1926	19.37	28.70	14.63	24.73	20.36	30.21	23.69	31.14	15.92	26.61
1927	19.30	28.59	13.81	23.76	20.30	30.72	23.18	30.80	16.80	26.73
1928	19.61	28.98	14.57	24.21	20.86	31.51	23.23	31.14	16.90	26.74
1929	19.40	28.76	13.71	23.53	21.00	31.72	23.17	31.03	16.55	26.28
1930	19.21	28.65	13.27	23.20	20.70	30.94	23.10	30.98	16.51	26.90
1931	19.73	29.15	14.52	24.55	21.01	31.71	23.44	31.16	16.97	26.97
1932	19.32	29.09	13.72	24.51	20.65	31.17	23.36	31.25	16.33	27.18
1933	19.35	28.49	14.08	24.13	20.25	30.43	23.34	30.41	16.63	26.92
1934	19.22	29.03	13.78	24.53	20.50	31.28	23.37	31.22	16.16	26.94
1935	19.21	28.76	13.84	23.41	20.39	31.15	23.07	30.85	16.41	26.88
1936	19.53	28.71	13.96	24.11	20.87	31.17	23.18	30.68	17.03	26.69
1937	19.25	28.70	14.11	24.13	20.39	30.84	23.40	31.22	16.02	26.26
1938	19.28	28.70	13.61	23.31	21.25	31.74	23.14	30.59	15.95	26.71
1939	19.16	28.85	13.95	24.25	20.08	30.76	23.23	31.06	16.29	27.05
									Continued	

Table 3.3.4: Rainfall Data

Year	Annual		Jan-Feb		Mar-May		June-Sept		Oct-Dec	
	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
1980	19.53	29.58	14.07	25.21	20.97	32.20	23.22	31.36	16.82	27.51
1981	19.25	29.32	13.94	24.90	20.67	31.64	23.14	31.34	16.17	27.24
1982	19.21	29.12	13.77	24.51	20.06	30.79	23.10	31.55	16.81	27.26
1983	19.14	29.11	13.57	24.62	20.10	30.84	23.41	31.48	16.20	27.23
1984	19.25	29.28	13.62	24.11	20.90	32.12	23.12	31.09	16.18	27.46
1985	19.30	29.61	13.93	25.29	20.94	32.51	22.98	31.28	16.33	27.35
1986	19.09	29.33	13.61	24.64	20.31	31.58	22.92	31.44	16.43	27.40
1987	19.42	29.72	13.81	25.07	20.32	31.37	23.53	32.24	16.80	27.82
1988	19.33	29.55	14.07	25.39	20.72	31.75	23.17	31.34	16.33	27.76
1989	18.96	29.18	13.02	24.51	20.18	31.35	22.93	31.11	16.41	27.57
1990	19.29	29.14	13.91	25.00	20.23	30.84	23.19	31.18	16.74	27.50
1991	19.29	29.32	13.73	24.74	20.63	31.46	23.29	31.45	16.34	27.40
1992	19.15	29.23	13.57	24.60	20.07	31.32	23.15	31.28	16.62	27.49
1993	19.34	29.55	13.91	25.31	20.41	31.61	23.25	31.47	16.69	27.74
1994	19.48	29.46	14.45	25.09	20.76	31.85	23.32	31.30	16.43	27.52
1995	20.39	30.18	14.99	25.68	21.47	32.40	24.16	32.01	17.84	28.52
1996	19.55	29.58	15.28	26.30	20.93	32.07	23.29	31.19	16.24	27.29
1997	19.21	29.05	13.13	24.63	20.14	31.26	23.45	31.77	17.21	26.65
1998	19.84	29.70	14.49	24.96	20.97	31.89	23.67	31.75	17.03	27.83
1999	19.53	29.81	14.43	25.16	20.85	32.45	23.24	31.55	16.65	27.95
2000	19.48	29.75	13.84	24.82	20.77	32.22	23.25	31.25	16.88	28.53
2001	19.49	29.99	13.60	25.88	21.04	32.61	23.36	31.62	16.95	28.13
2002	19.78	30.23	13.93	25.37	21.38	33.06	23.41	32.02	16.79	28.36
2003	19.70	29.75	14.32	25.32	21.00	32.05	23.56	31.72	16.76	27.70
2004	19.69	29.79	14.39	25.47	21.30	32.69	23.27	31.42	16.84	27.65
2005	19.58	29.60	14.63	24.96	20.85	31.81	23.46	31.84	16.43	27.50
2006	20.07	30.06	15.47	27.44	20.96	32.08	23.44	31.39	17.56	27.78
2007	19.69	29.84	14.47	25.73	21.06	32.32	23.59	31.40	16.62	28.03
2008	19.60	29.64	13.60	24.72	20.82	32.11	23.30	31.25	17.43	28.29
2009	19.94	30.30	14.95	26.51	21.15	32.57	23.59	32.24	17.20	27.96
2010	20.15	30.13	14.51	25.96	22.09	33.47	23.57	31.43	17.42	27.78
2011	19.58	29.82	13.84	25.33	20.68	32.07	23.56	31.55	17.16	28.23
2012	19.54	29.81	13.68	25.03	20.78	32.33	23.68	31.77	16.80	27.88
2013	19.83	29.81	14.38	25.58	21.14	32.58	23.61	31.33	16.82	27.83
2014	19.77	29.72	14.26	24.90	20.66	31.82	23.80	32.00	17.20	27.81
Source: Ministry of Earth Science (data.gov.in)										

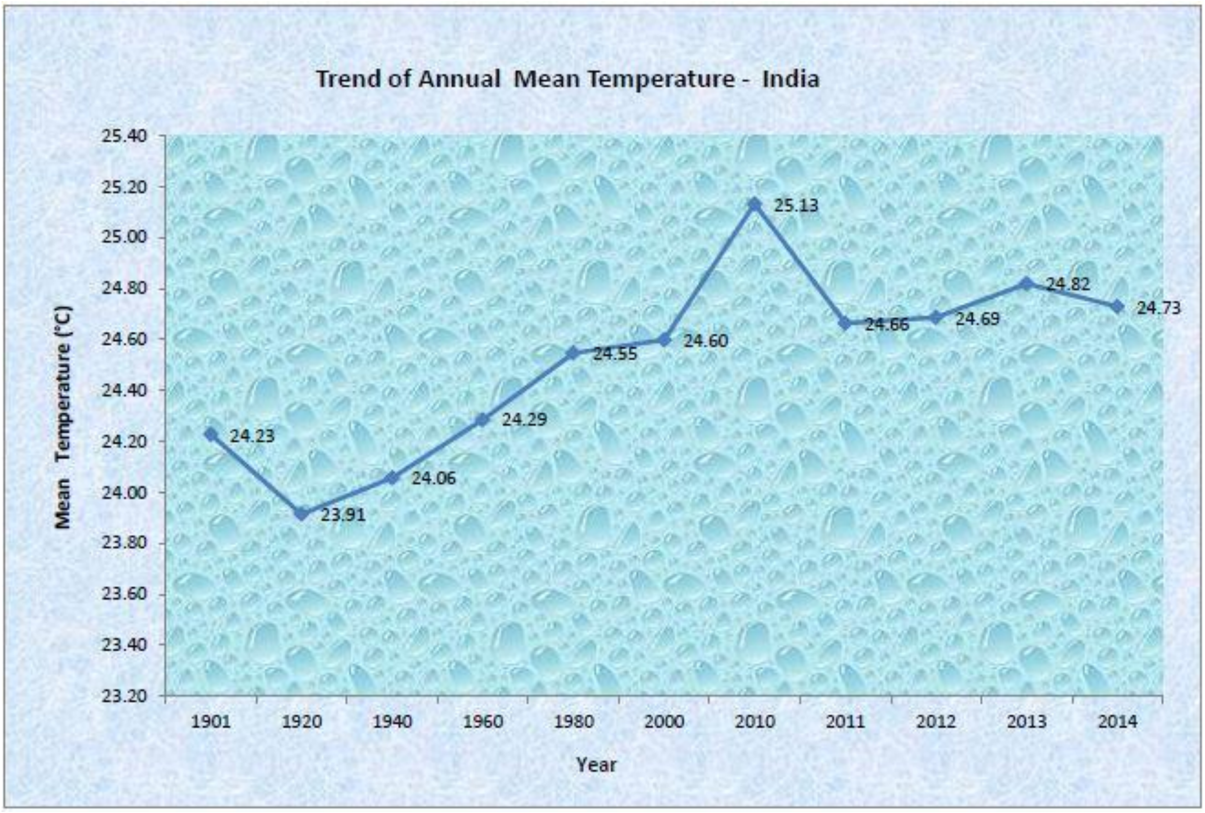


Figure 3.1: Trend of annual mean temperature - India

Table 3.5: Monthly and Annual Rainfall Data

Table 3.2.3 All India Area Weighted Monthly and Annual Rainfall (in mm) - India (1901-2014)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
1901	34.7	38.6	17.8	38.9	50.6	113.2	241.4	271.6	124.7	52.4	38.7	8.2	1030.8
1902	7.4	4.2	19.0	44.1	48.8	111.7	284.9	201.0	200.2	62.5	29.4	25.2	1038.4
1903	16.7	8.0	31.1	17.1	59.5	120.3	293.2	274.0	198.1	119.5	40.3	18.0	1195.9
1904	14.9	9.7	31.4	33.7	73.8	165.5	260.3	207.7	130.8	69.8	11.2	16.4	1025.1
1905	24.7	20.3	41.8	33.8	55.8	93.7	253.0	201.7	178.1	54.9	9.6	10.1	977.5
1906	21.4	49.9	31.4	15.8	37.2	177.0	286.5	251.4	183.9	50.6	17.7	26.3	1149.2
1907	16.0	45.5	37.4	62.0	32.7	153.1	225.4	308.3	95.4	23.0	23.1	12.9	1034.8
1908	19.9	17.1	8.3	31.0	45.4	125.6	320.5	306.0	150.8	38.4	6.8	7.4	1077.4
1909	22.7	15.2	6.6	61.6	51.2	207.2	302.3	228.7	157.7	37.5	10.0	27.9	1128.5
1910	13.5	10.3	13.7	29.0	40.8	211.9	247.2	283.4	185.9	108.2	34.6	5.4	1183.9
1911	40.4	5.5	43.0	23.1	48.2	191.3	163.1	209.9	178.5	71.5	42.4	12.1	1028.9
1912	20.3	21.6	19.9	37.9	43.8	107.1	326.3	259.2	119.2	58.2	51.7	5.3	1070.4
1913	6.3	38.1	23.7	25.7	72.9	214.8	269.8	192.6	109.6	68.6	16.8	23.2	1061.8
1914	5.0	26.9	25.4	42.8	67.9	157.0	342.0	239.7	191.3	45.5	20.7	21.6	1185.9
1915	19.8	37.5	44.1	33.6	63.9	155.1	227.9	226.9	171.7	90.5	45.2	8.2	1124.4
1916	4.6	20.1	11.0	35.2	59.4	232.0	265.0	309.7	199.6	139.2	46.3	2.9	1324.8
1917	7.6	37.9	20.5	40.1	74.0	230.7	282.7	292.8	278.1	161.3	29.1	9.3	1463.9
1918	11.8	4.0	36.6	35.8	103.6	212.3	183.8	240.9	111.8	19.5	44.7	15.5	1020.2
1919	48.8	20.2	19.1	32.7	59.5	194.7	304.6	285.3	163.1	91.5	50.1	18.2	1287.9
1920	23.9	21.3	55.1	38.2	52.5	163.7	295.7	191.6	123.0	45.9	25.2	3.0	1039.1
1921	37.6	7.4	17.8	43.9	51.2	193.9	293.7	274.4	203.3	70.5	16.1	15.3	1225.0
1922	28.9	9.8	14.3	33.0	48.8	204.9	314.9	218.9	199.8	62.0	55.6	13.3	1204.2
1923	21.6	38.9	21.2	31.0	58.1	102.0	337.8	272.8	173.8	58.0	17.6	15.8	1148.6
1924	21.1	21.9	14.0	30.7	61.4	136.8	328.7	255.4	238.4	65.8	57.1	14.6	1245.9
1925	13.0	11.2	15.3	44.1	100.8	204.7	300.9	234.5	140.2	67.2	41.5	16.1	1189.5
1926	28.3	10.3	55.7	39.4	57.8	98.7	316.9	330.5	210.1	57.3	10.9	10.3	1226.2
1927	13.1	34.7	22.4	36.3	50.4	177.7	346.6	253.2	173.6	69.3	57.2	10.1	1244.6
1928	20.9	40.3	21.1	34.6	54.4	178.9	303.5	229.0	144.0	127.7	21.6	24.4	1200.2
1929	29.6	18.6	14.4	54.6	65.9	194.1	296.7	241.0	125.5	92.9	19.6	40.1	1193.2
1930	23.5	23.2	28.9	51.0	55.9	181.5	288.6	212.0	174.1	96.7	53.0	10.3	1198.5
1931	12.4	32.9	19.0	37.3	59.4	134.5	319.6	303.9	191.1	120.5	41.4	21.0	1292.8
1932	9.2	22.9	20.1	31.0	85.7	141.7	328.3	237.9	181.9	69.4	60.3	14.4	1202.9
1933	16.5	29.6	25.1	48.1	102.4	215.1	279.7	313.4	211.6	93.6	20.5	16.5	1372.0
1934	23.3	11.5	16.1	46.8	47.3	217.7	284.8	294.4	166.8	65.8	32.4	10.5	1217.5
1935	26.9	20.7	19.0	41.5	36.8	159.4	313.5	246.9	185.3	49.9	16.7	11.2	1127.9
1936	12.3	41.8	37.8	33.5	82.7	245.8	292.5	236.7	193.9	66.4	57.2	21.2	1321.8
1937	6.3	50.6	19.0	56.3	58.0	162.2	336.2	208.2	174.0	94.6	20.3	18.9	1204.4
1938	29.9	30.7	33.4	34.2	70.9	273.4	300.2	249.7	171.6	75.4	16.2	5.0	1290.5
1939	13.3	32.1	30.6	40.7	40.6	172.9	272.4	231.5	154.9	91.2	29.6	1.7	1111.6

Table 3.6: Monthly and Annual Rainfall Data

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
1940	13.0	25.8	47.7	26.9	80.8	173.8	308.4	278.1	125.5	63.0	40.9	17.4	1201.3
1941	22.9	16.4	20.4	31.5	81.0	171.8	238.7	228.4	154.0	62.1	26.5	20.3	1073.9
1942	21.4	46.0	20.6	44.7	63.7	191.5	339.6	287.0	182.5	34.5	17.7	23.5	1272.9
1943	56.8	9.8	32.5	47.9	94.3	167.8	308.9	228.4	211.4	89.0	17.1	5.2	1269.2
1944	27.6	37.8	54.9	31.9	61.0	155.6	349.1	287.0	156.2	92.3	29.4	15.6	1298.5
1945	34.2	10.2	20.1	47.1	53.6	159.1	333.3	246.7	214.5	80.6	17.9	4.9	1222.0
1946	4.4	19.1	24.5	48.0	71.3	214.0	318.3	296.3	145.0	84.4	76.0	35.8	1337.2
1947	22.4	18.3	26.0	39.1	55.9	130.1	314.4	290.4	240.0	69.8	7.2	22.6	1236.3
1948	25.2	29.0	39.5	42.5	91.3	164.1	347.7	282.7	178.0	61.2	71.1	10.0	1342.2
1949	12.6	28.8	24.1	53.0	89.3	164.3	316.8	243.2	227.0	95.1	10.6	4.7	1269.6
1950	35.4	25.4	36.7	28.7	49.4	135.7	331.6	235.6	202.6	57.7	27.5	7.9	1174.2
1951	15.7	12.1	44.4	54.4	59.4	163.3	252.7	222.8	124.6	73.9	31.3	5.8	1060.6
1952	10.5	19.8	37.4	32.4	69.7	165.6	286.6	256.6	120.0	79.6	9.2	22.5	1110.1
1953	30.2	10.6	25.3	38.3	47.1	162.2	323.1	299.2	179.9	85.8	12.3	8.0	1222.1
1954	37.6	37.2	17.1	22.8	53.9	145.5	297.2	232.0	246.7	73.8	3.6	13.9	1181.4
1955	20.8	4.1	21.3	30.6	72.6	177.7	236.8	313.8	215.7	146.3	26.4	9.3	1275.4
1956	17.0	11.1	31.5	28.1	85.5	211.0	354.1	254.3	163.9	150.1	44.0	11.9	1362.6
1957	31.1	10.9	24.2	39.5	71.2	153.2	300.8	265.4	131.7	64.0	28.6	11.3	1131.9
1958	12.4	16.5	19.1	36.9	80.5	123.7	316.9	324.9	225.7	114.7	30.0	10.9	1312.3
1959	31.8	23.8	21.3	25.9	75.3	169.8	375.5	265.1	237.3	119.7	26.0	5.3	1376.9
1960	13.8	2.7	35.2	20.0	57.7	157.3	320.0	252.9	184.7	68.5	33.7	8.3	1154.8
1961	26.1	34.8	26.0	28.5	77.6	192.9	336.6	287.6	234.9	122.2	21.7	10.4	1399.2
1962	12.6	21.6	16.0	43.6	70.8	137.1	281.6	276.9	211.0	78.4	18.3	29.9	1198.0
1963	6.8	9.8	41.7	50.6	60.9	168.0	258.6	316.7	164.9	99.1	28.4	15.5	1220.9
1964	18.6	14.1	19.0	40.0	52.1	177.2	345.7	273.7	200.4	67.4	22.8	13.3	1244.4
1965	11.8	28.1	26.7	45.1	52.7	116.1	270.1	192.8	129.5	34.0	18.2	22.2	947.4
1966	13.1	25.4	20.3	30.6	57.2	178.8	252.5	212.5	143.9	56.1	51.0	16.7	1058.0
1967	11.1	14.2	63.3	29.5	42.8	144.0	305.6	264.3	170.3	40.6	12.1	56.1	1154.0
1968	29.4	19.8	27.5	32.6	46.7	149.6	309.9	212.8	129.5	67.1	21.8	12.6	1059.3
1969	12.7	14.5	20.1	39.7	63.4	130.2	317.8	273.4	172.7	55.0	35.8	12.7	1147.8
1970	23.2	27.3	25.9	29.2	69.7	215.9	245.6	313.0	212.7	75.3	15.7	1.6	1255.0
1971	16.1	23.6	10.8	52.8	75.0	229.9	267.2	267.3	146.5	99.9	15.9	12.0	1216.9
1972	10.3	27.6	21.6	37.1	55.3	123.3	204.0	219.5	127.5	65.7	31.4	23.7	947.1
1973	21.0	21.8	21.2	27.5	56.5	149.9	277.4	311.0	182.1	114.6	18.9	17.7	1219.5
1974	16.1	12.9	20.5	33.7	64.2	122.0	283.6	232.5	145.3	101.6	10.7	12.1	1055.3
1975	15.4	20.8	28.7	28.3	50.2	175.6	310.7	292.5	224.6	121.9	22.8	3.3	1294.8
1976	11.5	24.5	25.5	36.3	45.4	160.3	294.1	294.0	144.2	33.0	55.0	7.6	1131.6
1977	21.0	10.2	14.6	68.3	84.4	187.2	323.4	245.4	147.8	85.6	65.8	16.1	1269.7
1978	12.3	27.0	44.2	33.1	60.2	208.8	290.0	282.0	161.9	49.1	49.9	18.8	1237.2
1979	20.9	35.0	28.9	21.2	54.2	140.5	239.6	210.6	136.8	51.8	76.1	14.4	1030.2

