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Indian Monsoon Rainfall Projections for Future Using GCM Model Outputs Under Climate Change

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Abstract

Statistical downscaling technique is used for projection of Indian monsoon monthly rainfall (IMMR) at 0.25^0 resolution using 3 General circulation model outputs (GCMs) of Coupled Model Intercomparison Project Phase 5 (CMIP5) suite. General circulation models (GCMs) are the best tools available now to study the climate variables at coarse/global level. But these GCMs are poor at studying climate at fine/regional/local level. A statistical model, which relates large-scale climate variables (or predictors) to regional/local-scale climate/hydrologic variables(or predictand), is developed to derive the regional information about the climate/hydrologic variable. In the present study the projection is carried out based on a linear regression model in which statistical downscaling relation is developed between the standardized NCEP/NCAR data and APHRODITE observed precipitation. The relationship thus developed is applied to the GCM simulated output for projection of rainfall in the future. The results obtained from 3 GCMs are combined with multi model average (MMA) are represented in plots showing the change in the mean rainfall between the historic period (1980-2000) and future period (2010-2040). The probable distribution function (PDF) of MMA data is plotted for all over India. The present study highlights the IMMR projections in the effective management of water resources in the future due to impact of Climate change.

Keywords: Statistical downscaling, General circulation models, Standardization, Principal component analysis, Linear regression

1. INTRODUCTION

India summer monsoon rainfall (ISMR) is the source of 80% of India's annual rainfall. South Asian summer monsoon is the source of 75% of total annual rainfall in major parts of southern Asia. More than 22% of the world's population resides in southern Asia and depends totally on the monsoon as their primary source of water. General circulation models (GCMs) are mathematical models that take into consideration the physics involved in various atmospheric, oceanic, and land processes in the form of a set of linear and nonlinear partial differential equations, and project climatic variables globally at a very coarse resolution. GCMs developed by the Canadian Centre for Climate Modeling and Analysis, Atmosphere and Ocean Research Institute (University of Tokyo)and others, Max Planck Institute for Meteorology (MPI-M) are employed for this study. Here we use a statistical downscaling technique for projections of all-India monsoon rainfall at a resolution of 0.25^0 in latitude/longitude. The present statistical downscaling model utilizes a multivariate linear regression and develops a statistical relationship between large-scale climate variables from reanalysis data and fine-resolution observed rainfall, and then applies the relationship to coarse-resolution GCM outputs. Two of the more common approaches to downscaling are dynamic downscaling and statistical downscaling. Dynamic downscaling uses a numerical meteorological model to simulate the physical dynamics of the local climate while utilizing the climate projections from GCMs as initial boundary conditions. Though it captures the geographic details of a region unresolved by GCMs, the simulation is computationally demanding while its spatial resolution remains too coarse for many climate impact assessment studies (Wilby and Wigley, 2004). Unlike dynamic downscaling, it is flexible enough to incorporate any predictor variable and is relatively inexpensive. These methods are ill-suited for predicting extreme values of the climate variables (Aksornsingchai and Srinilta (2011)).

2. STATISTICAL DOWNSCALING

Statistical downscaling involves the establishment of empirical relationships between historical large-scale atmospheric and local climate characteristics. Once a relationship has been determined and validated, future large-scale atmospheric conditions projected by GCMs are used to predict future local climate characteristics. In other words, large-scale GCM outputs are used as predictors5 to obtain local variables or predictands. Statistical downscaling encompasses a heterogeneous group of methods that vary in sophistication and applicability. A statistical model, which relates large-scale climate variables (or predictors) to regional- or local-scale climate/hydrologic variables (or predictands), is developed to derive the regional information about the climate/hydrologic variable. .In other words Statistical Downscaling (SD) is defined as an effort to relate between global-scale (explanatory variables) and local scale climate variables (response variables). There are two approaches for downscaling, using regional data (obtained from a regional climate model, RCM), or global data (obtained from the general circulation models, GCM). The first approach is known as statistical dynamical downscaling, while the second is known as statistical downscaling (SD). Statistical downscaling based on the relationship between coarse-scale grid (predictor) with local-scale data (response) is expressed with a statistical model that can be used to translate a global scale anomaly which became an anomaly of some variables of local climate.

Statistical downscaling methods are computationally inexpensive in comparison to RCMs that require complex modeling of physical processes. Thus, they are a viable and sometimes advantageous alternative for institutions that do not have the computational capacity and technical expertise required for dynamical downscaling. Unlike RCMs, which produce downscaled projections at a spatial scale of 20–50 kilometers, statistical methods can provide station-scale climate information.

Assumptions and Caveats

Although statistical downscaling is efficient, computationally inexpensive, and consists of a diverse group of methods, it contains the following inherent assumptions:

- The statistical relationship between the predictor and predictand does not change over time.
- The predictor carries the climate change signal.
- There is a strong relationship between the predictor and predictand.
- GCMs accurately simulate the predictor.