Table 3.7: Monthly and Annual Rainfall Data

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
1980	12.8	22.3	32.5	34.6	55.3	227.8	295.0	263.8	145.7	49.3	24.2	19.0	1182.3
1981	29.3	20.4	48.0	37.3	67.1	151.3	309.1	237.0	184.5	45.1	27.4	14.0	1170.7
1982	23.8	24.2	45.7	49.8	59.0	137.8	230.8	276.9	124.9	51.7	46.0	13.9	1084.4
1983	18.5	23.3	43.4	57.0	70.1	150.8	282.2	304.3	251.6	85.9	10.8	22.9	1320.9
1984	19.0	35.9	22.8	45.3	60.4	192.3	291.9	256.5	144.6	61.0	15.7	15.3	1160.8
1985	23.2	9.9	20.1	39.5	63.0	156.5	290.1	231.7	149.6	114.1	18.8	28.4	1144.9
1986	15.5	36.6	29.9	50.0	49.4	182.6	264.2	228.3	128.4	74.7	49.6	28.4	1137.6
1987	13.2	23.8	28.8	43.9	67.0	133.9	223.2	242.1	152.2	94.4	44.4	21.9	1088.9
1988	10.4	28.7	53.7	41.7	70.4	161.8	374.8	295.3	217.7	53.6	16.2	17.8	1342.1
1989	15.4	15.3	28.8	34.6	57.5	184.7	302.3	236.2	163.1	51.9	20.3	17.2	1127.4
1990	16.0	44.2	54.0	43.8	112.9	191.3	282.9	293.6	197.4	104.1	30.2	31.0	1401.4
1991	14.3	28.1	27.8	51.7	68.9	184.7	279.2	268.1	140.7	61.8	30.2	14.7	1170.2
1992	16.0	16.5	24.8	26.1	59.3	139.7	262.5	274.0	171.7	64.7	41.6	5.6	1102.7
1993	18.2	25.6	41.6	27.0	71.3	172.1	305.4	203.2	208.5	87.9	30.5	16.5	1207.8
1994	25.0	27.9	25.2	45.9	53.1	205.7	350.0	282.2	149.4	82.8	25.5	22.6	1295.3
1995	31.3	29.4	28.3	32.4	82.4	143.3	323.4	269.0	179.0	78.0	36.8	9.2	1242.4
1996	22.9	23.2	32.1	31.4	56.0	185.7	262.1	292.4	146.1	100.5	13.6	16.9	1182.9
1997	14.3	10.4	30.3	46.0	48.6	171.7	281.5	261.9	151.4	61.1	57.6	48.3	1183.1
1998	16.4	28.2	39.1	36.3	49.2	163.9	278.4	243.8	196.5	107.4	39.3	10.3	1208.8
1999	13.7	11.2	8.8	19.3	94.9	169.9	261.7	213.2	183.0	117.2	20.0	3.7	1116.6
2000	18.4	28.2	17.9	34.7	71.6	179.0	263.5	221.1	134.5	41.9	14.6	10.0	1035.4
2001	6.7	11.6	19.9	44.6	62.9	221.2	281.1	205.5	111.0	100.4	19.7	16.1	1100.7
2002	17.1	20.1	23.8	38.6	59.8	172.6	143.8	246.1	137.9	55.6	15.6	5.0	935.9
2003	7.3	42.3	36.7	36.6	40.1	169.3	306.5	243.6	183.4	92.7	11.5	17.2	1187.3
2004	25.1	10.0	12.8	55.2	80.6	171.1	250.5	254.0	131.5	95.0	17.9	2.8	1106.5
2005	28.1	41.8	42.5	37.7	46.1	143.2	334.1	190.1	206.9	99.3	27.2	11.2	1208.3
2006	17.7	11.9	35.6	32.7	75.0	141.8	287.6	281.3	178.6	51.8	34.6	13.1	1161.6
2007	1.7	36.7	35.2	30.6	46.8	192.5	286.2	257.4	206.8	55.7	14.4	15.3	1179.3
2008	18.4	19.3	41.2	29.5	43.7	202.0	245.0	265.8	165.1	51.6	25.5	11.0	1118.0
2009	12.0	12.0	14.2	25.1	56.0	85.7	280.7	192.5	139.4	71.4	53.7	11.1	953.7
2010	7.5	17.0	14.0	39.0	73.8	138.1	300.7	274.7	197.7	69.0	61.4	22.7	1215.5
2011	6.8	25.8	22.4	41.1	53.1	183.5	246.0	284.9	186.9	38.1	20.1	7.6	1116.3
2012	26.5	12.7	11.3	47.5	31.7	117.8	250.2	262.4	193.5	58.7	30.7	11.7	1054.7
2013	11.3	40.1	15.7	30.3	57.8	219.8	310.1	254.9	152.6	129.3	14.0	6.7	1242.6
2014	19.3	27.4	36.1	22.1	72.9	95.2	261.1	237.4	187.9	60.1	14.4	10.7	1044.6

Source: Ministry of Earth Science (data.gov.in)

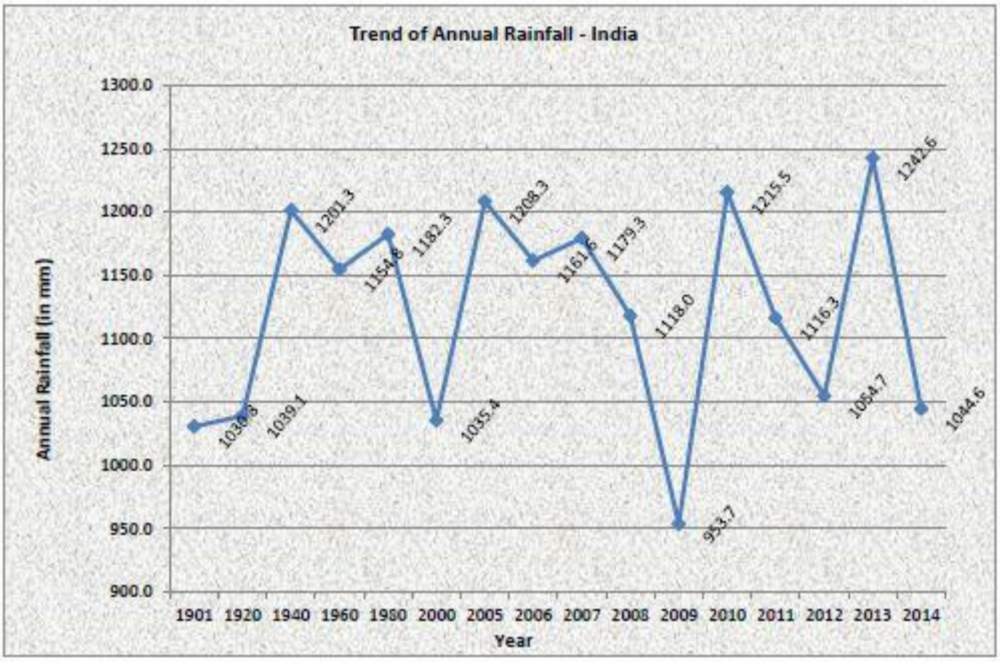


Figure 3.2: Trend of annual rainfall - India

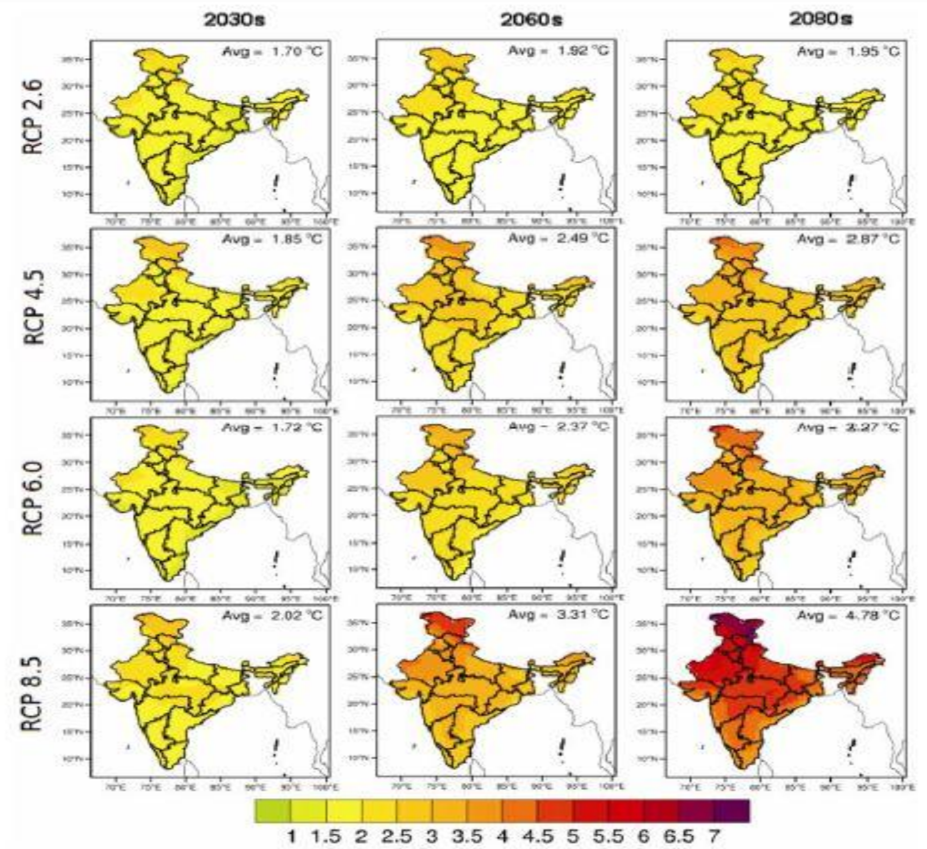


Figure 3.3: Temperature change in the RCP scenarios

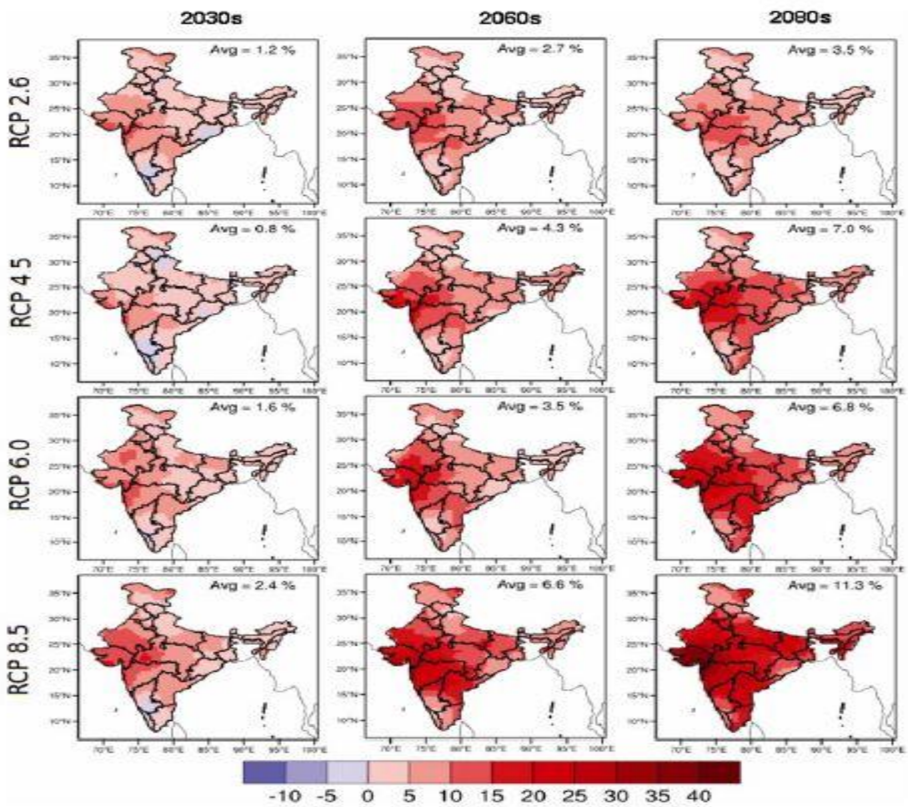


Figure 3.4: Temperature changes in RCP scenarios

CHAPTER 4: METHODOLOGY

4.1 Weather Typing

Weather typing approaches involve grouping local, meteorological data in relation to prevailing patterns of atmospheric circulation. Future regional climate scenarios are created, either by re–sampling from the observed data distributions (conditional on the circulation patterns produced by a GCM), or by first generating synthetic sequences of weather patterns using Monte Carlo techniques and re–sampling from observed data. The main appeal of circulation–based downscaling is that it is founded on sensible linkages between climate on the large scale and weather at the local scale. The technique is also valid for a wide variety of environmental variables and also multi–site applications. But, weather typing schemes are often parochial,a poor basis for downscaling rare events, and entirely dependent on stationary circulation–to–surface climate relationships. Potentially, the most serious limitation is that precipitation changes produced by changes in the frequency of weather patterns are seldom consistent with the changes produced by the host GCM (unless additional predictors such as atmospheric humidity are employed)

4.2 Regression based Modelling

Regression–based downscaling methods rely on empirical relationships between local scale predictands and regional scale predictor(s). Individual downscaling schemes differ according to the choice of mathematical transfer function, predictor variables or statistical fitting procedure. To date, linear and non–linear regression, artificial neural networks, canonical correlation and principal components analyses have all been used to derive predictor–predictand relationships. The main strength of regression downscaling is the relative ease of application, coupled with their use of observable trans–scale relationships. The main weakness of regression–based methods is that the models often explain only a fraction of the observed climate variability (especially in precipitation series). In common with weather typing methods, regression methods also assume validity of the model parameters under future climate conditions, and regression–based downscaling is highly sensitive to the choice of predictor variables and statistical transfer function (see below). Furthermore, downscaling future extreme events using regression methods is problematic since these phenomena, by definition, tend to lie at the limits or beyond the range of the calibration data sets.

4.3 SDSM Structure

Downscaling is justified whenever GCM (or RCM) simulations of variable(s) used for impacts modelling are unrealistic at the temporal and spatial scales of interest, either because the impact scales are below the climate model's resolution, or because of model deficiencies. Downscaling may also be used to generate scenarios for exotic variables that cannot be obtained directly from GCMs and RCMs. However, the host GCM must have demonstrable skill for large–scale variables that are strongly correlated with local processes. In practice, the choice of downscaling technique is also governed by the availability of archived observational and GCM data because both are needed to produce future climate scenarios. The SDSM software reduces the task of statistically downscaling daily weather series into seven discrete processes (denoted by heavy boxes in Figure 4.1):

1. quality control and data transformation;
2. screening of predictor variables;
3. model calibration;
4. weather generation (observed predictors);
5. statistical analyses;
6. graphing model output;
7. scenario generation (climate model predictors).

4.3.1 Quality Control and Data transformation

It handles the missing and incomplete data which is necessary for practical situations. It identifies missing data, gross data errors and outliers. Transform functions converts data to suitable forms such as log, exponential.

4.3.2 Screen Variables

It helps the user to select proper predictor variables .It checks the highest correlation. Seasonal variations can also be taken into account.

4.3.3 Model Calibration

This enables the user to specify predictand along with a set of predictors. It calculates the parameter of multiple linear regression with the forced entry method. Whether annual, monthly or seasonal analysis is to be done can be specified by the user. Also conditional factors can be added.

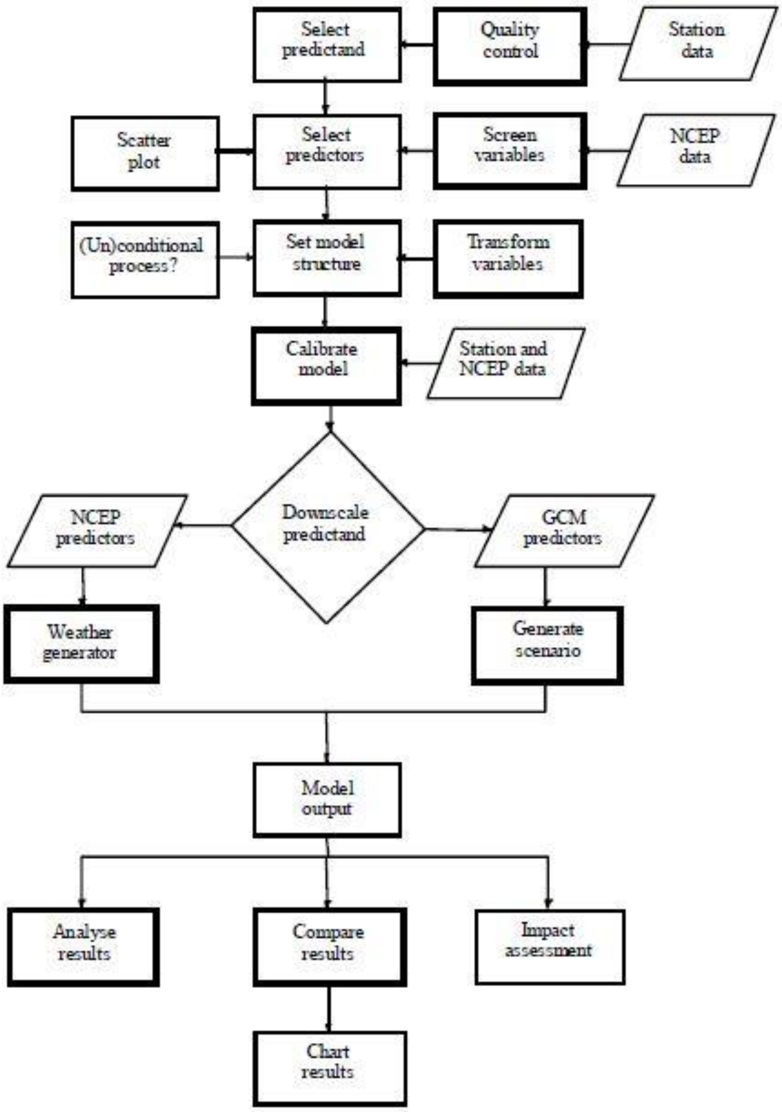


Figure 4.1: SDSM methodology flow chart

4.3.4 Weather Generator

The User selects a calibrated model and SDSM automatically links all necessary predictors to regression model weights. The User must also specify the period of record to be synthesised as well as the desired number of ensemble members. Synthetic time series are written to specific output files for later statistical analysis and/or impacts modelling.

4.3.5 Data Analysis

This analyses both the observed data and the simulated data produced.

4.3.6 Graphical comparison

This generates and compares the graphs. Time series Plot analyses the data as monthly, seasonal, annual or water year periods for statistics such as Sum, Mean, Maximum, Winter/Summer ratios.

4.3.7 Scenario Generator

Generate Scenario operation produces ensembles of synthetic daily weather series given atmospheric predictor variables supplied by a climate model (either for current or future climate experiments), rather than observed predictors. It is similar to weather generator except it is necessary to specify convention for model dates and predictor variables.

4.4 Trend Detection Analysis

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. Temperature and precipitation has the maximum influence on the water resources. For instance, increasing trend in temperature will enhance the evaporation, decreasing trend in precipitation will result in less run off. There are many tests to detect the trend in a time series on each climatic parameter. The test can be parametric or non-parametric. 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).

4.4.1 Mann-Kendall test

The Mann-Kendall test is a nonparametric trend test which has the same power as the Spearman's rho test in detecting monotonic trends (Yue et al., 2002). It is appropriate for data that do not display seasonal variation, or for seasonally corrected data, with negligible autocorrelation.

The non- seasonal Mann-Kendall test (M-K) is applicable in cases when the data values Yi of a time series can be assumed to obey the model

$$Y_i = f(T_i) + \varepsilon_i$$

where $f(T_i)$ is a continuous monotonic increasing or decreasing function of time and the residuals åi can be assumed to be from the same distribution with zero mean. It is therefore assumed that the variance of the distribution is constant in time.

The M-K test is based on the statistic S (Gilbert, 1987). When only one datum per time period is taken, each pair of observed values Yi, Yj ($i > j$) of the random variable is inspected to find out whether $Yi > Yj$ or $Yi < Yj$. Let the number of the former type of pairs be P, and the number of the latter type of pairs be M. Then S is defined as

$$S = P - M$$

If n is 10 or less, the absolute value of S is compared directly to the theoretical distribution of S derived by Mann and Kendall (Gilbert, 1987). Then Ho is rejected in favor of H1 if the probability value corresponding to the absolute value of S is less than the a priori specified á significance level of the test. A positive (negative) value of S indicates an upward (downward) trend. For time series time series with 10 or more data points the normal approximation is used. The test procedure is to first compute S using the above equation (S = P – M) as described before. Then compute the variance of S by the following equations:

$$\mathrm{Var(S)} = \begin{cases} \dfrac{\mathrm{n(n-1)(2n+5)} - \sum_{j=1}^{p} t_j(t_j-1)(2t_j+5)}{18} & if\ ties \\ \dfrac{\{n(n-1)(2n+5)\}}{18} & no\ ties \end{cases}$$

where n is the number of data, p is the number of tied groups in the data set and t_j is the number of data points in the jth tied group.

Then S and Var(S) are used to compute the test statistic Z as follows:

$$Z = \begin{cases} \dfrac{S-1}{Var(S)^{1/2}} & if\ S > 0 \\ 0 & if\ S = 0 \\ \dfrac{S+1}{Var(S)^{1/2}} & if\ S < 0 \end{cases}$$

There is a correction for ties (±1 added to the S) when yi = yj (Salas, 1993, as cited in (Gilbert, 1987).

The standardized test statistic Z is approximately normally distributed. A positive (negative) value of Z indicates an upward (downward) trend. To test for the either upward or downward trend (a two-tailed test) at the α level of significance, Ho is rejected if $|Z| > Z_{(1-(\alpha/2)}$. If the alternative hypothesis is for an upward trend (a one-tailed test), Ho is rejected if $Z > Z_{(1-(\alpha))}$.

We reject Ho in favor of the alternative hypothesis of a downward trend if Z is negative and $|Z| > Z_{(1-(\alpha))}$. Using P- value calculated for Z, Ho is rejected if $P < \alpha$.

The Kendall's correlation coefficient, a measure of the strength of the correlation, can be calculated as (Kendall, 1975)

$$\tau = \frac{S}{D}$$

Where

$$\mathrm{Var(S)} = \begin{cases} \sqrt{\left\{\dfrac{n(n-1)}{2} - \displaystyle\sum_{j=1}^{p} t_j\ (t_j - 1)\right\}}\sqrt{\left(\dfrac{n(n-1)}{2}\right)} & if\ ties \\ \dfrac{n(n-1)}{2} & no\ ties \end{cases}$$

4.4.2 Sen Slope estimator

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

$$N = \frac{x_j - x_i}{j - i}$$

where, x_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 as:

$$Q = T_{\frac{n+1}{2}} \qquad\qquad If\ N\ is\ odd$$

$$Q = \frac{1}{2}\left(T_{\frac{n}{2}} + T_{\frac{n+1}{2}}\right) \qquad If\ N\ is\ even$$

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.

4.5 Multilinear 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. Following shows a simple linear regression equation

$$E(y/x)=a + bx$$

In a multiple linear regression model, the numbers of predictor variables are more than one. This leads to the following "multiple regression" mean function:

$$(y/x)=a+b_1x_1+ b_2x_2+ \ldots\ldots\ b_nx_n$$

where, a is called the intercept and the b_n are called slopes or coefficients.

CHAPTER 5: RESULTS AND DISCUSSION

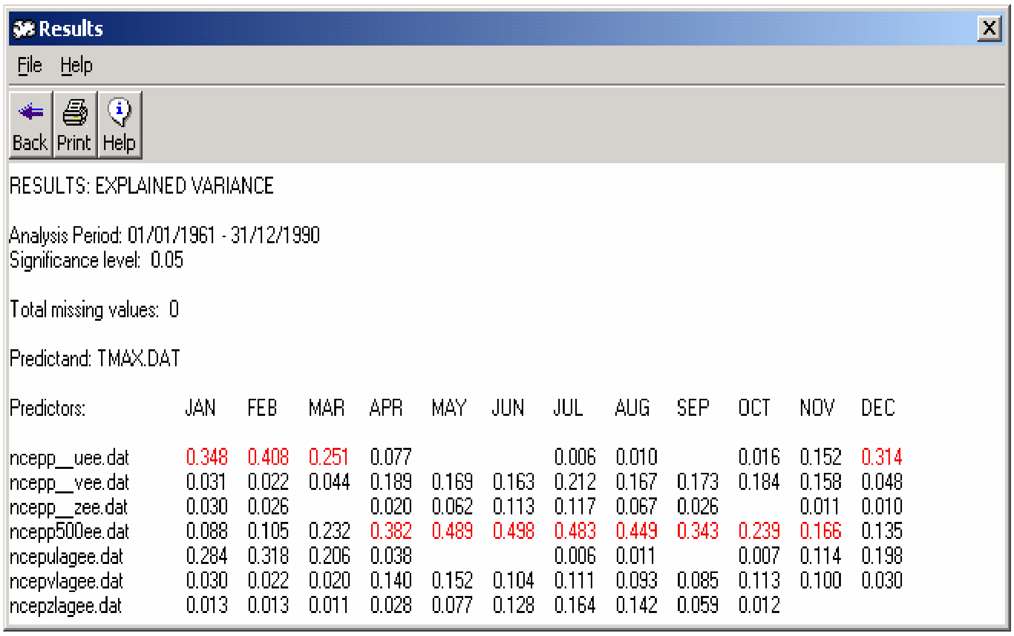
5.1 SDSM

Statistical downscaling model (SDSM) is used to simulate climatic data under current and future conditions for maximum temperature, minimum temperature and precipitation at the six stations. 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 the six stations' data for the period of 1961-1990. This 40 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 predictand and predictors are assumed while conditional processes are done with intermediate processes.

Table 5.1: Predictors used in the analysis.

Predictors	Abbreviation
Surface variables	
Specific humidity (g/kg)	q
Maximum temperature (°C)	T_{max}
Minimum temperature (°C)	T_{min}
Mean sea-level pressure (hPa)	mslp
Zonal velocity component	U_s
Meridional velocity component	V_s
Strength of the resultant flow (hPa)	F_s
Vorticity (hPa)	Z_s
Divergence (hPa)	D_s
Upper-atmosphere variables (500 hPa)	
500 hPa geopotential height (m)	H_{500}
Vorticity (hPa)	Z_{500}
Strength of the resultant flow (hPa)	F_{500}
Zonal velocity component	U_{500}
Meridional velocity component	V_{500}
Divergence (hPa)	D_{500}

For each station the variance was analysed. The following is the case of Rourkela in figure 5.1. The strongest correlation in each month is shown in red, indicating that the relationship between maximum temperature and p500 and p__u are most important. Blanks represent insignificant relationships at the chosen Significance Level



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RESULTS: EXPLAINED VARIANCE

Analysis Period: 01/01/1961 - 31/12/1990
Significance level: 0.05

Total missing values: 0

Predictand: TMAX.DAT

Predictors:	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
ncepp__uee.dat	0.348	0.408	0.251	0.077			0.006	0.010		0.016	0.152	0.314
ncepp__vee.dat	0.031	0.022	0.044	0.189	0.169	0.163	0.212	0.167	0.173	0.184	0.158	0.048
ncepp__zee.dat	0.030	0.026		0.020	0.062	0.113	0.117	0.067	0.026		0.011	0.010
ncepp500ee.dat	0.088	0.105	0.232	0.382	0.489	0.498	0.483	0.449	0.343	0.239	0.166	0.135
ncepulagee.dat	0.284	0.318	0.206	0.038			0.006	0.011		0.007	0.114	0.198
ncepvlagee.dat	0.030	0.022	0.020	0.140	0.152	0.104	0.111	0.093	0.085	0.113	0.100	0.030
ncepzlagee.dat	0.013	0.013	0.011	0.028	0.077	0.128	0.164	0.142	0.059	0.012		

Figure 5.1: Explained variance

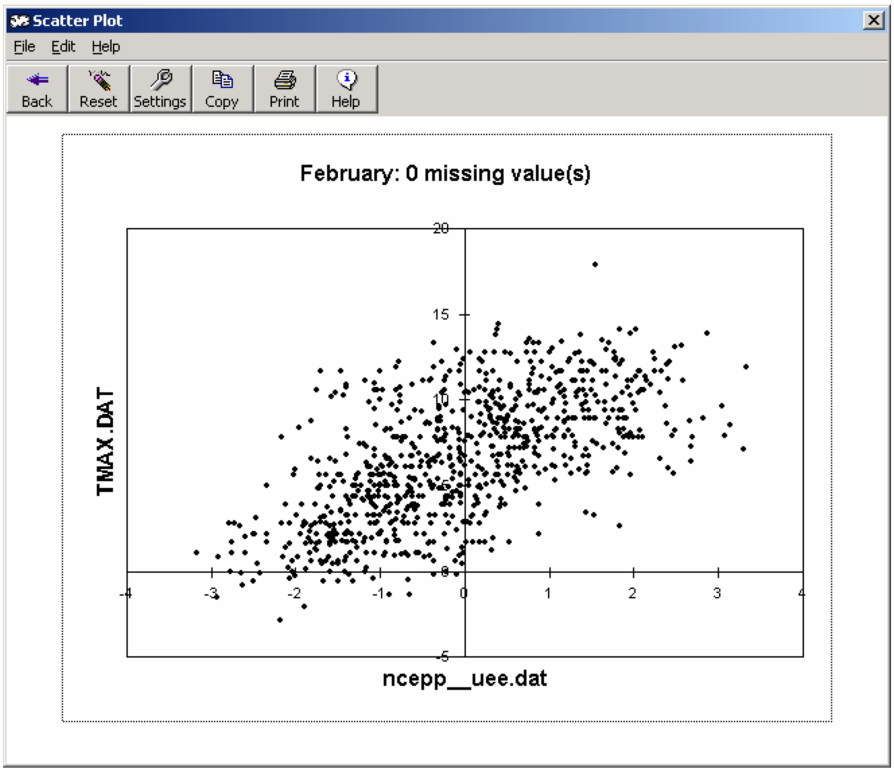
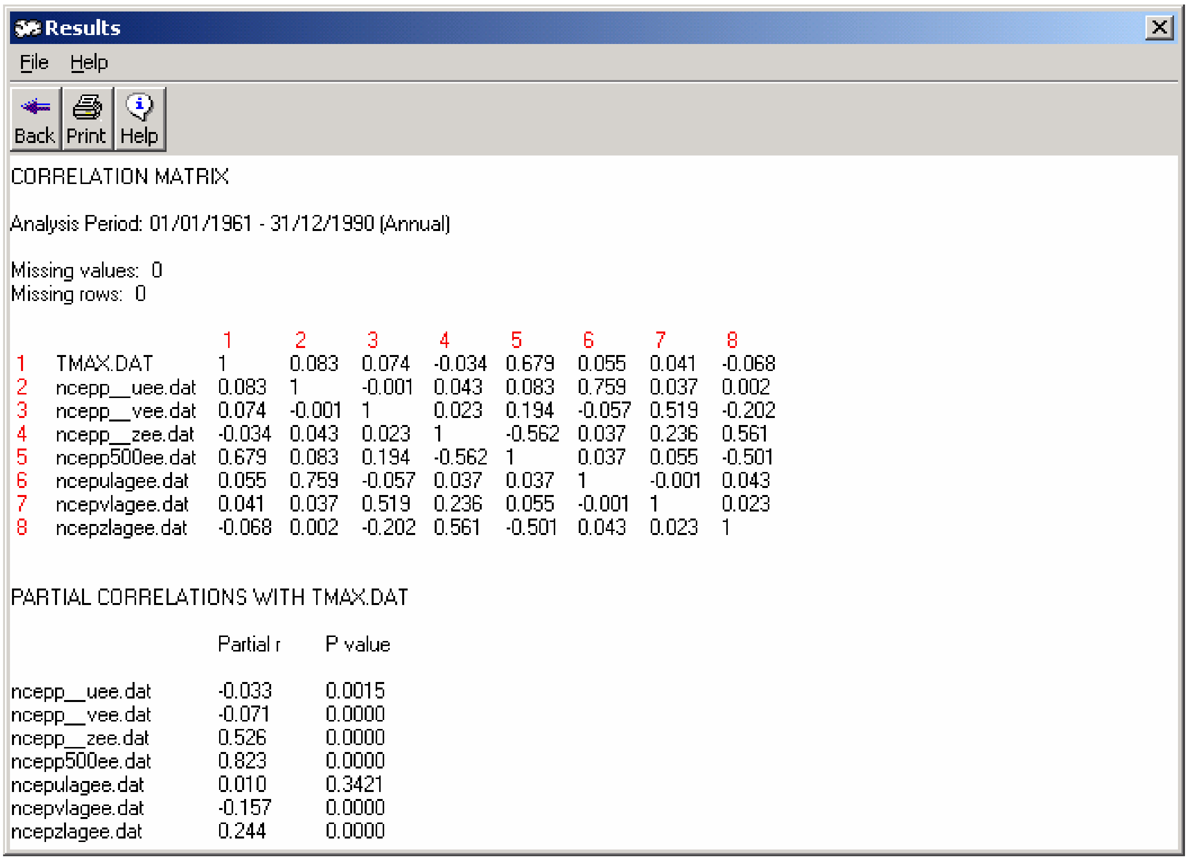


Figure 5.2: Scatter plot diagram



CORRELATION MATRIX

Analysis Period: 01/01/1961 - 31/12/1990 (Annual)

Missing values: 0
Missing rows: 0

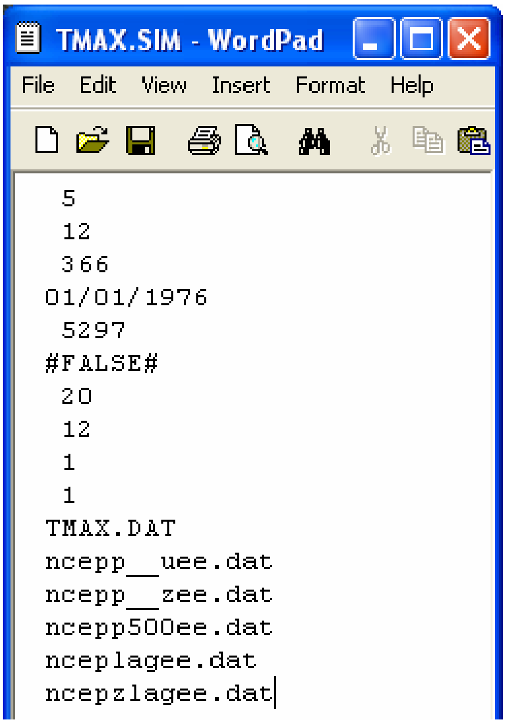
		1	2	3	4	5	6	7	8
1	TMAX.DAT	1	0.083	0.074	-0.034	0.679	0.055	0.041	-0.068
2	ncepp__uee.dat	0.083	1	-0.001	0.043	0.083	0.759	0.037	0.002
3	ncepp__vee.dat	0.074	-0.001	1	0.023	0.194	-0.057	0.519	-0.202
4	ncepp__zee.dat	-0.034	0.043	0.023	1	-0.562	0.037	0.236	0.561
5	ncepp500ee.dat	0.679	0.083	0.194	-0.562	1	0.037	0.055	-0.501
6	ncepulagee.dat	0.055	0.759	-0.057	0.037	0.037	1	-0.001	0.043
7	ncepvlagee.dat	0.041	0.037	0.519	0.236	0.055	-0.001	1	0.023
8	ncepzlagee.dat	-0.068	0.002	-0.202	0.561	-0.501	0.043	0.023	1

PARTIAL CORRELATIONS WITH TMAX.DAT

	Partial r	P value
ncepp__uee.dat	-0.033	0.0015
ncepp__vee.dat	-0.071	0.0000
ncepp__zee.dat	0.526	0.0000
ncepp500ee.dat	0.823	0.0000
ncepulagee.dat	0.010	0.3421
ncepvlagee.dat	-0.157	0.0000
ncepzlagee.dat	0.244	0.0000

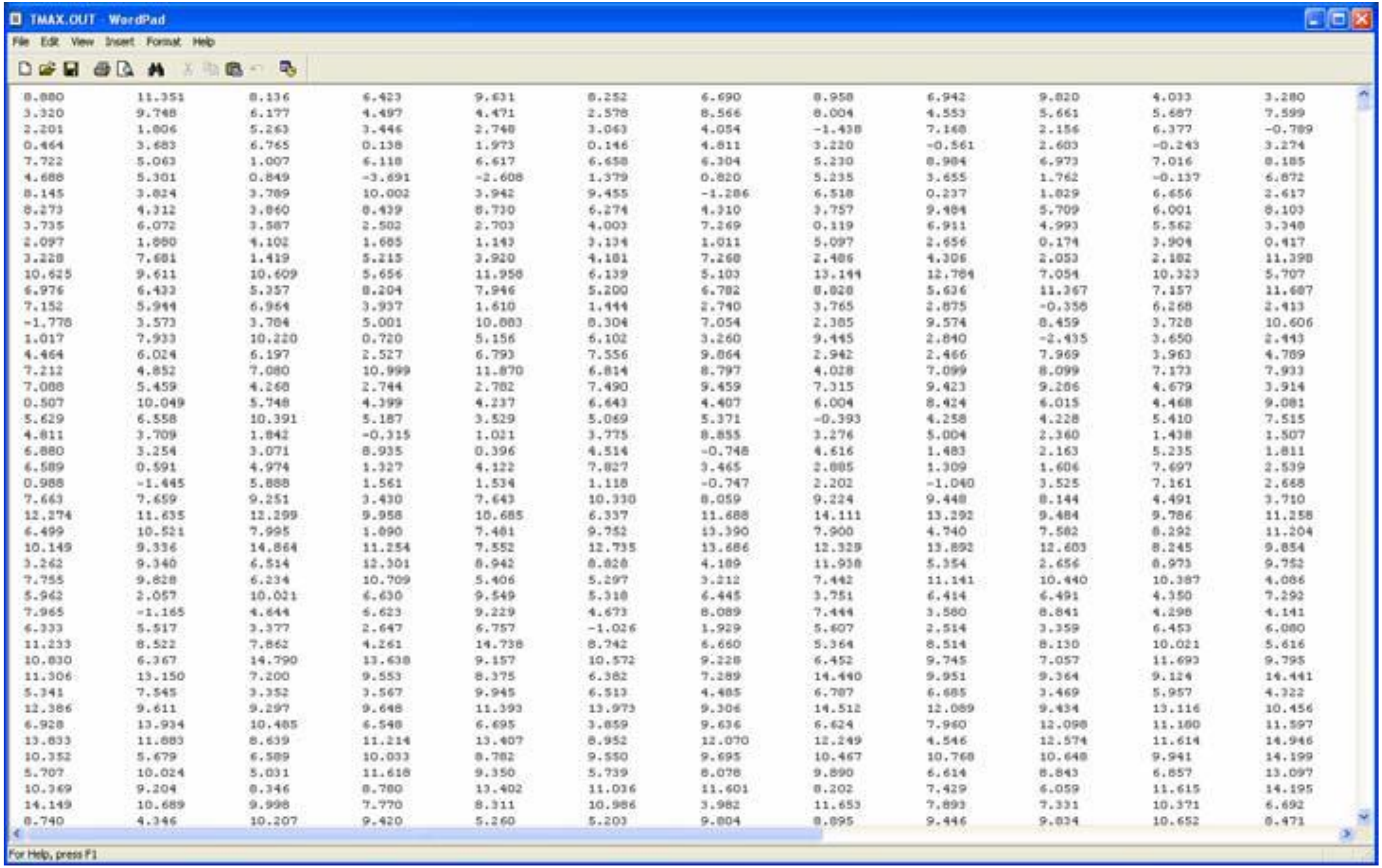
Figure 5.3: Correlation Matrix

Partial correlations indicate that p500 and p__z have the strongest association with TMAX once the influence of all other predictors has been removed**.**



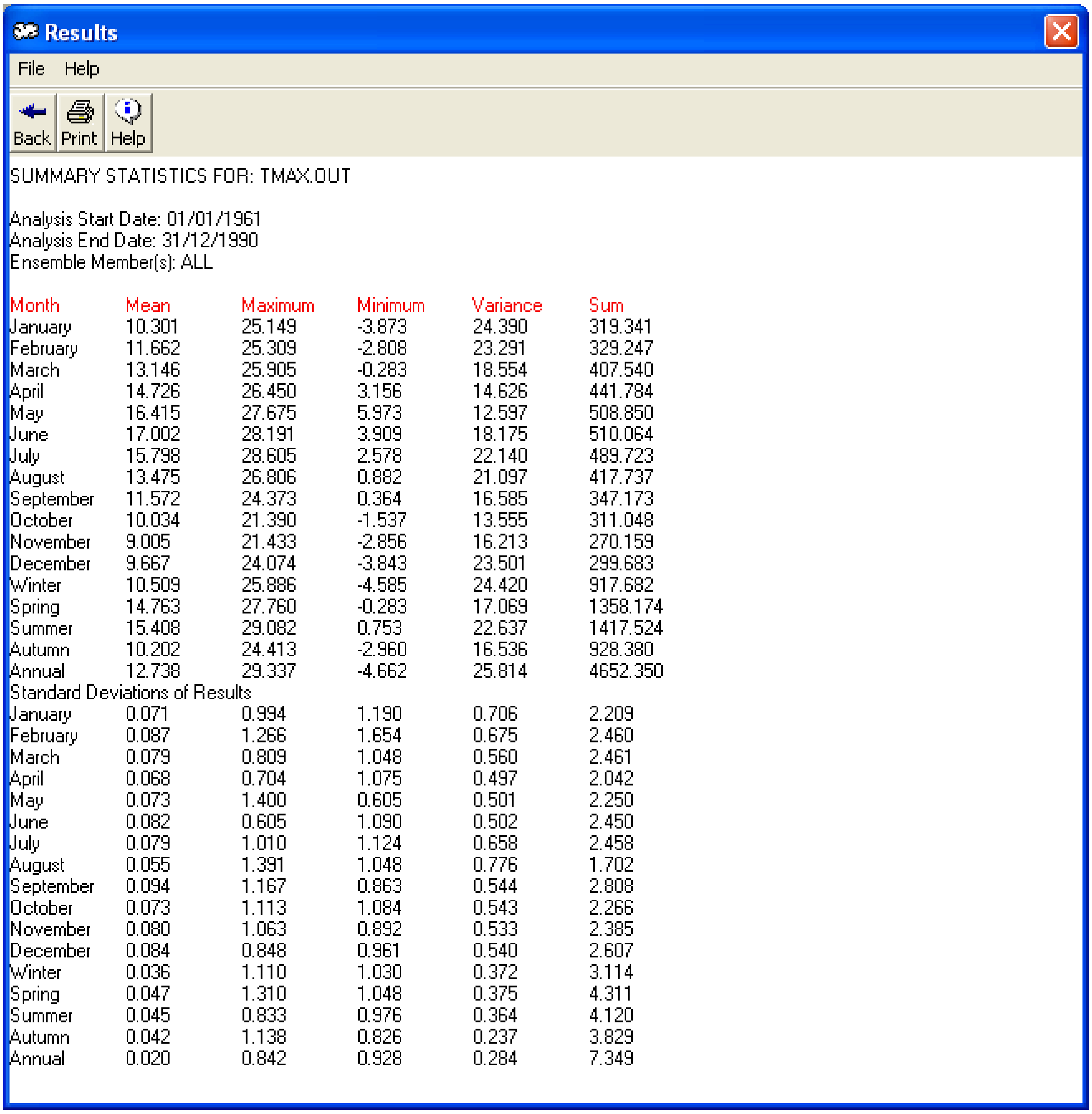

```
 5
 12
 366
01/01/1976
 5297
#FALSE#
 20
 12
 1
 1
TMAX.DAT
ncepp__uee.dat
ncepp__zee.dat
ncepp500ee.dat
nceplagee.dat
ncepzlagee.dat
```