The first point is known as the stationarity assumption and postulates that the statistical relationship between the predictor and predictand remains stable into the future. Whether relationships based on present associations will be upheld under future climate conditions is unknown. The second is the assumption that the large-scale variable represents the climate system and captures any change that may occur in the future. Assumption three implies that the strength of the relationship should be initially evaluated to determine its validity. Assumption four relates to the ability of a GCM to simulate climate variables observed in the past as well as their future evolution. Predictor validations are usually performed prior to a given GCM's use in downscaling schemes.

Statistical downscaling (SD) approaches are computationally cheap and relatively simple and easy to apply. Thus, a wide range of SD techniques have been developed. They fall into three main categories:

a) Transfer function

b) Weather typing

c) Weather generator

In many cases, statistical downscaling studies use more than one of these categories (Wilby and Wigley 1997) and refer Wilby et al (2004) for further information.

3. DATA

The following listed datasets have been used for downscaling precipitation on a daily basis at a site resolution.

3.1 NCEP/NCAR Reanalysis data:

The National Center for Environmental Prediction (NCEP) and National Center for Atmospheric Research (NCAR) have together contributed to a project referred to as "reanalysis", to produce a record of 50 years of global analysis of climatic data in the form of atmospheric fields (Table 4.2). This product is primarily useful for researchers and climate monitoring bodies and policy makers. The data is generated from a combination of sources like land surface readings, ships, aircrafts, satellites and other data sources. It is then processed for quality control and assimilitated with a complex and superior data assimilation system that is kept unchanged over the entire reanalysis period. The products can be obtained from NCEP/NCAR and the National Oceanic and Atmospheric Administration/ Climate Diagnostics Center (NOAA/CDC). The NCEP/NCAR Reanalysis data has a resolution of 2.5° * 2.5° and is considered as a proxy to observed data. It is available at a temporal coverage of 4-times daily, daily, monthly from 1948 to present (Kistler et al., 2001). The data also provides long term monthly means that is available for 17 pressure levels which can be selected depending on the requirement of the study.

Table 1: NCEP/NCAR variables

Description	Name	Units
Zonal wind component	U	m s -1
Meridional wind component	V	m s -1
Geopotential Height	ZA	M
Temperature	T	K
Specific Humidity	Q	Kg kg- 1
Surface pressure	PS	Pa
Sea Level Pressure	SLP	Pa

The NCEP/NCAR reanalysis data (Kalnay et al., 1996), used for the predictors, are extracted for latitudes 5^0N–40^0N and longitude 60^0E–120^0E, encompassing the entire India. This is a global gridded product and continually updated through data assimilation to judiciously blend physical observations and model simulations dating back to 1948. The Reanalysis data is a surrogate for observed data for any predictor variable. The resolution of NCEP/NCAR reanalysis product is 2.5^0 lat * 2.5^0long. For downscaling purposes, India is first subdivided into seven meteorological subdivisions as per India Meteorological Department (IMD) categorization (Parthasarathy et al., 1996) and the spatial extent of the predictors for different zones are different. They are selected based on the correlation between the spatially averaged rainfall and gridded predictors (Salvi et al., 2013). In the current study, 40years data was used for each station from 1975-2005 on an average. The dataset, available in NetCDF format was read in MATLAB.

3.2 Observed Data from APHRODITE Observed data was used for the calibration and validation of the downscaling model with the NCEP-NCAR data and the GCM respectively. Since statistical downscaling was performed at a station-level/site-level; rainfall was required for each station. The monthly data of the above stated variables were provided by the Asian Precipitation Highly Resolved Observational Data Integration towards Evaluation of Water Resources (APHRODITE) at 0.25^0 resolutions. The gridded rainfall data, provided by APHRODITE (Yatagai et al., 2012) is used as the predictand, and is obtained at monthly intervals for the spatial resolution 0.25^0. They are based on (i) GTS (Global Telecommunication system) data (ii) data compiled by the organizations from the respective countries like, India Meteorological Department (IMD) for India, and (iii) APHRODITE's own data collection system with proper quality control (Yatagai et al., 2012). The data is available for 0.5 °x0.5 ° and 0.25 ° x0.25° grids at http: www.chikyu.ac.jp/precip/.

3.3 CMIP5 simulations

The CMIP5 (Coupled Model Intercomparison Project 5) is a comprehensive set of experiments prepared by the World Climate Research Programme's working group on coupled modeling. The data has an extensive list of outputs. It is available in netCDF-3 format and conforms to CF metadata standards. The CMIP5 is one of the few GCMs that provide monthly simulations.

For historic and future simulations, we selected 3 GCMs, from CMIP5 archives, and obtained the outputs at monthly time scale. The list of GCMs is provided in Table 3. The GCM simulated predictors are obtained from the Program for Climate Model Diagnosis and Intercomparison (PCMDI). For future rainfall projections of ISMR, Representative Concentration Pathways 8.5 (RCP 8.5) is considered for the present work.

Table 2 List of GCMs used in monthly Rainfall Downscaling.