Figure 5.4: Simulated file for Rourkela



8.880	11.351	8.136	6.423	9.631	8.252	6.690	8.958	6.942	9.820	4.033	3.280
3.320	9.748	6.177	4.497	4.471	2.578	8.566	8.004	4.553	5.661	5.687	7.599
2.201	1.806	5.263	3.446	2.748	3.063	4.054	-1.438	7.168	2.156	6.377	-0.789
0.464	3.683	6.765	0.138	1.973	0.146	4.811	3.220	-0.561	2.603	-0.243	3.274
7.722	5.063	1.007	6.118	6.617	6.658	6.304	5.230	8.984	6.973	7.016	8.185
4.688	5.301	0.849	-3.691	-2.608	1.379	0.820	5.235	3.655	1.762	-0.137	6.872
8.145	3.824	3.789	10.002	3.942	9.455	-1.286	6.518	0.237	1.829	6.656	2.617
8.273	4.312	3.860	8.439	8.730	6.274	4.310	3.757	9.484	5.709	6.001	8.103
3.735	6.072	3.587	2.502	2.703	4.003	7.269	0.119	6.911	4.993	5.562	3.348
2.097	1.880	4.102	1.685	1.143	3.134	1.011	5.097	2.656	0.174	3.904	0.417
3.228	7.681	1.419	5.215	3.920	4.181	7.268	2.486	4.306	2.053	2.182	11.398
10.625	9.611	10.609	5.656	11.958	6.139	5.103	13.144	12.784	7.054	10.323	5.707
6.976	6.433	5.357	8.204	7.946	5.200	6.782	8.828	5.636	11.367	7.157	11.687
7.152	5.944	6.964	3.937	1.610	1.444	2.740	3.765	2.875	-0.358	6.268	2.413
-1.778	3.573	3.784	5.001	10.883	8.304	7.054	2.385	9.574	8.459	3.728	10.606
1.017	7.933	10.220	0.720	5.156	6.102	3.260	9.445	2.840	-2.435	3.650	2.443
4.464	6.024	6.197	2.527	6.793	7.556	9.864	2.942	2.466	7.969	3.963	4.789
7.212	4.852	7.080	10.999	11.870	6.814	8.797	4.028	7.099	8.099	7.173	7.933
7.088	5.459	4.268	2.744	2.782	7.490	9.459	7.315	9.423	9.286	4.679	3.914
0.507	10.049	5.748	4.399	4.237	6.643	4.407	6.004	8.424	6.015	4.468	9.081
5.629	6.558	10.391	5.187	3.529	5.069	5.371	-0.393	4.258	4.228	5.410	7.515
4.811	3.709	1.842	-0.315	1.021	3.775	8.855	3.276	5.004	2.360	1.438	1.507
6.880	3.254	3.071	8.935	0.396	4.514	-0.748	4.616	1.483	2.163	5.235	1.811
6.589	0.591	4.974	1.327	4.122	7.827	3.465	2.885	1.309	1.606	7.697	2.539
0.988	-1.445	5.888	1.561	1.534	1.118	-0.747	2.202	-1.040	3.525	7.161	2.668
7.663	7.659	9.251	3.430	7.643	10.330	8.059	9.224	9.448	8.144	4.491	3.710
12.274	11.635	12.299	9.958	10.685	6.337	11.688	14.111	13.292	9.484	9.786	11.258
6.499	10.521	7.995	1.090	7.481	9.752	13.390	7.900	4.740	7.582	8.292	11.204
10.149	9.336	14.864	11.254	7.552	12.735	13.686	12.329	13.892	12.603	8.245	9.854
3.262	9.340	6.514	12.301	8.942	8.828	4.189	11.938	5.354	2.656	8.973	9.752
7.755	9.828	6.234	10.709	5.406	5.297	3.212	7.442	11.141	10.440	10.387	4.086
5.962	2.057	10.021	6.630	9.549	5.318	6.445	3.751	6.414	6.491	4.350	7.292
7.965	-1.165	4.644	6.623	9.229	4.673	8.089	7.444	3.580	8.841	4.298	4.141
6.333	5.517	3.377	2.647	6.757	-1.026	1.929	5.607	2.514	3.359	6.453	6.080
11.233	8.522	7.862	4.261	14.738	8.742	6.660	5.364	8.514	8.130	10.021	5.616
10.830	6.367	14.790	13.638	9.157	10.572	9.228	6.452	9.745	7.057	11.693	9.795
11.306	13.150	7.200	9.553	8.375	6.382	7.289	14.440	9.951	9.364	9.124	14.441
5.341	7.545	3.352	3.567	9.945	6.513	4.485	6.787	6.685	3.469	5.957	4.322
12.386	9.611	9.297	9.648	11.393	13.973	9.306	14.512	12.089	9.434	13.116	10.456
6.928	13.934	10.485	6.548	6.695	3.859	9.636	6.624	7.960	12.098	11.180	11.597
13.833	11.883	8.639	11.214	13.407	8.952	12.070	12.249	4.546	12.574	11.614	14.946
10.352	5.679	6.589	10.033	8.782	9.550	9.695	10.467	10.768	10.648	9.941	14.199
5.707	10.024	5.031	11.618	9.350	5.739	8.078	9.890	6.614	8.843	6.857	13.097
10.369	9.204	8.346	8.780	13.402	11.036	11.601	8.202	7.429	6.059	11.615	14.195
14.149	10.689	9.998	7.770	8.311	10.986	3.982	11.653	7.893	7.331	10.371	6.692
8.740	4.346	10.207	9.420	5.260	5.203	9.804	8.895	9.446	9.834	10.652	8.471

Figure 5.5: Simulated file for Rourkela



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SUMMARY STATISTICS FOR: TMAX.OUT

Analysis Start Date: 01/01/1961
Analysis End Date: 31/12/1990
Ensemble Member(s): ALL

Month	Mean	Maximum	Minimum	Variance	Sum
January	10.301	25.149	-3.873	24.390	319.341
February	11.662	25.309	-2.808	23.291	329.247
March	13.146	25.905	-0.283	18.554	407.540
April	14.726	26.450	3.156	14.626	441.784
May	16.415	27.675	5.973	12.597	508.850
June	17.002	28.191	3.909	18.175	510.064
July	15.798	28.605	2.578	22.140	489.723
August	13.475	26.806	0.882	21.097	417.737
September	11.572	24.373	0.364	16.585	347.173
October	10.034	21.390	-1.537	13.555	311.048
November	9.005	21.433	-2.856	16.213	270.159
December	9.667	24.074	-3.843	23.501	299.683
Winter	10.509	25.886	-4.585	24.420	917.682
Spring	14.763	27.760	-0.283	17.069	1358.174
Summer	15.408	29.082	0.753	22.637	1417.524
Autumn	10.202	24.413	-2.960	16.536	928.380
Annual	12.738	29.337	-4.662	25.814	4652.350
Standard Deviations of Results					
January	0.071	0.994	1.190	0.706	2.209
February	0.087	1.266	1.654	0.675	2.460
March	0.079	0.809	1.048	0.560	2.461
April	0.068	0.704	1.075	0.497	2.042
May	0.073	1.400	0.605	0.501	2.250
June	0.082	0.605	1.090	0.502	2.450
July	0.079	1.010	1.124	0.658	2.458
August	0.055	1.391	1.048	0.776	1.702
September	0.094	1.167	0.863	0.544	2.808
October	0.073	1.113	1.084	0.543	2.266
November	0.080	1.063	0.892	0.533	2.385
December	0.084	0.848	0.961	0.540	2.607
Winter	0.036	1.110	1.030	0.372	3.114
Spring	0.047	1.310	1.048	0.375	4.311
Summer	0.045	0.833	0.976	0.364	4.120
Autumn	0.042	1.138	0.826	0.237	3.829
Annual	0.020	0.842	0.928	0.284	7.349

Figure 5.6: Mean and standard deviation of diagnostics for a 20 member ensemble

Results

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SUMMARY STATISTICS FOR: TMAXCCF.OUT

Analysis Start Date: 01/01/1961
Number of Days: 7200
Ensemble Member(s): ALL

Month	Mean	Maximum	Minimum	Variance	POT
January	7.061	18.116	-6.528	17.729	0.000
February	6.986	17.161	-3.462	13.680	0.000
March	9.371	22.377	-3.330	18.267	0.008
April	11.987	21.829	1.254	12.358	0.000
May	14.920	25.778	3.967	12.116	0.200
June	19.041	29.871	9.017	12.119	4.233
July	19.612	28.749	10.400	10.097	4.733
August	19.946	30.046	10.930	10.582	6.417
September	17.989	27.125	8.819	9.607	1.050
October	14.137	23.270	4.153	10.305	0.000
November	9.696	20.185	-0.403	12.872	0.000
December	7.343	19.562	-5.138	18.047	0.000
Winter	7.130	18.280	-5.043	16.485	0.000
Spring	12.093	23.328	0.630	14.247	0.069
Summer	19.533	29.555	10.116	10.932	5.128
Autumn	13.941	23.526	4.190	10.928	0.350
Annual	13.174	23.672	2.473	13.148	1.387

Figure 5.7: Summary of Rourkela maximum temperature using GCM HADCM 3

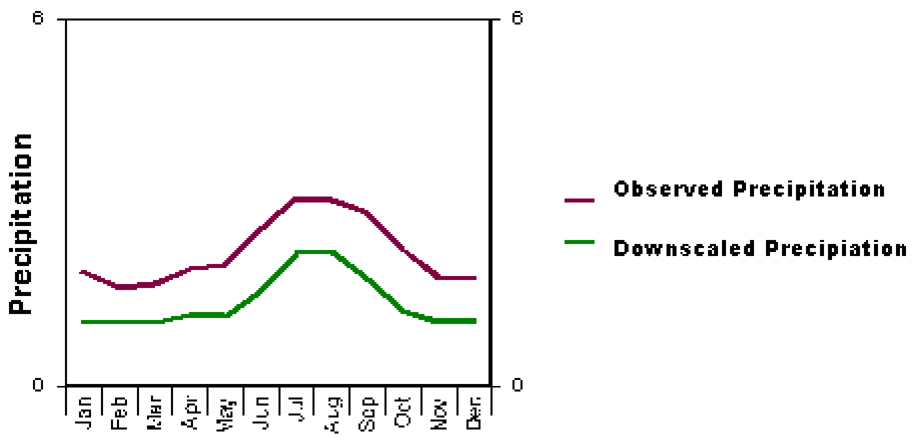


Figure 5.8: Wet spell days

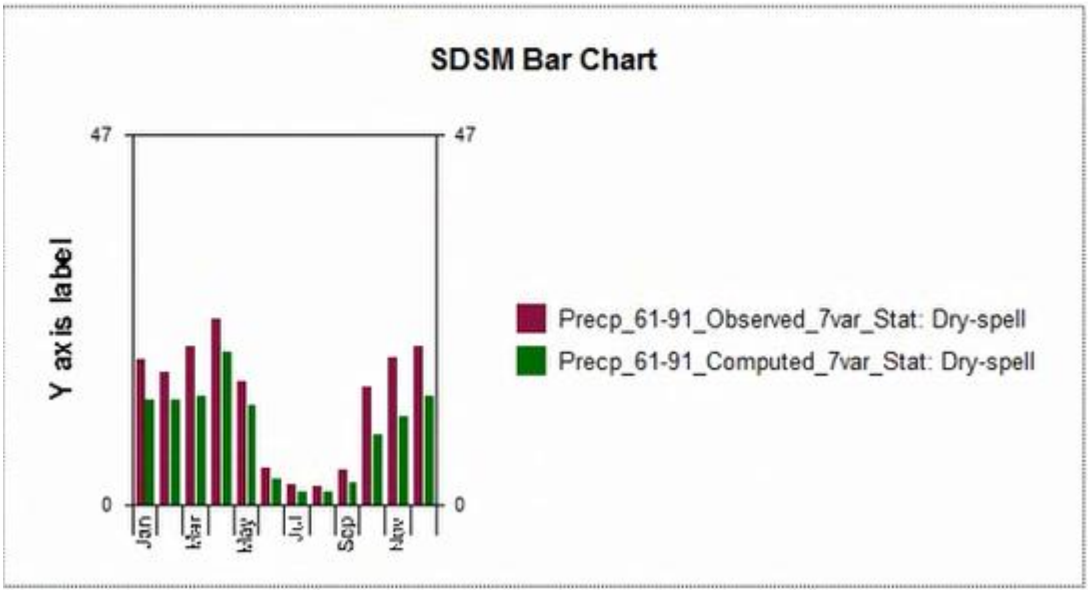


Figure 5.9: Dry spell days

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.

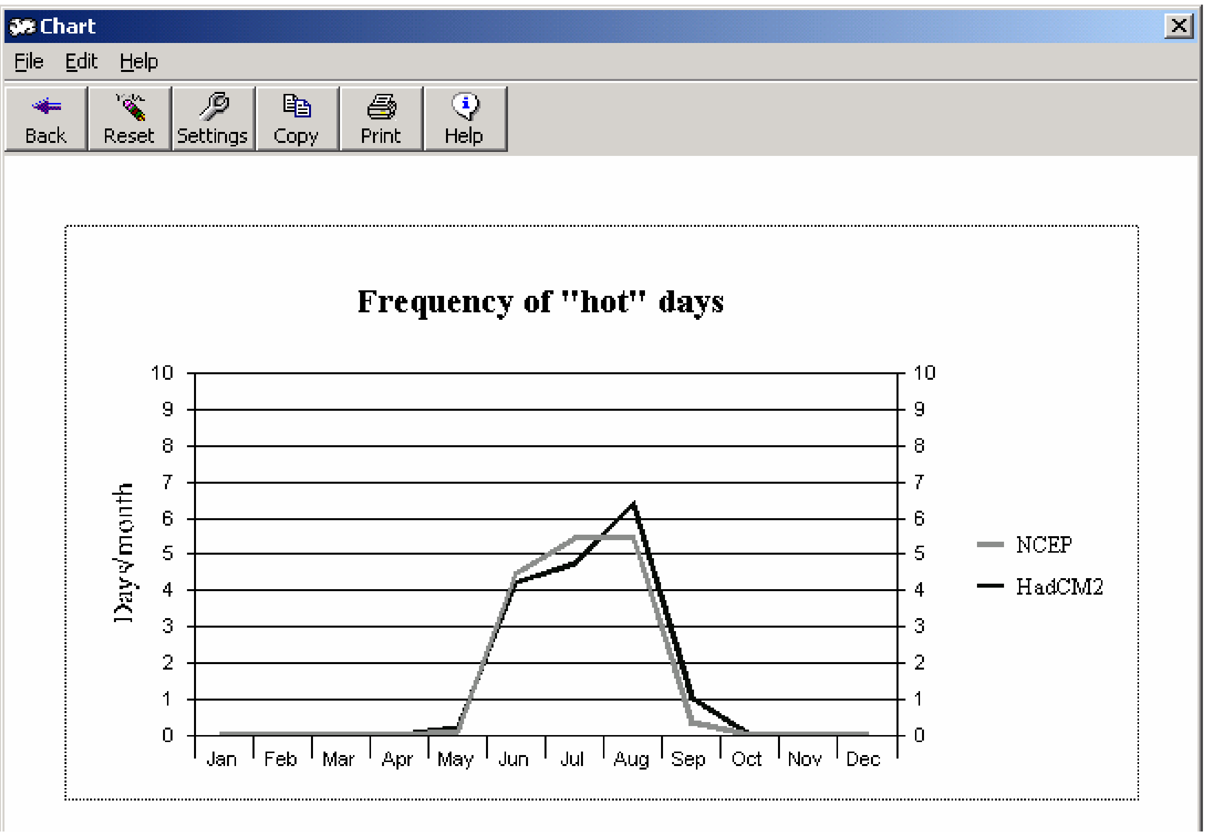


Figure 5.10: Frequency (days) greater than 25 degree Celsius in Rishikesh

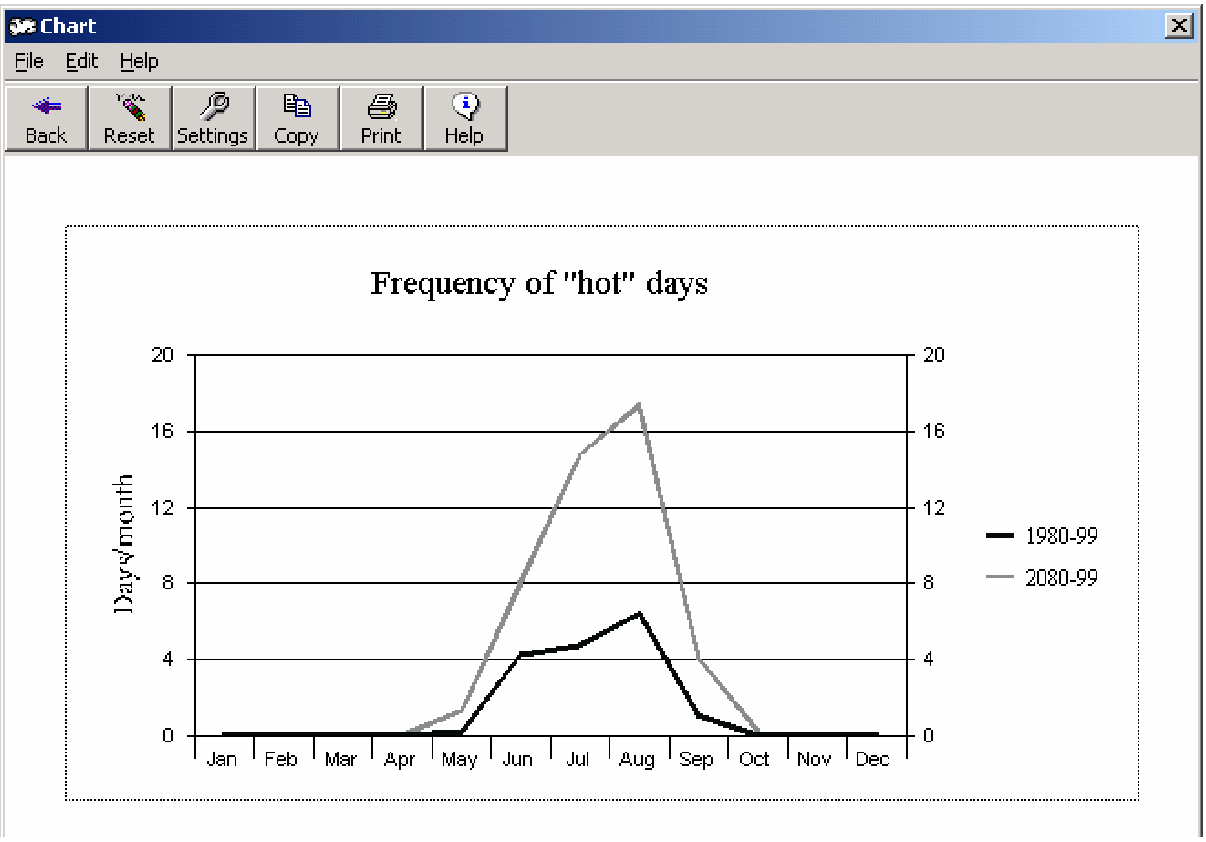


Figure 5.11: Monthly frequency of "hot" days (>25ºC) at Rishikesh downscaled using HadCM2 predictors under current (1960–1989) and future (2080–2099) forcing.

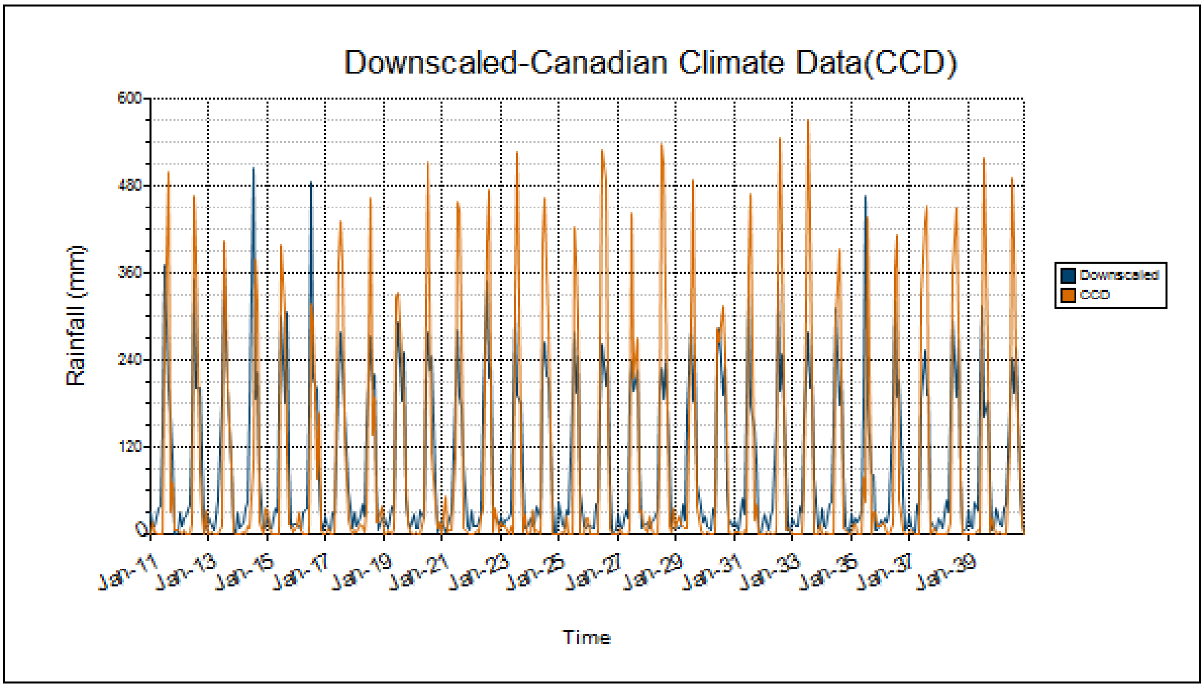


Figure 5.12: Downscaled Precipitation and CCDS downscaled Precipitation and for A2 scenario in 2020s

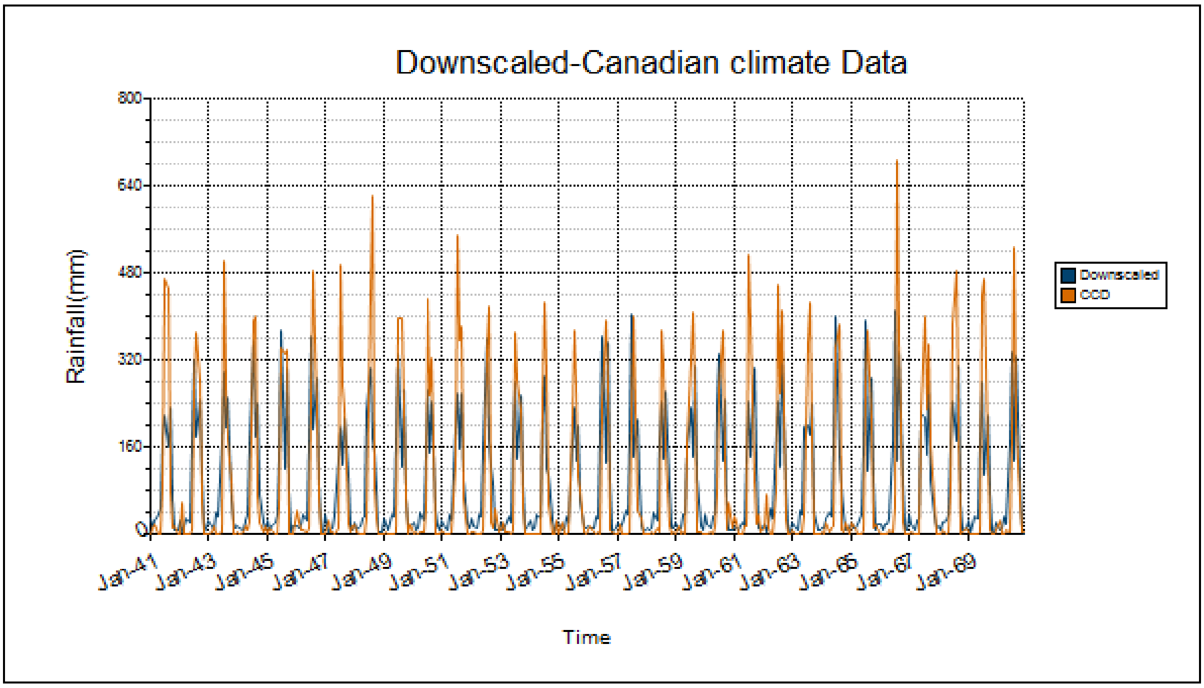


Figure 5.13: Downscaled Precipitation and CCDS downscaled Precipitation and for A2 scenario in 2050s

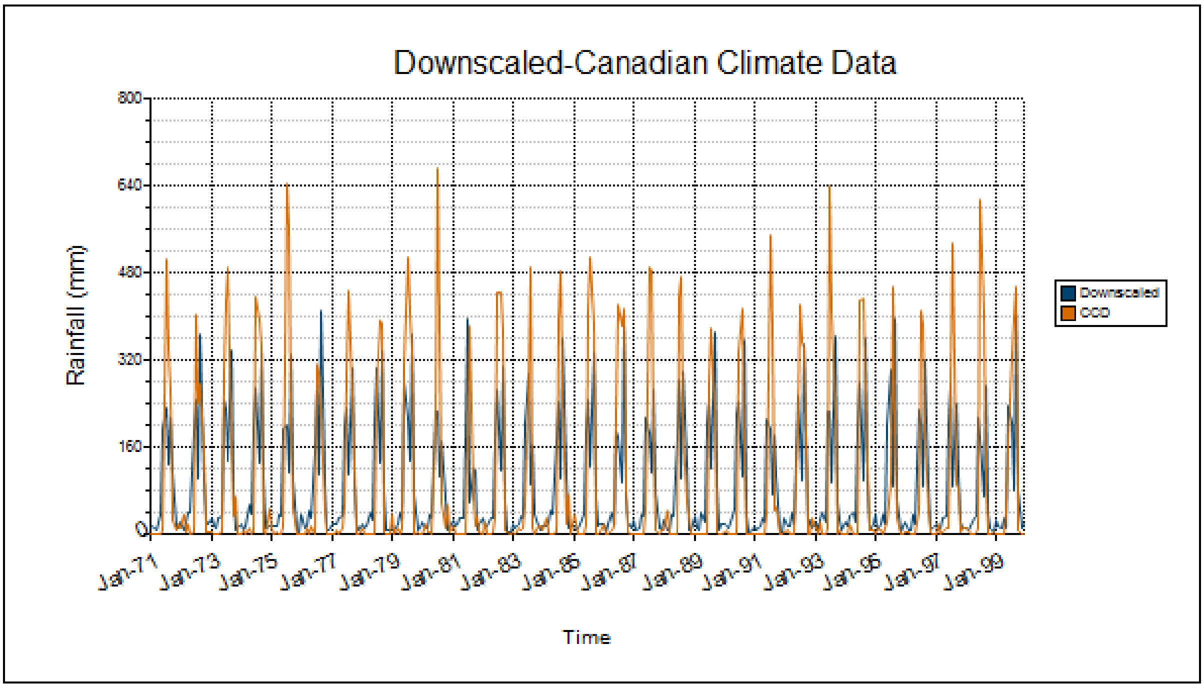


Figure 5.14: Downscaled Precipitation and CCDS downscaled Precipitation and for A2 scenario in 2080s

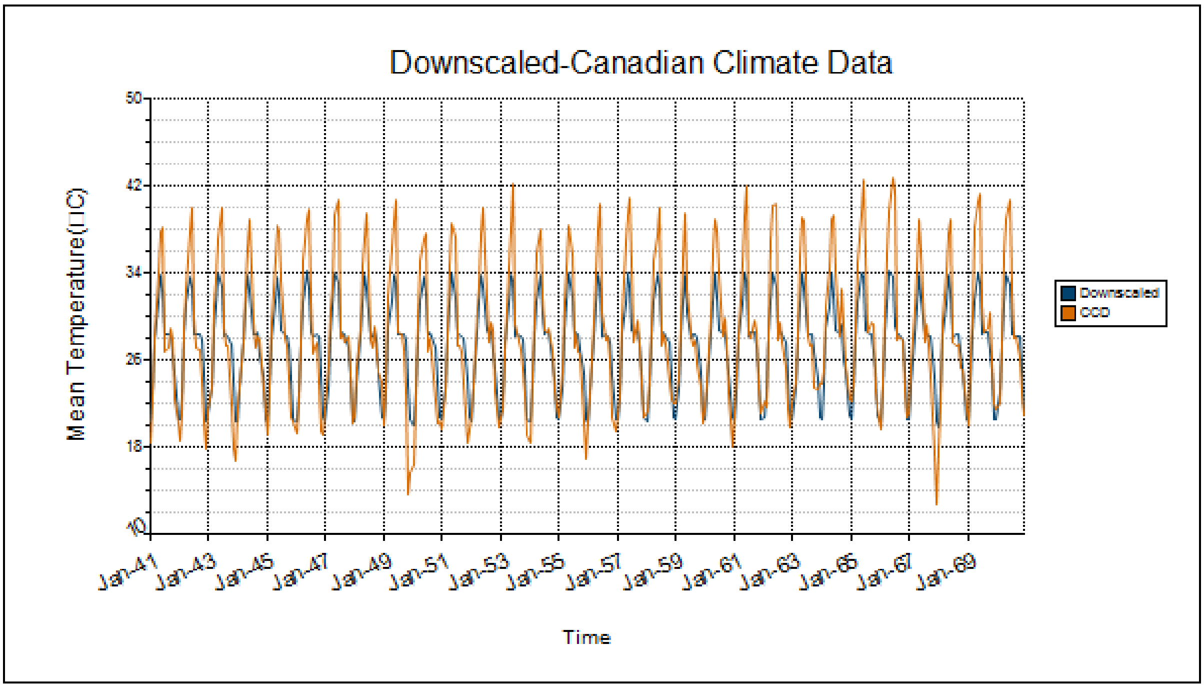


Figure 5.15: Downscaled Mean temperature and CCDS downscaled Mean temperature for A2 scenario in 2050s.

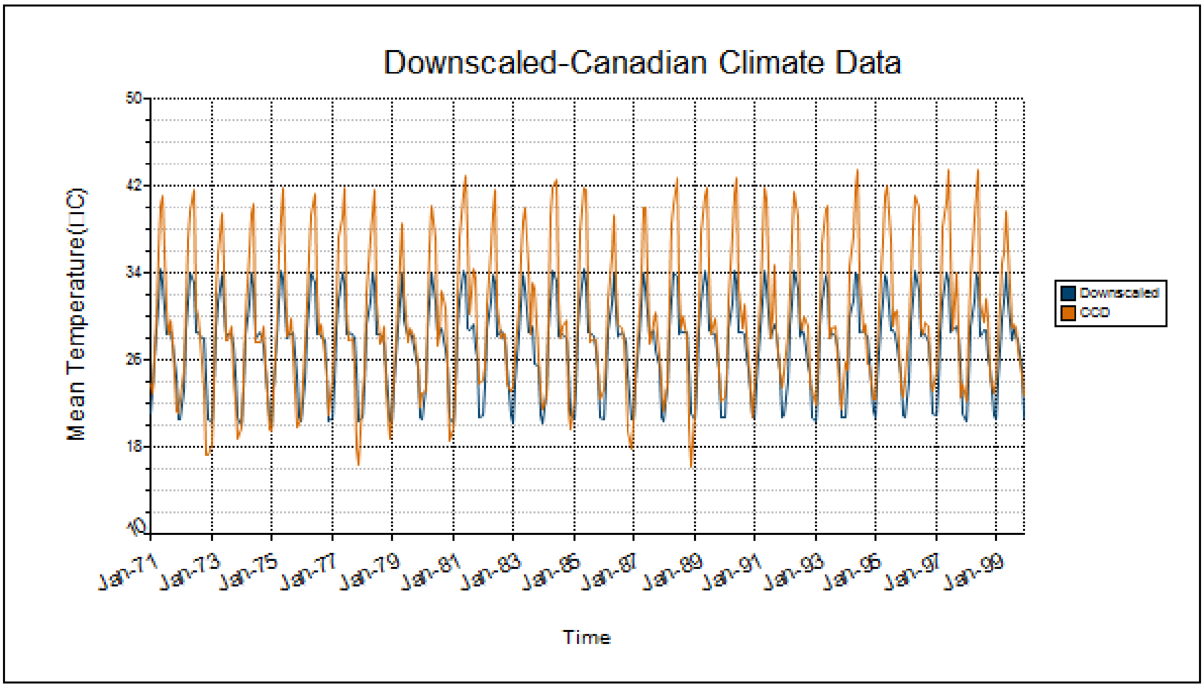


Figure 5.16: Downscaled Mean temperature and CCDS downscaled Mean temperature for A2 scenario in 2080s.

For the available observed data, plots are made for summer, monsoon, winter and annual periods to show the trend using Mann Kendall test 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.