S.No.	Name	Institution	Resolution	
			Latitude(^{0})	Longitude(^{0})
1.	MIROC-ESM	Atmosphere and Ocean Research Institute (University of Tokyo)and others	2.8	2.8
2.	CCCma-CAN-ESM2	Canadian Centre for Climate Modelling and Analysis	2.8	2.8
3.	MPI-M	Max Planck Institute for Meteorology (MPI-M)	1.8652	1.875

The selection of predictors is a crucial step in developing a statistical downscaling model. The output of the statistical downscaling method is sensitive to the choice of predictor variables. The criteria used for selections of predictors are that they should be reliably simulated by GCMs, available in the GCM archive and physically associated with the variable of interest (Wilby et al., 2004). Considering these criteria, the predictors used for ISMR downscaling (also used in Salvi et al., 2013; Kannan and Ghosh, 2013; Shashikanth et al., 2013) are air temperature, wind velocities (U and V wind), specific humidity at both 500 hPa pressure level and the surface and the Mean Sea Level Pressure (MSLP). These predictors are based on the study by Shashikanth et al. (2013) for ISMR.

4. METHODOLOGY

A statistical relationship has been derived between observed small scale (station level) variables and larger (NCEP/NCAR Reanalysis data) scale variables, using a transfer function. GCM Projections (CMIP5 simulations) was used to drive the statistical relationship, in order to estimate the smaller-scale details of future climate. A statistical downscaling model (fig.2) first develops an empirical relationship between synoptic scale circulation patterns (predictors) and the local variable of interest (predictand i.e. rainfall). The relationship is then further applied to the GCM simulations of the future to project the regional climate scenarios. Here, we use the National Centre for Environmental Prediction/National Centre for Atmospheric Research (NCEP/NCAR) reanalysis data as predictors and the gridded rainfall as the predictand. Statistical downscaling starts with regridding the monthly GCM output (e.g., MIROC model 2.8^0 resolution) into the resolution of NCEP/NCAR (i.e 2.5^0). Later standardization and principal component analysis is done on both GCM output and NCEP/NCAR reanalysis data and identified the principal components of both the data. By using linear regression technique a transfer function is generated between the principal components of NCEP/NCAR and the observed rainfall data which is obtained from APHRODITE (Asian Precipitation Highly Resolved Observational

Data Integration towards Evaluation of Water Resources) at 0.25^0 resolution. After training of transfer function it is applied to the principal components of GCM to obtain rainfall projection.

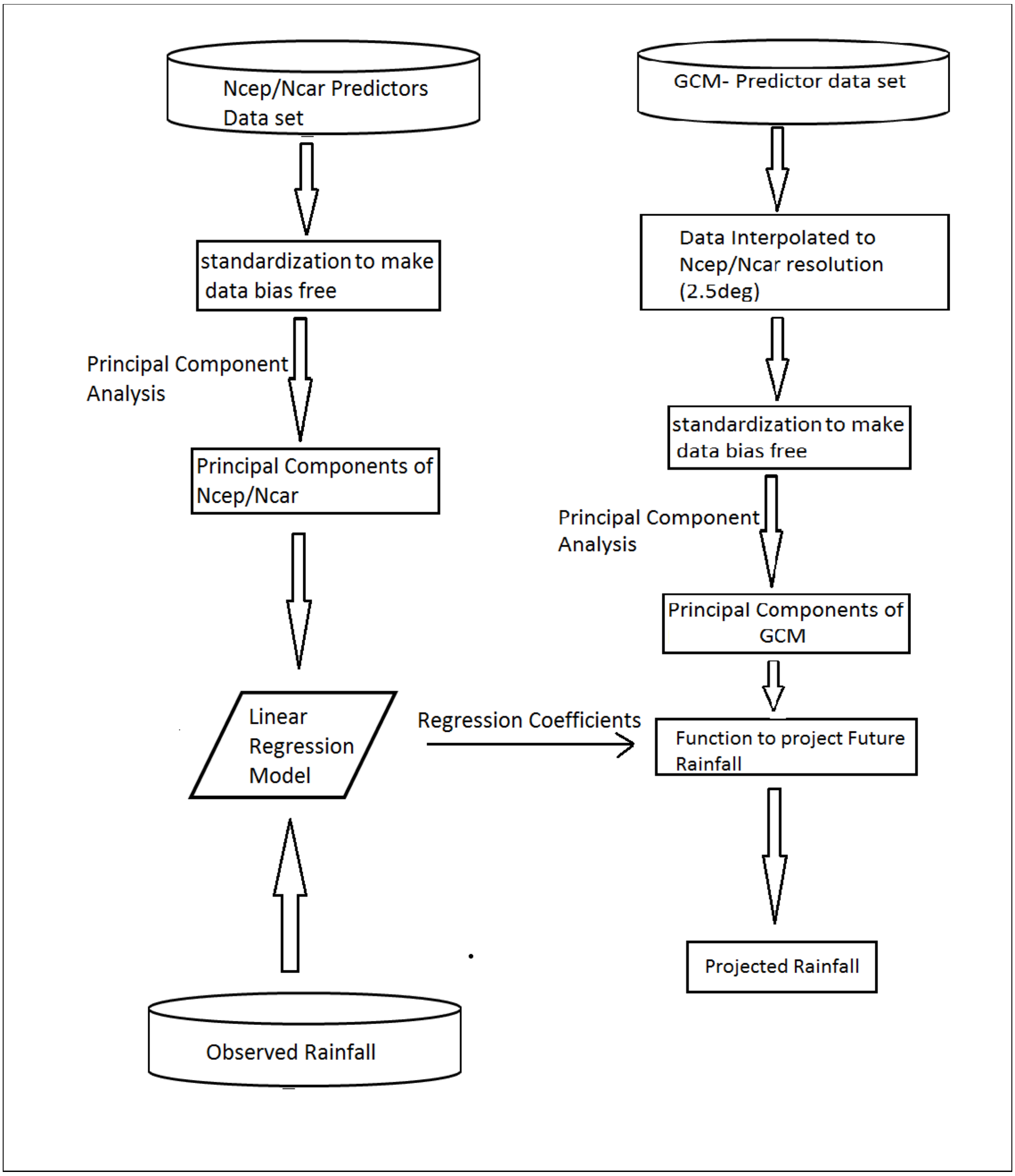

Figure.1 Statistical downscaling (SD) algorithm

4.1 Standardization of NCEP/NCAR reanalysis data and GCM output

The numerically solved fundamental equations in GCM contain certain systematic errors (known as bias), that needs to be corrected based on the observed data. Standardization is primarily done to reduce the systematic biases in the mean and variance of GCM predictors in relation to reanalysis data. The standardization process scales down the data and eliminates the dimensions in each variable.

Standardization is used before statistical downscaling to reduce the systematic bias in the mean and variances of GCM predictors relative to NCEP/NCAR data. Standardization has been performed by subtracting the mean from each value and dividing by the standard deviation. The predictors for the simulated period and the future period have also been standardized based on the baseline period. The baseline period was taken as a 30 year; which is considered sufficient to establish reliable climatological trend.

4.3 Principle Component Analysis

Principal component analysis (PCA) is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it is orthogonal to the preceding components. The resulting vectors are an uncorrelated orthogonal basis set. The principal components are orthogonal because they are the eigenvectors of the covariance matrix, which is symmetric. PCA is sensitive to the relative scaling of the original variables.

$$Z_j = a_j^T X$$

Where Z_j =j^{th} principal component

X = ‘n’ variable vector

a_j^T = Transpose of Data set

After the PCA, the variability of the PCs will satisfy the following condition.

$$\text{Variability } (Z_1) > \text{variability } (Z_2) > \text{variability } (Z_3) > \dots\dots\dots \text{ variability } (Z_n)$$

4.4 Linear Regression

Linear regression is a method of estimating the projected value of predictand (Eg. rainfall) given the values of predictor variables(principal components). The relationship between predictor and predictand may be represented by the equation. Linear regression is an approach for modeling the relationship between a scalar dependent variable *y* and one or more explanatory variables (or independent variable) denoted *X*. The case of one explanatory variable is called simple linear regression. For more than one explanatory variable, the process is called multiple linear regression. Linear regression was the first type of regression analysis to be studied rigorously, and to be used extensively in practical applications.[4] This is because models which depend linearly on their unknown parameters are easier to fit than models which are non-linearly related to their parameters and because the statistical properties of the resulting estimators are easier to determine.

In the present study after finding out the prinicipal components by PCA and future rainfall projection is carried out based on following equation.

$$\text{Rain}_{\,t} = \beta_0 + \sum \beta_t * Z_j$$

Where Rain $_t$ = rainfall in a month t.

β_t = j^{th} coefficient for linear regression

Z_j = j^{th} principal component of month t.

The above equation is fitted and β_t values are obtained and used for projection of rainfall.

In linear regression, data are modelled using linear predictor functions, and unknown model parameters are estimated from the data. Such models are called models. Most commonly, linear regression refers to a model in which the conditional mean of *y* given the value of *X* is an affine function of *X*. Less commonly, linear regression could refer to a model in which the median, or some other quantile of the conditional distribution of *y* given *X* is expressed as a linear function of *X*. Like all forms of regression analysis, linear regression focuses on the conditional probability distribution of *y* given *X*, rather than on the joint probability distribution of *y* and *X*, which is the domain of multivariate analysis.

Linear regression has many practical uses. Most applications fall into one of the following two broad categories:

- If the goal is prediction, or forecasting, or reduction, linear regression can be used to fit a predictive model to an observed data set of *y* and *X* values. After developing such a model, if an additional value of *X* is then given without its accompanying value of *y*, the fitted model can be used to make a prediction of the value of *y*.
- Given a variable *y* and a number of variables X_1, ..., X_p that may be related to *y*, linear regression analysis can be applied to quantify the strength of the relationship between *y* and the X_j, to assess which X_j may have no relationship with *y* at all, and to identify which subsets of the X_j contain redundant information about *y*.

5. RESULTS AND DISCUSSIONS

We all know Rainfall is a function of different climatic variables such as temperature, humidity, U wind, V wind, sea level pressure etc. The GCM data of all the climatic variables was collected from CMIP5 project and it is interpolated to the level of desired resolution of 0.25^0 resolution and made as bias free by standardisation technique. Now to project the future rainfall it is not possible by a linear regression technique when there are multi variables. Principal components analysis which reduce the dimensionality of the multi variables in to a single variable which will resemble the characteristics of all the climatic variables causing rainfall. The rainfall projections at 0.25^0 resolution (Approx. 25km) are made by linear regression model using the PCs in which the monthly projections are performed in Historic and future period. The projections in future are carried by using the RCP8.5 scenario of CMIP5 project. The same statistical relationship developed for historical period is used to project the rainfall in future time period i.e. 2010-2040.