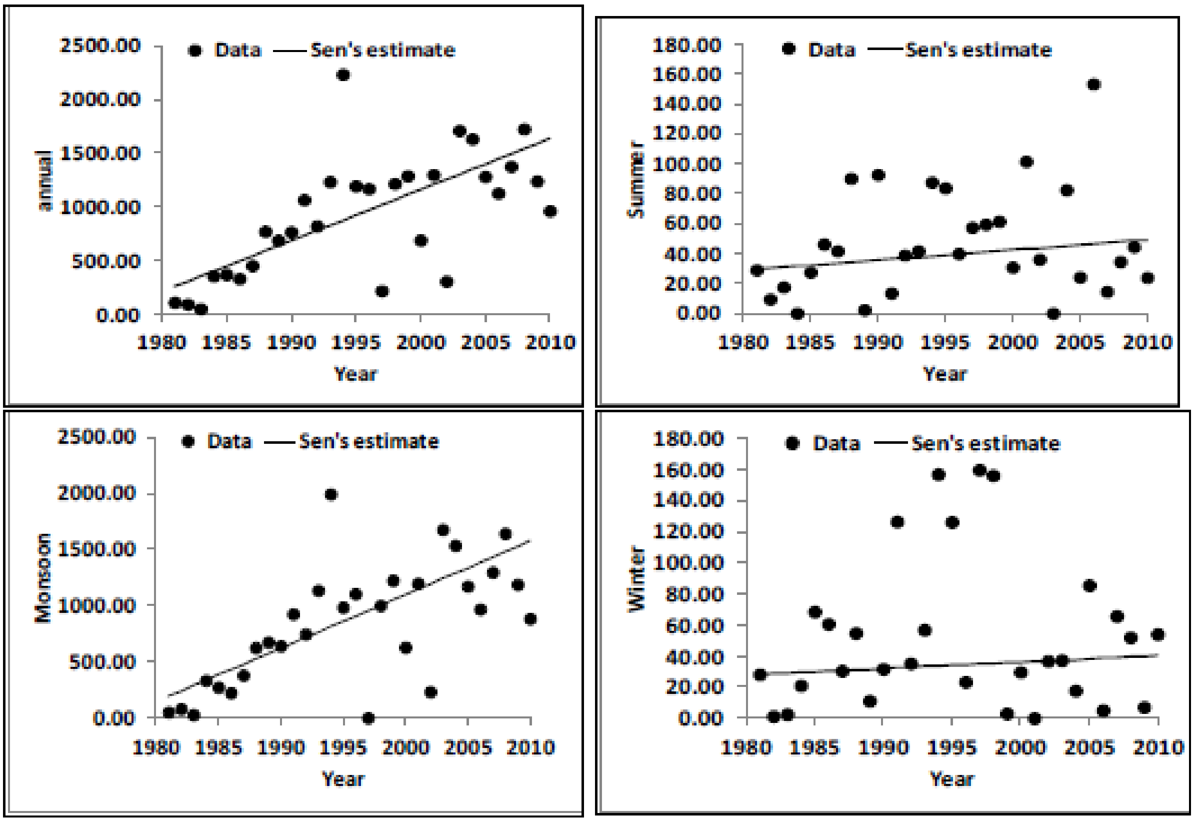


Figure 5.17: Trend of Rainfall in Rourkela

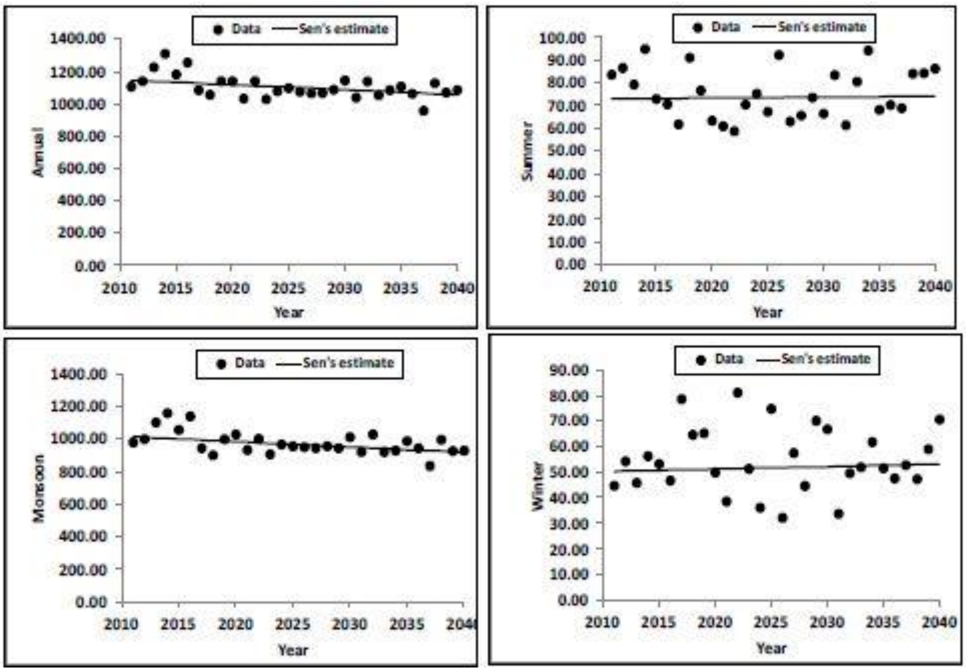


Figure 5.18: Trend of rainfall in 2020s using A2 scenario

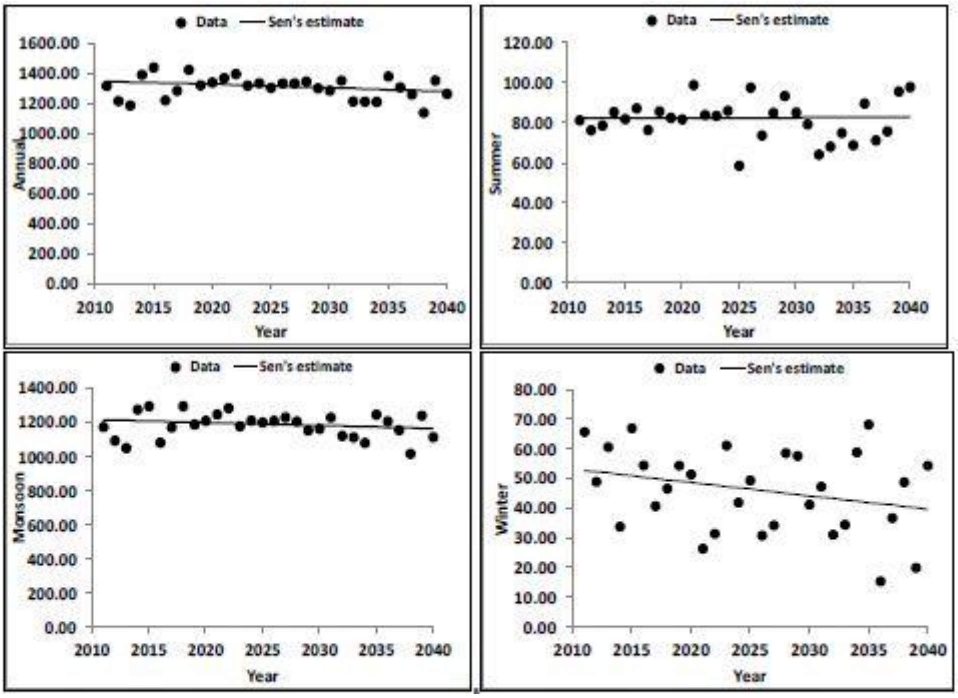


Figure 5.19: Trend of rainfall in 2030s using B2 scenario

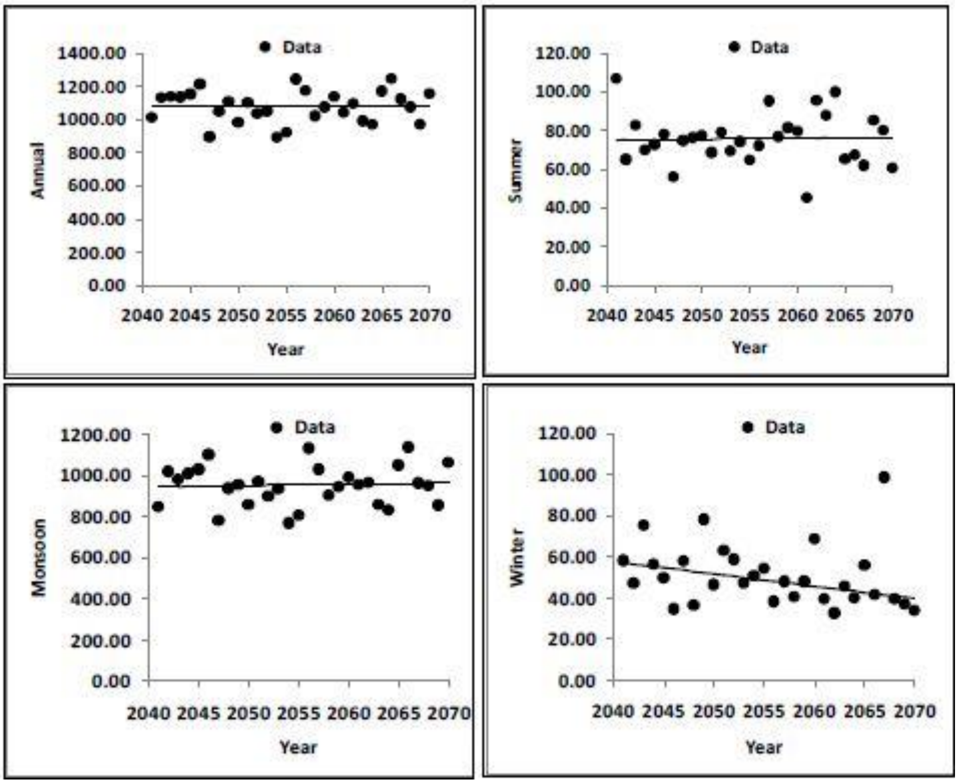


Figure 5.20: Trend of rainfall in 2050s using A2 scenario

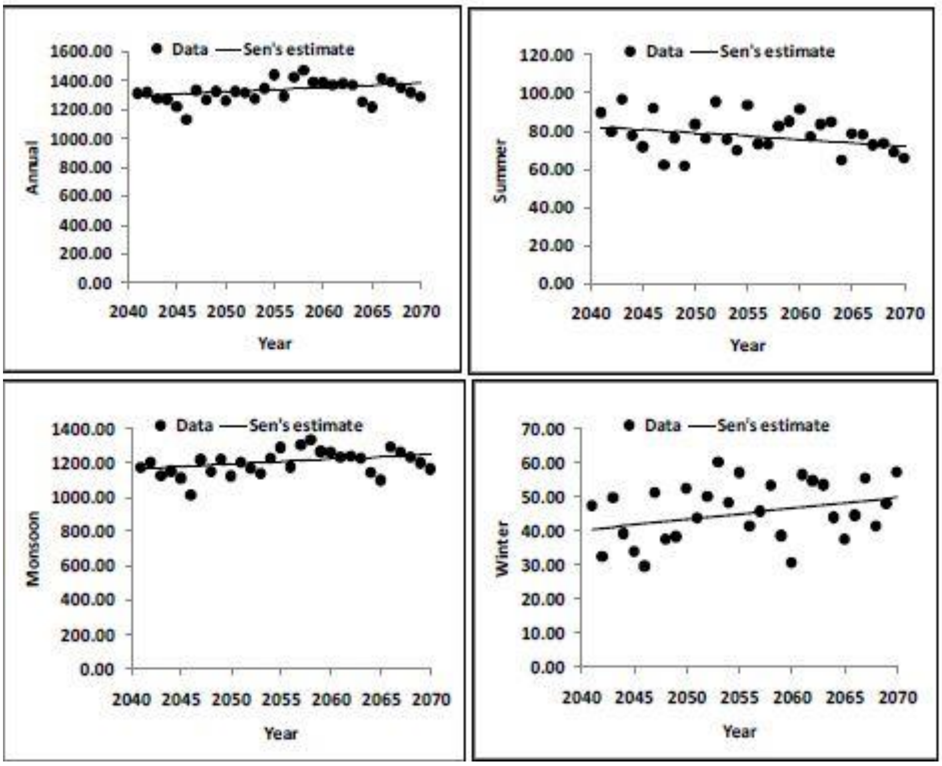


Figure 5.21: Trend of Rainfall in 2050s in Rourkela in B2 scenario

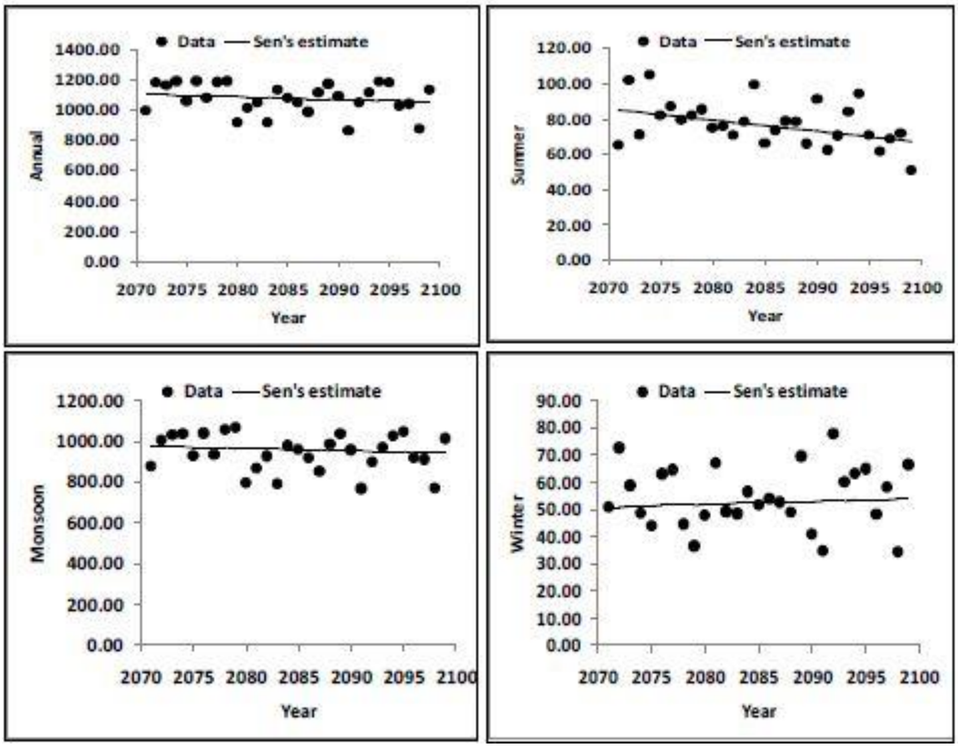


Figure 5.22: Trend of rainfall in 2080s in Rourkela using A2 scenarios

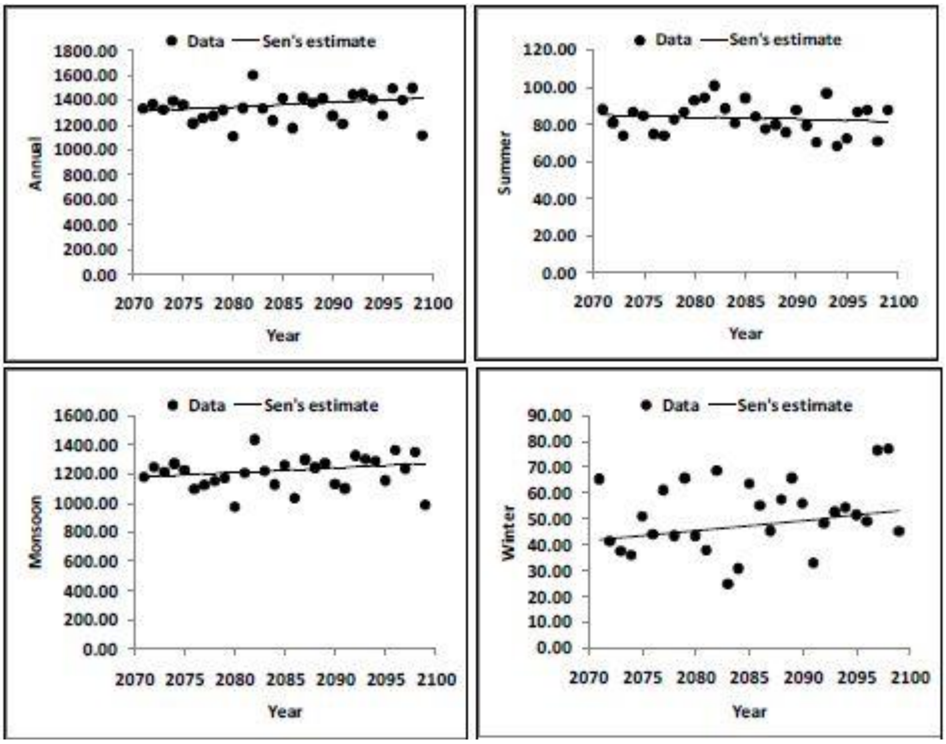


Figure 5.23: Trend of Rainfall in 2080s in B2 scenarios of Rourkela

mumbai 2011-2040 rainfall(mm)

TsNumber	6
Name	RCP 8.5
Years	2011 - 2040
n	30
Test S	
Test Z	6.08
Signific.	***
Q	4.23E+01
Qmin99	3.33E+01
Qmax99	5.05E+01
Qmin95	3.55E+01
Qmax95	4.84E+01
B	2.57E+03
Bmin99	2.70E+03
Bmax99	2.46E+03
Bmin95	2.65E+03
Bmax95	2.50E+03

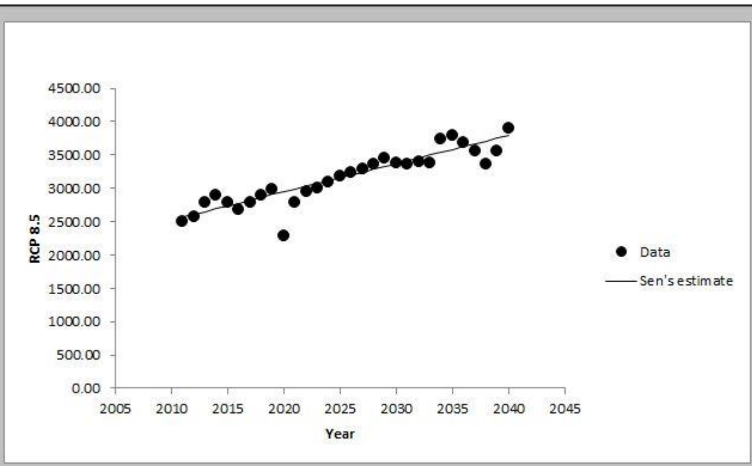


Figure 5.24: Mumbai 2011-2040 rainfall

mumbai 2011-2040 rainfall(mm)

TsNumber	5
Name	RCP 6
Years	2011 - 2040
n	30
Test S	
Test Z	6.68
Signific.	***
Q	3.58E+01
Qmin99	2.69E+01
Qmax99	4.32E+01
Qmin95	2.93E+01
Qmax95	4.11E+01
B	2.57E+03
Bmin99	2.73E+03
Bmax99	2.47E+03
Bmin95	2.69E+03
Bmax95	2.50E+03

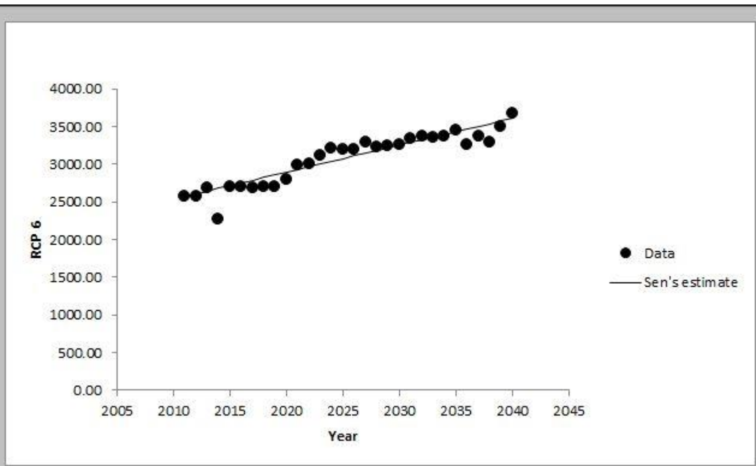
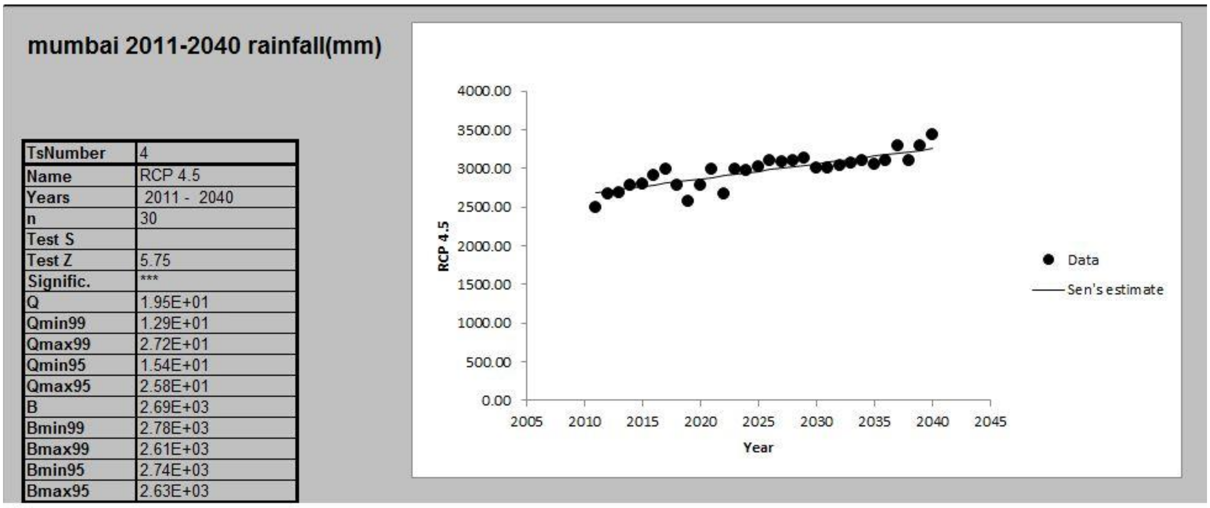
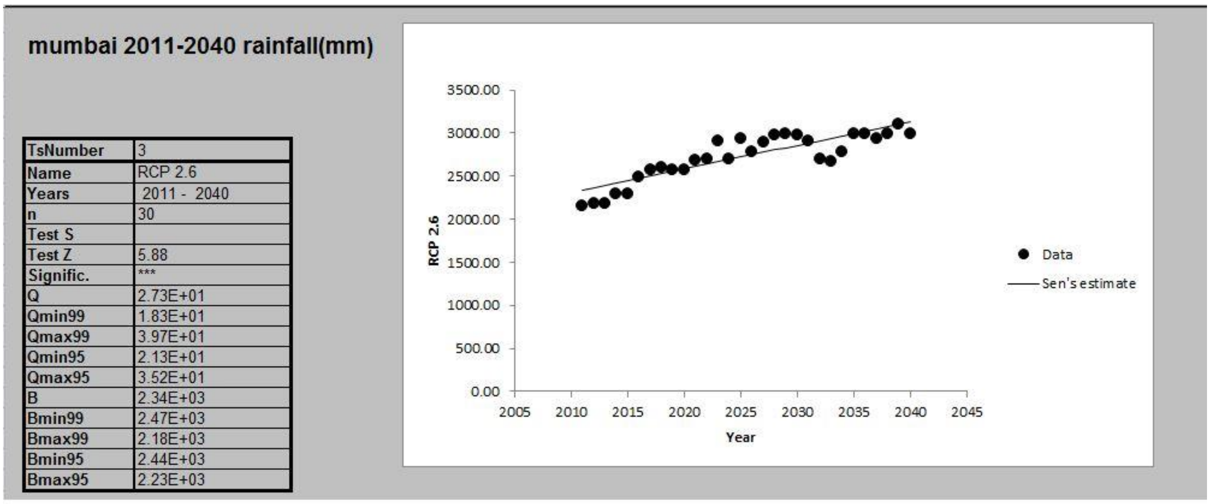


Figure 5.25: Mumbai 2011-2040 rainfall


mumbai 2011-2040 rainfall(mm)

TsNumber	4
Name	RCP 4.5
Years	2011 - 2040
n	30
Test S	
Test Z	5.75
Signific.	***
Q	1.95E+01
Qmin99	1.29E+01
Qmax99	2.72E+01
Qmin95	1.54E+01
Qmax95	2.58E+01
B	2.69E+03
Bmin99	2.78E+03
Bmax99	2.61E+03
Bmin95	2.74E+03
Bmax95	2.63E+03

Figure 5.26: Mumbai 2011-2040 rainfall


mumbai 2011-2040 rainfall(mm)

TsNumber	3
Name	RCP 2.6
Years	2011 - 2040
n	30
Test S	
Test Z	5.88
Signific.	***
Q	2.73E+01
Qmin99	1.83E+01
Qmax99	3.97E+01
Qmin95	2.13E+01
Qmax95	3.52E+01
B	2.34E+03
Bmin99	2.47E+03
Bmax99	2.18E+03
Bmin95	2.44E+03
Bmax95	2.23E+03