Table 3: Details of Application periods

Scenario	Application period
Historic	1960-1979(Training period) 1980-1999 (Base line period)
RCP8.5	2010-2039(future period)

5.1 Historic

The following plot (fig4) shows the comparison between means of observed rainfall and projected rainfall data for the projected base line period (1980-2000) of MMA and different GCMs (MIROC, CCCMA, and MPI).The multi model average (MMA) of monthly mean rainfall simulated by 3 GCMs show a good result in projection and in spatial distribution of rainfall with observed monthly mean. It can be found from the plots that the statistical downscaled linear regression model holds good in projecting Indian summer monsoon rainfall (ISMR).The difference in the mean plot indicate that most of nodes have the difference in mean is 1mm/month, which is considered to be satisfactory. Similar plots are generated for other GCMs at 0.25^0 resolution in the same manner.

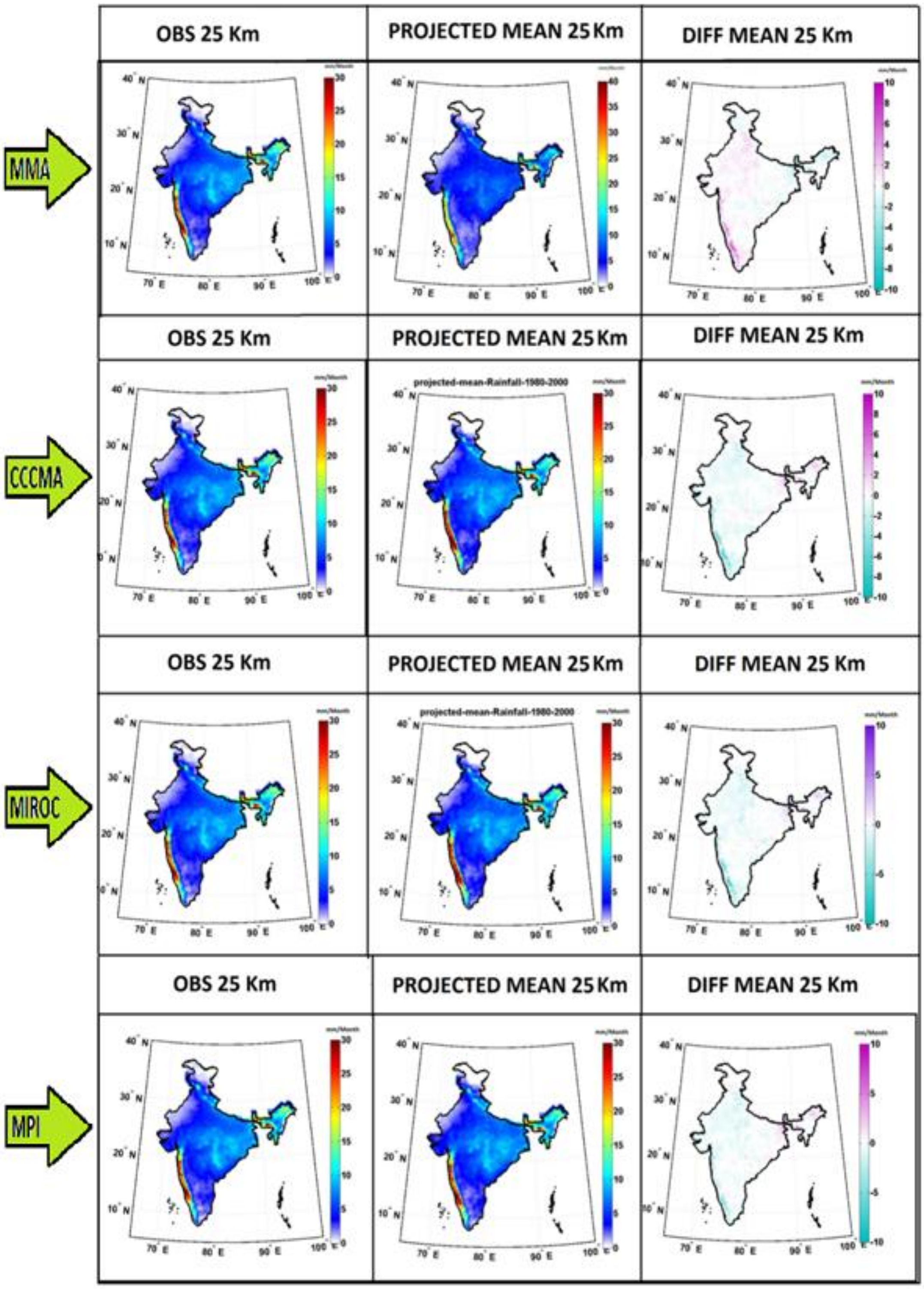

Figure 2: Shows the mean observed & projected rainfall of MMA and 3 GCMs and the difference

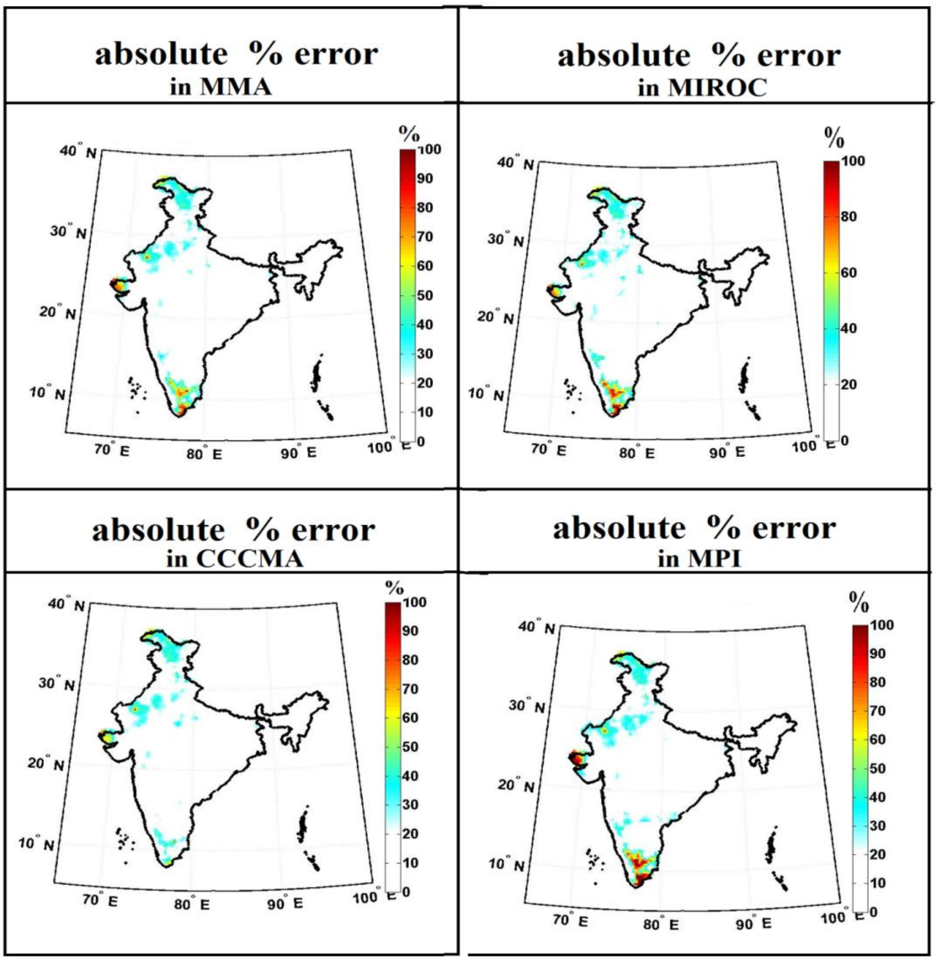

Figure 3: Shows the absolute percentage error in the projected monthly mean rainfall of different models and MMA with respect to Observed monthly mean rainfall in the base line period(1980-1999)

5.2 RCP 8.5

RCPs describe a wide range of potential issues concerning climate change like greenhouse gases, air pollutants, emissions and land use. RCPs have broken new grounds in several ways. They include some of the highest and lowest scenarios of greenhouse gases that have been recently examined by the climate research community. They include scenarios with climate mitigation, unlike the Special Report of Emission Scenarios (SRES), that focuses on a no climate policy only. Each RCP has been developed based on different combinations socio-economic, technological, population, institutional policy, land use changes etc (IPCC, 2011). . The lowest scenario aims to limit the extent of global warming in terms of global mean temperature to less than 2º C. The gridded data include climatic forcers such as sulphur aerosol and greenhouses gases. It has been generated upto the year 2300 for long-term climate research.