Figure 5.27: Mumbai 2011-2040 rainfall

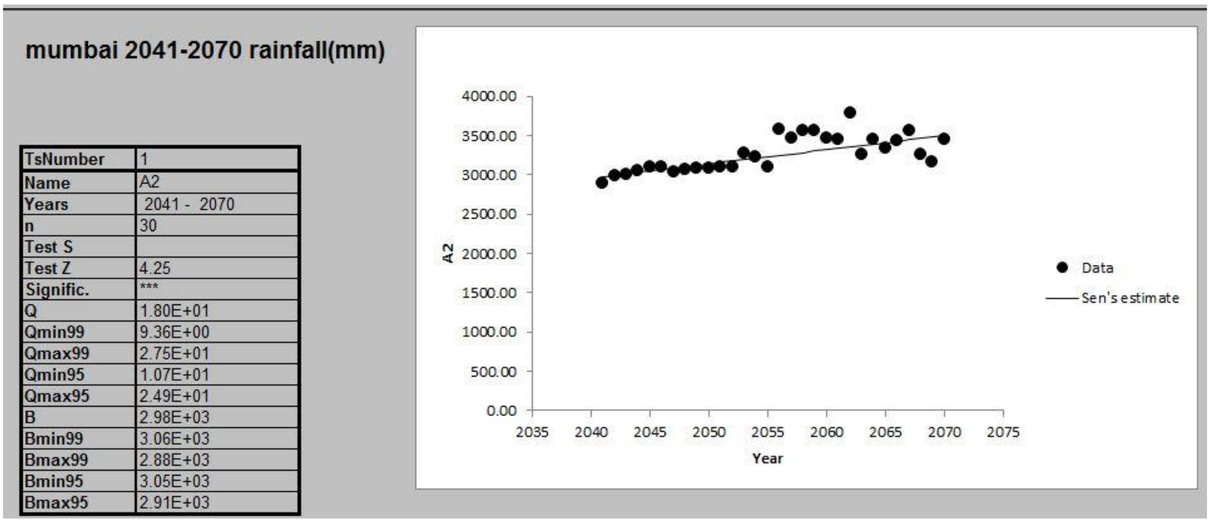


Figure 5.28: Mumbai 2041-2070 rainfall

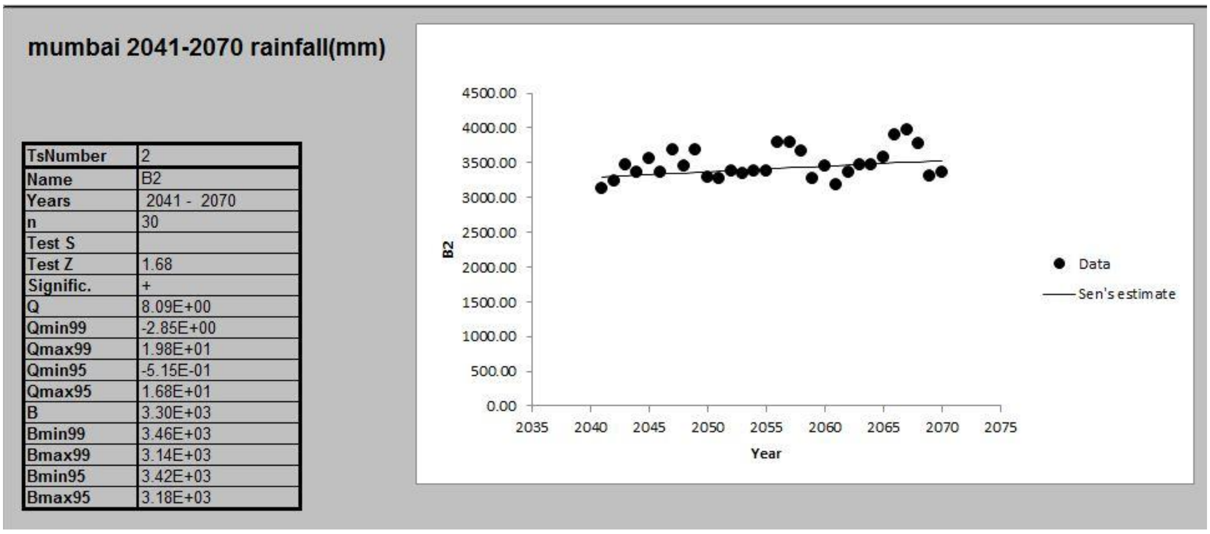
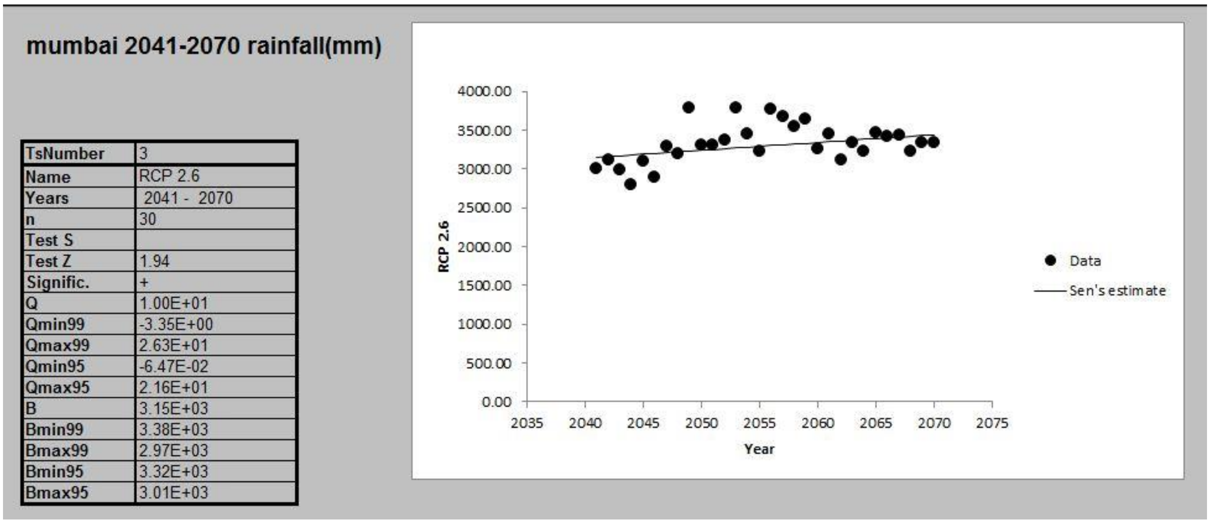
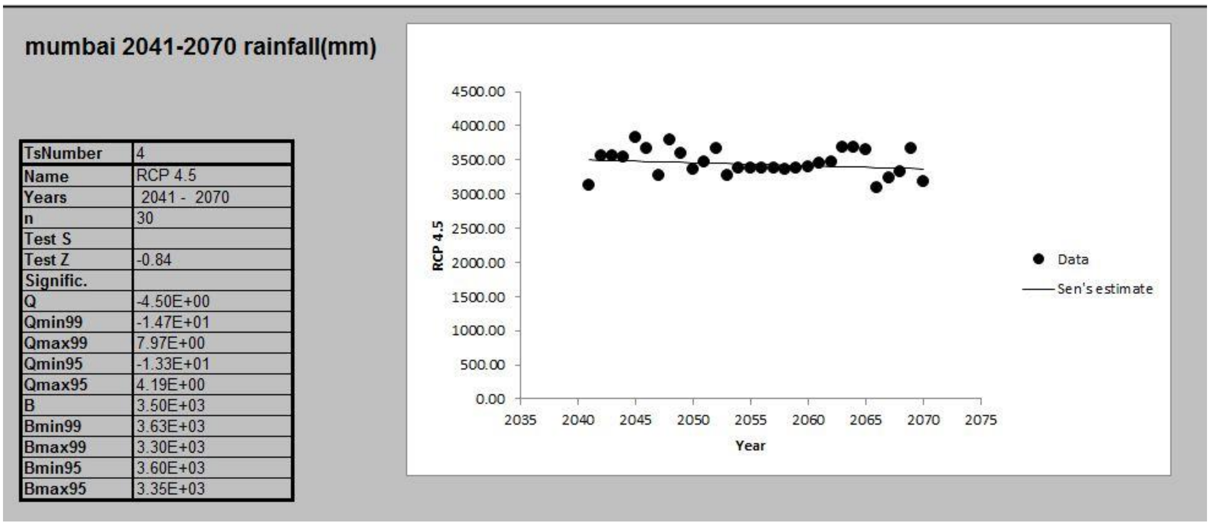


Figure 5.29: Mumbai 2041-2070 rainfall



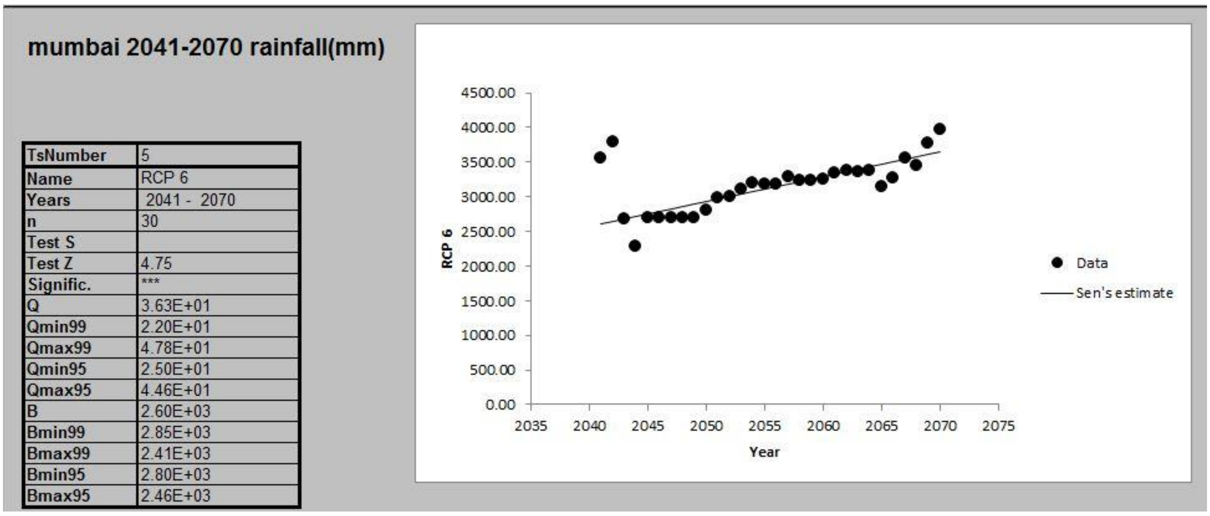
TsNumber	3
Name	RCP 2.6
Years	2041 - 2070
n	30
Test S	
Test Z	1.94
Signific.	+
Q	1.00E+01
Qmin99	-3.35E+00
Qmax99	2.63E+01
Qmin95	-6.47E-02
Qmax95	2.16E+01
B	3.15E+03
Bmin99	3.38E+03
Bmax99	2.97E+03
Bmin95	3.32E+03
Bmax95	3.01E+03

Figure 5.30: Mumbai 2041-2070 rainfall



TsNumber	4
Name	RCP 4.5
Years	2041 - 2070
n	30
Test S	
Test Z	-0.84
Signific.	
Q	-4.50E+00
Qmin99	-1.47E+01
Qmax99	7.97E+00
Qmin95	-1.33E+01
Qmax95	4.19E+00
B	3.50E+03
Bmin99	3.63E+03
Bmax99	3.30E+03
Bmin95	3.60E+03
Bmax95	3.35E+03

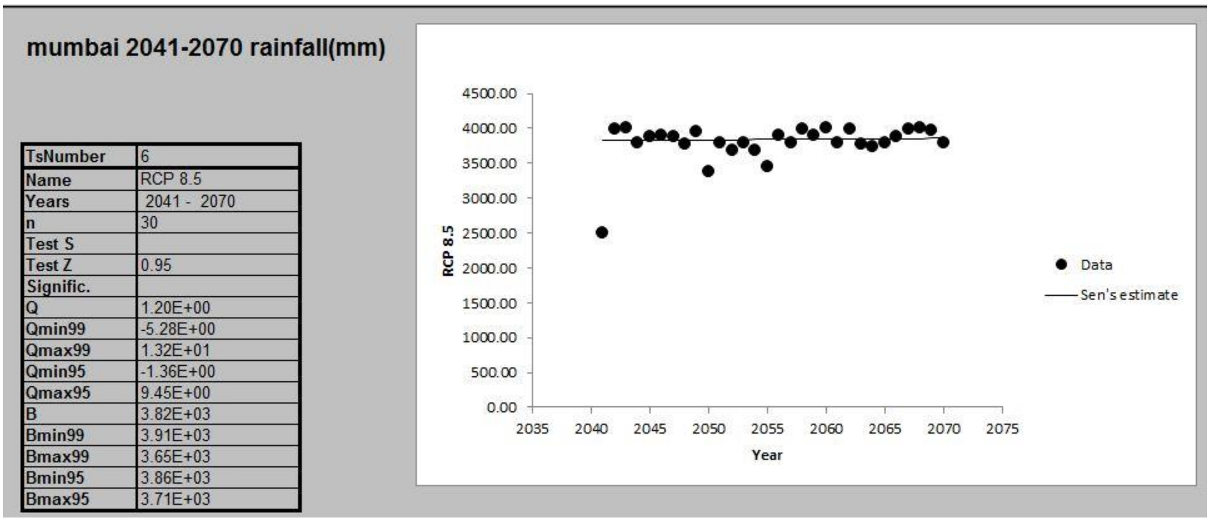
Figure 5.31: Mumbai 2041-2070 rainfall



mumbai 2041-2070 rainfall(mm)

TsNumber	5
Name	RCP 6
Years	2041 - 2070
n	30
Test S	
Test Z	4.75
Signific.	***
Q	3.63E+01
Qmin99	2.20E+01
Qmax99	4.78E+01
Qmin95	2.50E+01
Qmax95	4.46E+01
B	2.60E+03
Bmin99	2.85E+03
Bmax99	2.41E+03
Bmin95	2.80E+03
Bmax95	2.46E+03

Figure 5.32: Mumbai 2041-2070 rainfall



mumbai 2041-2070 rainfall(mm)

TsNumber	6
Name	RCP 8.5
Years	2041 - 2070
n	30
Test S	
Test Z	0.95
Signific.	
Q	1.20E+00
Qmin99	-5.28E+00
Qmax99	1.32E+01
Qmin95	-1.36E+00
Qmax95	9.45E+00
B	3.82E+03
Bmin99	3.91E+03
Bmax99	3.65E+03
Bmin95	3.86E+03
Bmax95	3.71E+03

Figure 5.33: Mumbai 2041-2070 rainfall

mumbai 2071-2100 rainfall(mm)

TsNumber	1
Name	A2
Years	2041 - 2070
n	30
Test S	
Test Z	4.25
Signific.	***
Q	1.80E+01
Qmin99	9.36E+00
Qmax99	2.75E+01
Qmin95	1.07E+01
Qmax95	2.49E+01
B	2.98E+03
Bmin99	3.06E+03
Bmax99	2.88E+03
Bmin95	3.05E+03
Bmax95	2.91E+03

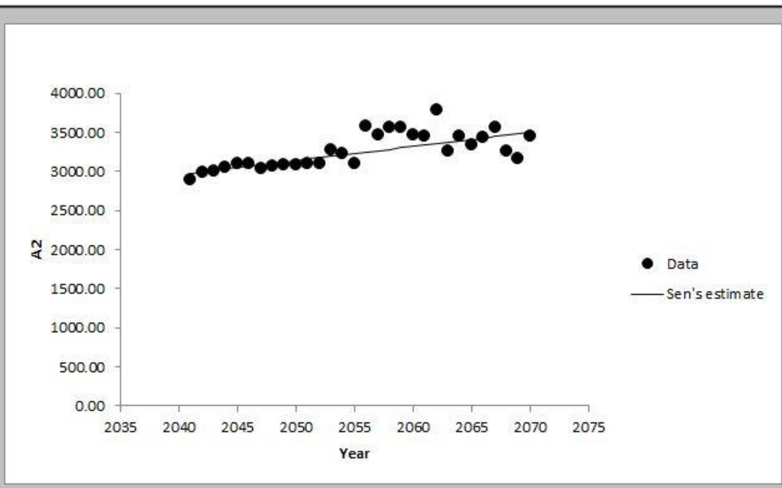


Figure 5.34: Mumbai 2071-2100 rainfall

mumbai 2071-2100 rainfall(mm)

TsNumber	2
Name	B2
Years	2071 - 2100
n	30
Test S	
Test Z	1.68
Signific.	+
Q	8.09E+00
Qmin99	-2.85E+00
Qmax99	1.98E+01
Qmin95	-5.15E-01
Qmax95	1.68E+01
B	3.30E+03
Bmin99	3.46E+03
Bmax99	3.14E+03
Bmin95	3.42E+03
Bmax95	3.18E+03

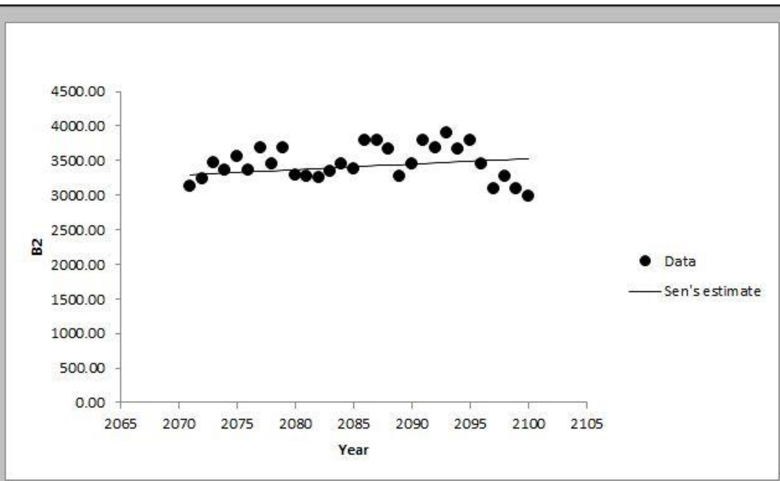


Figure 5.35: Mumbai 2071-2100 rainfall

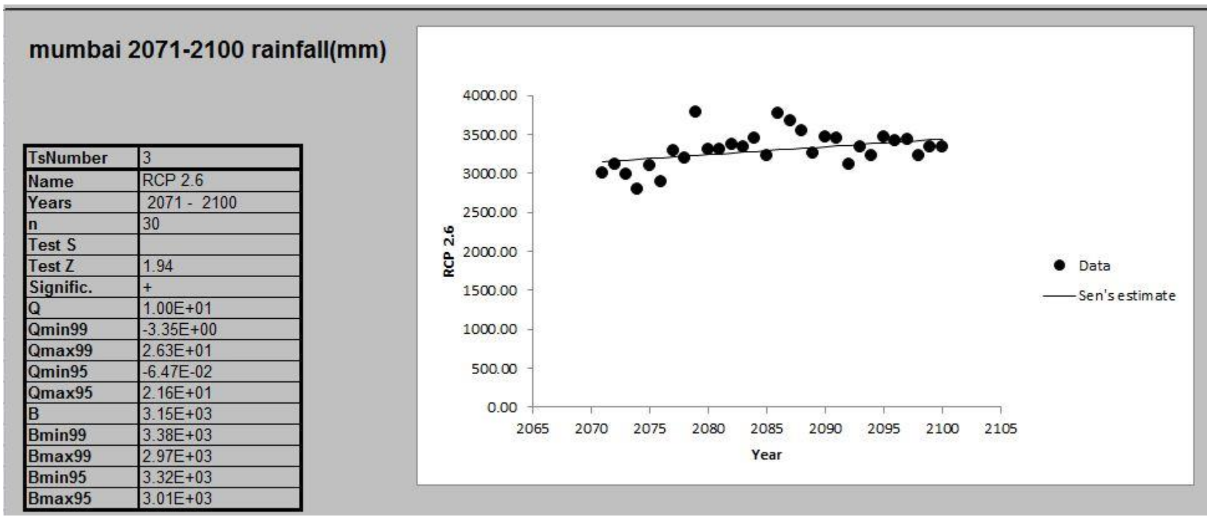


Figure 5.36: Mumbai 2071-2100 rainfall

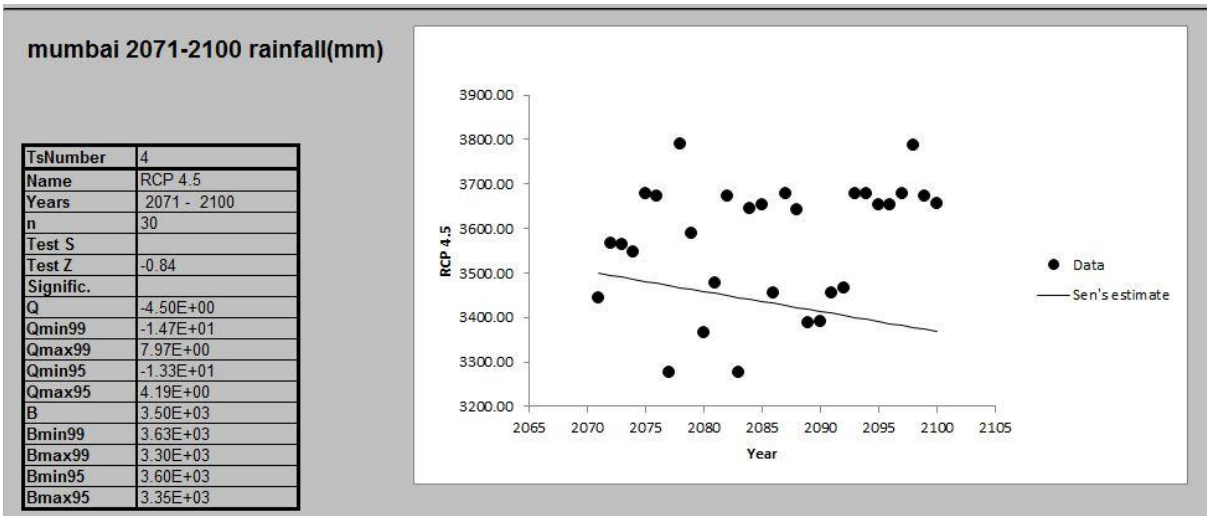
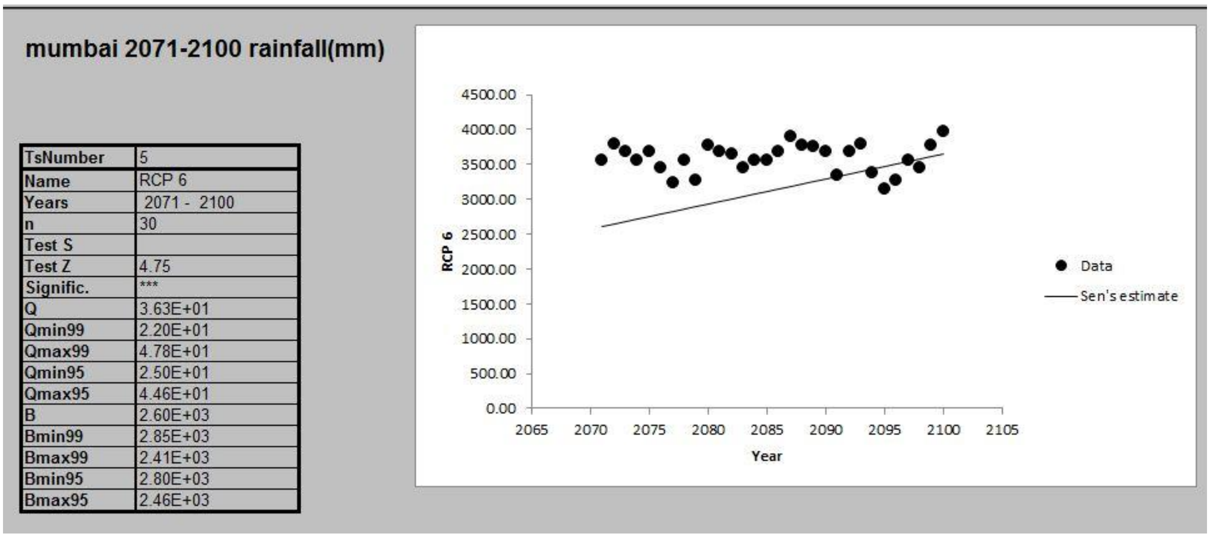