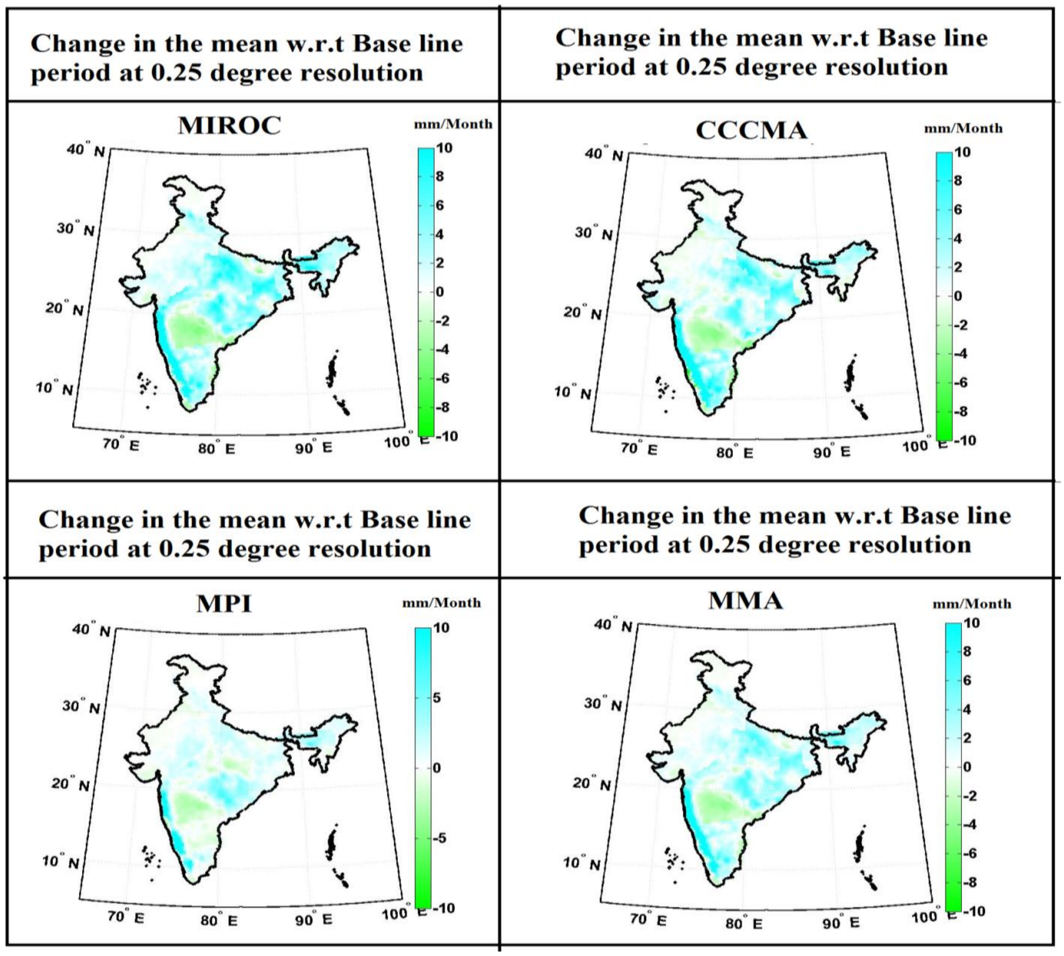

Figure 4: Discusses the changes in the mean monthly rainfall projections future (2010-2039) of MMA and other GCMs at 0.25^0 resolution with respect to Historical Base line period (1980-1999).

There are several RCPs: RCP4.5, RCP8.5, RCP2.6 and RCP6 etc. These RCPs are defined on the basis of their total radiative forcing (cumulative measure of human emissions of GHGs measured in watts per square meter) pathway by 2100 . They are derived from a broad range of climate outcomes, based on past literature. It is important to note that RCPs are neither forecasts nor predictions or recommendations for future policies (IPCC). The RCPs are not forecasts for potential emissions, land use, or climate change. They were chosen for scientific purposes to represent the radiative forcing at the time of their selection and thus facilitate the mapping of the broad climate space (wise et al 2009).

In the present study for future rainfall projections, RCP 8.5 scenario is considered in the CMIP5 scenarios. The figure 6.3 discusses the changes in the mean monthly rainfall for projections future (2010-2039) across all zones of India at 0.25^0 resolution. There is decrease in the rainfall with respect to historical base line period (1980-1999) in the Central India and in south India. There is increase in rainfall in the western

India, northern India and west coast of India. There are mixed increase and decrease in the mean monthly rainfall in the north east of India. Further detailed studies are required in this region. The projections obtained with MMA (Figu 7d) shows spatially non-uniform projected changes of ISMR. Increases in the precipitation are projected in the Gangetic west Bengal and regions of central India. We found that the projections in the low rainfall regions are on positive side i.e. statistical model is over predicting the rainfall in low rainfall regions. The behaviour of the Random Variable (Predictand) is completely described by its Probability law which intern may be characterised by either Probability Density function(PDF) or Cumulative Distribution function(CDF). Further the use of statistics alone does not allow for comparison of the entire data distribution and hence an evaluation of how well climate models can simulate entire distribution of a simulated variable is clearly required. The PDF based measurements is substantially better than direct comparison of means between model and observed data (Perkins et al. 2007).

5.3 PDF of Overall India:

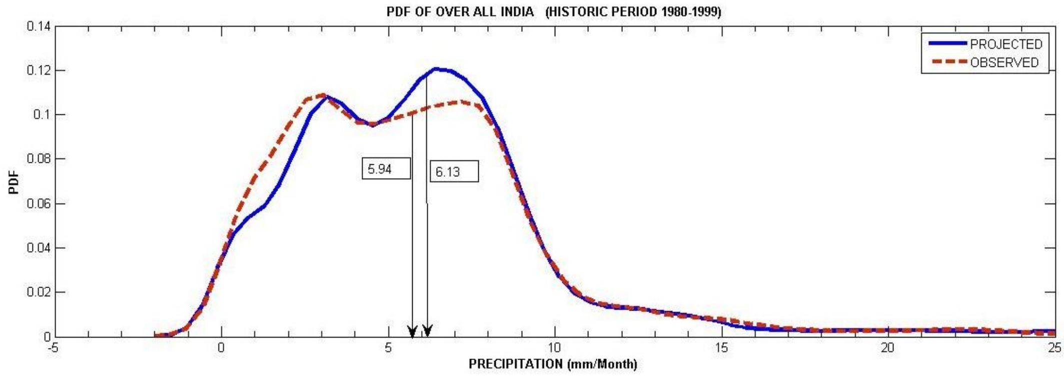

Figure 5: Error in Probability Distribution of Observed and Projected Mean monthly ISMR in overall India. Arrows indicating the respective mean of the Distribution.