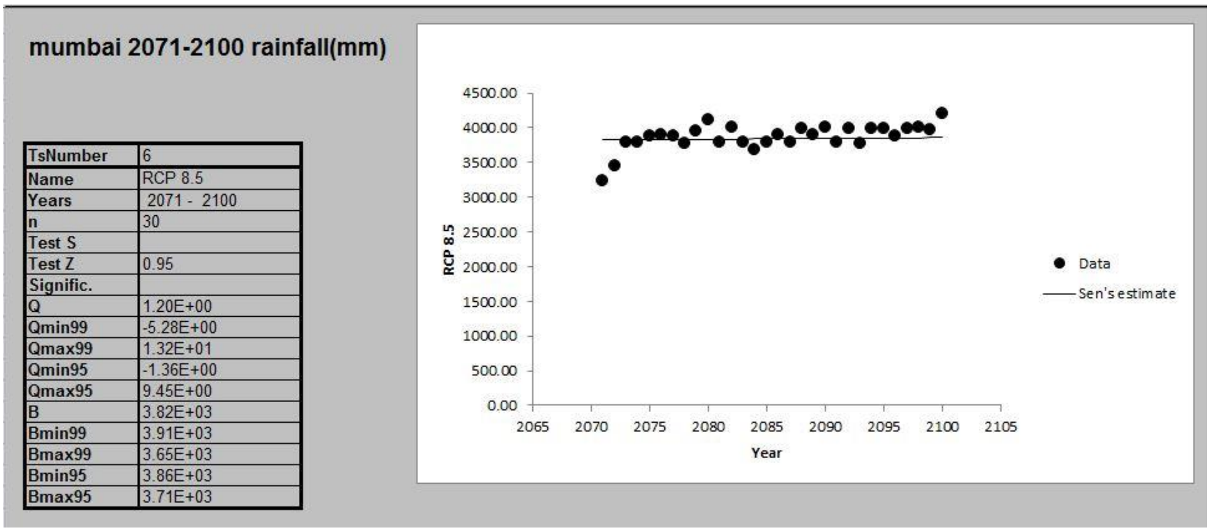
Figure 5.37: Mumbai 2071-2100 rainfall



mumbai 2071-2100 rainfall(mm)

TsNumber	5
Name	RCP 6
Years	2071 - 2100
n	30
Test S	
Test Z	4.75
Signific.	***
Q	3.63E+01
Qmin99	2.20E+01
Qmax99	4.78E+01
Qmin95	2.50E+01
Qmax95	4.46E+01
B	2.60E+03
Bmin99	2.85E+03
Bmax99	2.41E+03
Bmin95	2.80E+03
Bmax95	2.46E+03

Figure 5.38: Mumbai 2071-2100 rainfall



mumbai 2071-2100 rainfall(mm)

TsNumber	6
Name	RCP 8.5
Years	2071 - 2100
n	30
Test S	
Test Z	0.95
Signific.	
Q	1.20E+00
Qmin99	-5.28E+00
Qmax99	1.32E+01
Qmin95	-1.36E+00
Qmax95	9.45E+00
B	3.82E+03
Bmin99	3.91E+03
Bmax99	3.65E+03
Bmin95	3.86E+03
Bmax95	3.71E+03

Figure 5.39: Mumbai 2071-2100 rainfall

Table 5.2: Inter-variable correlations (source: Wilby et al 2000)

Variable pair		DJF		JJA	
		Observed	HadCM2	Observed	HadCM2
T_{max}	T_{min}	**0.87**	**0.77**	**0.65**	**0.81**
	q	**0.69**	**0.73**	**0.32**	**0.21**
	D_s	−0.37	−0.38	−0.28	−0.41
	H_{500}	**0.71**	**0.60**	**0.81**	**0.84**
	F_{500}	−0.21	0.03	**−0.55**	**−0.50**
	Z_{500}	−0.32	−0.27	−0.46	−0.48
T_{min}	q	**0.79**	**0.79**	**0.82**	**0.59**
	V_s	0.33	0.41	0.52	0.65
	D_s	−0.37	−0.47	**−0.58**	**−0.67**
	H_{500}	**0.62**	**0.44**	**0.73**	**0.75**
	Z_{500}	−0.27	−0.29	−0.33	−0.44
q	V_s	0.29	0.36	**0.48**	**0.62**
	D_s	−0.33	−0.43	**−0.52**	**−0.63**
	H_{500}	**0.49**	**0.49**	**0.48**	**0.32**
D_s	V_s	**−0.88**	**−0.87**	**−0.89**	**−0.91**
	H_{500}	−0.40	−0.33	−0.39	−0.45
	Z_{500}	0.47	0.45	0.29	0.30
Z_s	mslp	**−0.55**	**−0.55**	**−0.55**	**−0.56**
H_{500}	V_s	0.37	0.30	0.34	0.47
F_{500}	H_{500}	−0.28	−0.15	**−0.60**	**−0.54**
	U_{500}	0.31	0.25	0.36	0.43
D_{500}	mslp	0.38	0.44	0.17	0.29
	V_{500}	**−0.87**	**−0.88**	**−0.85**	**−0.85**
Z_{500}	V_s	−0.41	−0.40	−0.24	−0.30
	H_{500}	**−0.63**	**−0.56**	**−0.64**	**−0.62**

The pairs listed are the top 25 when ranked according to the overall strength of correlations, with all regions, both seasons and both data sources combined. Correlations in bold are discussed in the main body text.

Table lists the strongest inter-variable correlations, on a daily scale, arising from the analysis of propinquitous predictor variables and lumping all regions together. Given the large sample sizes, correlation coefficients exceeding 0.1 are significant at a significance level of a-0.001 (even when using the effective sample sizes, n%, in order to account for autocorrelation; n% is always\100). However, significance does not necessarily imply that the variable is a useful predictor since the amount of explained variance may be low. Furthermore, certain variable pairs are necessarily strongly correlated: such as Ds and Vs, or D500 and V500, because of the way divergence is defined. Strong correlations are also expected a priori between Tmax and Tmin, and between q and both Tmax and (especially) Tmin given the temperature dependency of the saturation specific humidity. These variable pairs aside, the strongest DJF correlations were between H500 and Tmax:Tmin, H500 and q, Zs and mslp, and the equivalent upper atmosphere correlation between Z500 and H500. The same or stronger correlations occur in JJA, with the exception of the weaker correlation between Tmax and q. Additional strong correlations that are either non-existent or noticeably weaker in DJF occur between F500 and H500, Tmax and F500 (partly because of high correlations between Tmax and H500, and F500 and H500), q and Ds, q and Vs (because of the strong Vs–Ds link), and Tmin and Ds (arising partly through the correlations between Tmin and q, and q and Ds).Overall, the inter-variable correlation strengths for observed and HadCM2 daily data were remarkably similar in both seasons providing a strong indication of the GCM's internal consistency and realism relative to the real world. In terms of explained variance the most notable differences occur in the correlations between: Tmax and Tmin (both seasons, with the GCM showing a stronger link in JJA and a weaker link in DJF); Tmax and H500 (DJF, GCM correlation weaker); Tmin and q (JJA, GCM correlation weaker); Tmin and Vs (JJA, GCM correlation stronger); Tmin and H500 (DJF, GCM correlation weaker); q and Vs and Ds (JJA, GCM correlations stronger); and q and H500 (GCM correlation weaker). Thus, the inter-variable correlation skill of the GCM was generally greater in DJF than in JJA.

CHAPTER 6: CONCLUSIONS AND FUTURE SCOPE

6.1 Conclusion

Impact of climate change on the hydrology of six point regions of India was carried out using Statistical Downscaling Model (SDSM), Mann Kendall Test, Sen¡¦s slope estimator.

The conclusions were:

- Rainfall prediction can play an important role in planning and management of water resources. Downscaling models have been used to predict the amount of rainfall in a local scale. 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 results from the present study for temperature and precipitation for Rourkela location and same GCM (HadCM3) model from the Canadian Climate Data and Scenarios (CCDS).

- But the rcp scenarios of CanESM 2 were not found suitable for the region of Rourkela and Rishikesh .

- RCP scenarios were found to be suitable for Mumbai region using CanESM2 and hence were used in the analysis.

- 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

- Modelling 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.

6.2 Scope for future work

The study could have been far more extensive if more GCM data were used. As stated earlier, the NCEP suffers from limitation due to its relatively coarse grid. A comparison of its performances with the recently developed finer grid data (10 km), such as the Canadian daily dataset (Hutchison et al, 2009) may help towards the search for a more accurate source of alternative database.

The weather generator used in the study is set that it can be applied to daily data only. Modification of the algorithm for a finer temporal scale is recommended.

Uncertainty calculations can be done more extensively using IDF methods.

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APPENDIX A:

Atmosphere-Ocean Global Climate Models

Criteria for Selecting Climate Scenarios

Five criteria that should be met by climate scenarios if they are to be useful for impact researchers and policy makers are suggested by IPCC (2007) and are quoted here:

Criterion 1: Consistency with global projections. They should be consistent with a broad range of global warming projections based on increased concentrations of greenhouse gases. This range is variously cited as 1.4¢XC to 5.8¢XC by 2100, or 1.5¢XC to 4.5¢XC for a doubling of atmospheric CO2 concentration (otherwise known as the "equilibrium climate sensitivity").

Criterion 2: Physical plausibility. They should be physically plausible; that is, they should not violate the basic laws of physics. Hence, changes in one region should be physically consistent with those in another region and globally. In addition, the combination of changes in different variables (which are often correlated with each other) should be physically consistent.

Criterion 3: Applicability in impact assessments. They should describe changes in a sufficient number of variables on a spatial and temporal scale that allows for impact assessment. For example, impact models may require input data on variables such as precipitation, solar radiation, temperature, humidity and wind speed at spatial scales ranging from global to site and at temporal scales ranging from annual means to daily or hourly values.

Criterion 4: Representative. They should be representative of the potential range of future regional climate change. Only in this way can a realistic range of possible impacts be estimated.

Criterion 5: Accessibility. They should be straightforward to obtain, interpret and apply for impact assessment. Many impact assessment projects include a separate scenario development component which specifically aims to address this last point. The DDC and this guidance document are also designed to help meet this need.

Challenges in using AOGCMs

GCMs depict the climate using a three dimensional grid over the globe (Figure), typically having a horizontal resolution of between 250 and 600 km, 10 to 20 vertical layers in the atmosphere and sometimes as many as 30 layers in the oceans. Their resolution is thus quite coarse relative to the scale of exposure units in most impact assessments, hence only partially fulfilling criterion 3. Moreover, many physical processes, such as those related to clouds, also occur at smaller scales and cannot be properly modeled. Instead, their known properties must be averaged over the larger scale in a technique known as parameterization. This is one source of uncertainty in GCM based simulations of future climate. Others relate to the simulation of various feedback mechanisms in models concerning, for example, water vapor and warming, clouds and radiation, ocean circulation and ice and snow albedo. For this reason, GCMs may simulate quite different responses to the same forcing, simply because of the way certain processes and feedbacks are modeled.

However, while these differences in response are usually consistent with the climate sensitivity range described in criterion 1, they are unlikely to satisfy criterion 4 concerning the uncertainty range of regional projections. Even the selection of all the available GCM experiments would not guarantee a representative range, due to other uncertainties that GCMs do not fully address, especially the range in estimates of future atmospheric composition.

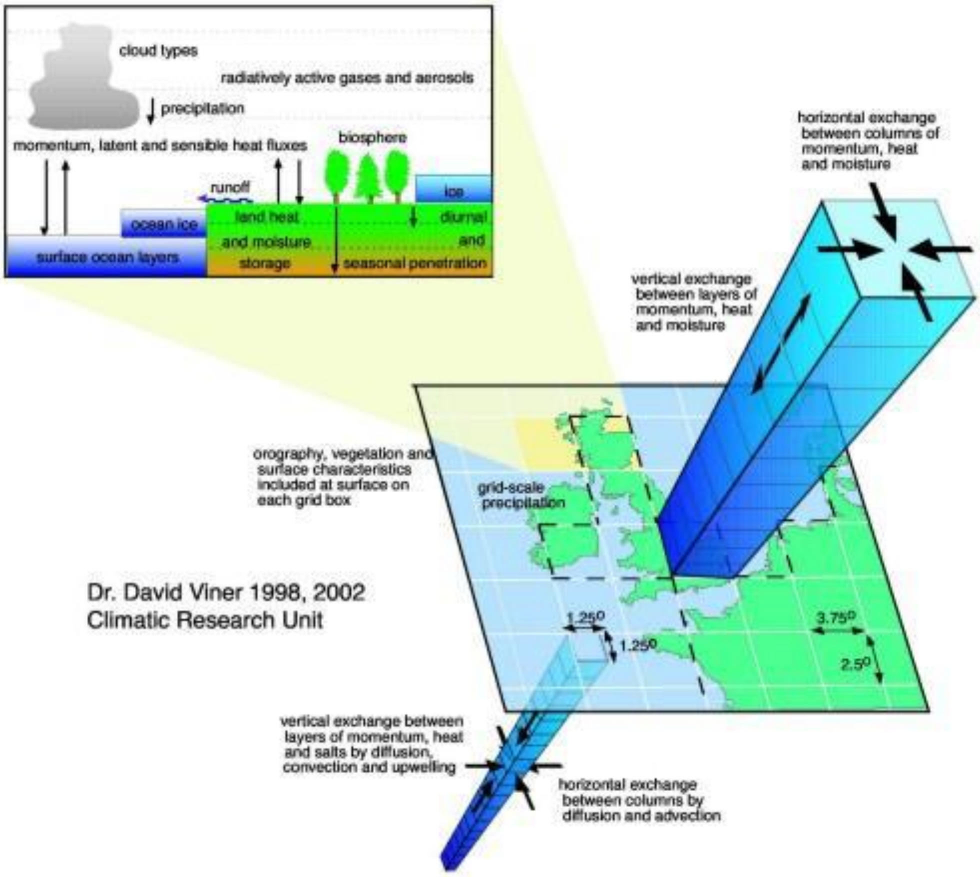

Figure A.1: Climatic Research Unit

APPENDIX B:

Atmosphere-Ocean Global Climate Models Used

Canadian Coupled Global Climate Model

The third generation Coupled Global Climate Model (CGCM3) was created in 2005 by the Canadian Centre for Climate Modelling and Analysis (CCCma) in Victoria, BC for use in the IPCC 4th assessment report to run complex mathematical equations which describe the earth.s atmospheric and oceanic processes. The CGCM3 climate model includes four major components: an atmospheric global climate model, an ocean global climate model, a thermodynamic sea-ice model, and a land surface model (Hengeveld, 2000) and consists of two resolutions, T47 and T63. The T47 version has a surface grid whose spatial resolution is roughly 3.75 degrees lat/lon and 31 levels in the vertical. The ocean grid shares the same land mask as the atmosphere, but has four ocean grid cells underlying every atmospheric grid cell. The ocean resolution in this case is roughly 1.85 degrees, with 29 levels in the vertical.

The T63 version has a surface grid whose spatial resolution is roughly 2.8 degrees latitude/longitude and 31 levels in the vertical. As before the ocean grid shares the same land mask as the atmosphere, but in this case there are 6 ocean grids underlying every atmospheric grid cell. The ocean resolution is therefore approximately 1.4 degrees in longitude and 0.94 degrees in latitude. This provides slightly better resolution of zonal currents in the Tropics, more nearly isotropic resolution at mid latitudes, and somewhat reduced problems with converging meridians in the Arctic. (Compiled from http://www.ec.gc.ca/ccmac-cccma/default.asp?lang=En&n=1299529F-1)

Commonwealth Scientific and Industrial Research Organization’s Mk3.5 Climate Systems Model

Australia‟s Commonwealth Scientific and Industrial Research Organization created the AOGCM CSIROMK3.5, which is an improved version of the MK climate systems model. The model consists of several components: atmosphere, land surface, ocean and polar ice. The dynamic framework of the atmospheric model is based upon the spectral method with the equations cast in the flux form that conservs predicted variables. The atmospheric moisture variables (vapour, water and ice) are advected by a Semi- Lagrangian Transport (SLT) algorithm (McGregor, 1993). The most recent version (MK3.5) has included a representation of the Great Lakes and changes in land surface scheme and it‟s representation of surface albedo under freezing than it‟s previous versions. The MK3.5 version provides improved information by including the spatially varying eddy transfer coefficients (Visbeck et al, 1997) and the Kraus-Turner mixed layer (1967) scheme. Improvements have also been done in it‟s oceanic behavior in the high latitude Southern ocean, where the stratification and circulation are generally more realistic than the prior models. The spatial resolution of the model is 1.875 × 1.875. Compiled from (http://www.cawcr.gov.au/publications/technicalreports/CTR_021.pdf)

Max Planck Institute for Meteorology’s ECHAM5AOM Model

ECHAM5 is the 5th generation of the ECHAM global climate model. Depending on the configuration the model resolves the atmosphere up to 10 hPa for tropospheric studies, or up to 0.01 hPa for middle atmosphere studies. The current version differ in the vertical extent of the atmosphere as well as the relevant processes than it‟s earlier versions. It is capable of hosting sub-models (chemistry, aerosol and vegetation) going beyond the meteorological processes of a AOGCM. The model can be used as a part of a coupled ocean GCM, in assimilation by linear relaxation and as a standalone column model.

For integrations to start, the model requires several files. These file contain information for the description of the initial or re-start state of the atmosphere (boundary conditions at the surface, the ozone distribution and tables of constants of LW radiation schemes), the description of assumed conditions during the integration, e.g. sea surface temperature, or the initialization of parameterizations. (Compiled from http://www.mpimet.mpg.de/en/science/models/echam/echam5.html)

Meteorological Institute, University of Bonn Meteorological Research Institute of KMA Model and Data Groupe at MPI-M's ECHO-G Model

The climate model ECHO-G (Legutke and Voss, 1999) is a coupled climate model consisting of the atmospheric model ECHAM4 (Roeckner et al., 1996) and the ocean model HOPE (Wolff et al., 1997).

The ECHAM4-model is based on primitive equations. The prognostic variables are vorticity, divergence, logarithm of surface pressure, temperature, specific humidity, mixing ratio of total cloud water and optionally a number of trace gases and aerosols.The vertical extension is up to a pressure level of 10 hPa, which corresponds to a height of approximately 30km. A hybrid sigma-pressure coordinate system is used with 19 irregularly ordered levels and with highest resolution in the atmospheric boundary layer.

The bottom level is placed at a height of about 30m above the surface corresponding approximately to the surface layer. In this study the ECHAM4 model has a horizontal resolution of about 3.75lat x 3.75lon. The ocean model HOPE (Hamburg Ocean Primitive Equation) is an ocean global climate model (OGCM) based on primitive equations with the representation of thermodynamic processes. It is a non-eddy resolving circulation model. HOPE-G has a horizontal resolution of approximately 2.8lat x 2.8lon with a grid refinement in the tropical regions over a band from 10N to 10S. This meridional grid refinement reaches a value of 0.5 at the equator allowing for a more realistic representation of ENSO variability in the tropical Pacific Ocean . The ocean model has 20 vertical, irregularly ordered layers.

The coupling as well as the interpolation between the atmosphere and the ocean model is controlled by the coupling software OASIS (Terray et al., 1998). Concerning the coupling dynamics, at a distinct frequency the atmospheric component of the model passes heat, fresh water and momentum to the ocean and gets information about surface conditions of the ocean. This frequency is equal for all exchange fields and describes a 'coupled time step'. The fields that are exchanged are averaged over the last coupled time step. Further aspects of the exchange processes are flux corrections due to the interactive coupling between ocean and atmosphere in order to prevent climate drift. These heat- and freshwater fluxes were diagnosed in a coupled spin-up integration. Accordingly, the seasurface- temperature and sea-surface salinity were restored to their climatological observed values. This flux adjustment is constant in time and its global average vanishes. Quoted from (http://coast.gkss.de/staff/wagner/midhol/model/model_des.html)

Goddard Institute for Space Studies¡ Atmospheric Ocean Model

The North American Space Association and the Goddard Institute for Space Studies developed the GISS-AOM climate model, first in 1995 and then a revised version was created with smaller grids in 2004 for the IPCC 4th assessment report. The model requires two kinds of input, specified parameters and prognostic variables, and generates two kinds of output, climate diagnostics and prognostic variables. The specified input parameters include physical constants, the Earth's orbital parameters, the Earth's atmospheric constituents, the Earth's topography, the Earth's surface distribution of ocean, glacial ice, or vegetation, and many others. The time varying prognostic variables include fluid mass, horizontal velocity, heat, water vapour, salt, and subsurface mass and energy fields. The resolution for the model is 4„a longitude by 3„a latitude (PCMDI, 2005). The atmospheric grid has 12 vertical layers (PCMDI, 2005).

Model for Interdisciplinary Research on Climate version 3.2

The Japanese Model for Interdisciplinary Research on Climate version 3.2 (MIROC3.2)was developed in two resolutions: the high resolution (MIROC3.2HIRES) in 1.125„a ¡Ñ 1.125„a grid and the medium resolution (MIROC3.2MEDRES) in 2.8„a ¡Ñ 2.8„a grid. For present study, two emissions scenarios from MIROC3.2HIRES (A1B and B1) and three scenarios (A1B, A2 and B1) from MIROC3.2MEDRES were used.