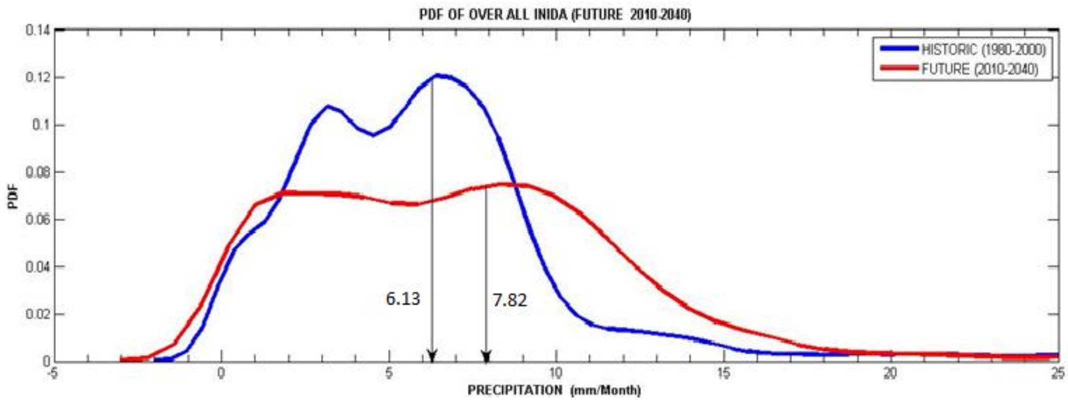

Figure 6: Change in Projected Future Mean monthly ISMR with respect to Base line period in overall India. Arrows indicating the respective Mean of the Distribution.

PDF carried out in all over India to compare the data distribution of mean monthly rainfall projected with respect to observed Rainfall of Historic/Base line period (1980-1999). In fig 5 shows that the projected Rainfall is somewhat positive side but the error is comparatively satisfactory.

After Training the model, future rainfall is projected assuming that the same trend of climatic variables. The fig 6 shows that the change in the mean monthly projected Rainfall (2010-2040) with respect to Base line period (1980-1999). By observation there is an increase in the mean of ISMR in future 2010-2040 scenario.

6. SUMMARY &CONCLUSIONS

The Monthly Projections of the Indian summer monsoon Rainfall are made in the seven meteorological Zones of India at 0.25^0 Resolution by statistical downscaling technique using General Circulation model Output. Considered all the Climatic variables which have affect on the ISMR and Reducing the multi variability of data set in to principal components (PCs) by sample principal component analysis (PCA). Later a Linear regression model is utilized to project the rainfall using the Predictors data set and Respective PCs. Estimation of monthly rainfall projections at 0.25^0 resolution is carried out in the base line period(1980-2000) using the Predictors data set of the training period (1960-1980) to train the model. Satisfactory results are observed in base line period. The absolute percentage error in many parts of the India is less than 20%. By assuming that the same climatic trend will follow in feature we projected the ISMR for the Future period (2010-2040).

6.1 Conclusions

- The work reported in this report contributes towards developing methodology for predicting the state of rainfall at regional scale for seven IMD zones of India from large-scale GCM output of climatological data.
- The statistical downscaling model appears to effectively capture individual zone means & spatial patterns in the Historic Period (1980-1999).
- Multi model average technique holds good in Projecting the ISMR compared to single GCM.
- The model also reveals spatially non-uniform changes in rainfall in future (2010-2040), with a possible increase in Rainfall for the south and north India zones
- The model shows an overall increase in the monthly mean rainfall all over India, highlighting the need for a detailed hydrologic study that includes future projections regarding water availability which may be useful for water resource policy decisions.

REFERENCES

[1] Aksornsingchai, P.,Srinilta, C. (2011). “Statistical Downscaling for Rainfall and Temperature Prediction in Thailand”. In, *International MultiConference of Engineers and Computer Scientists* Hong Kong.

[2] Ghosh S., Mujumdar, P.P. (2006). “Future rainfall scenario over Orissa with GCM projections by statistical downscaling”. *Current Science, 90.*

[3] Ghosh,S., Mujumdar, P.P.(2008). “Statistical downscaling of GCM simulations to streamflow using relevance vector machine”. *Advances in Water Resources, 31,* 132-146

[4] Hewitson, B.C.,Crane, R.G. (1996). “Climate downscaling: techniques and application”. *Climate Research, 7,* 85-95

[5] Huth, R. (2002). “Statistical downscaling of Daily Temperature in Central Europe”. *American Meteorological Society, 15,* 1731-174.

[6] Kalnay, N.Y. et al., 1996. The NCEP/NCAR 40-years reanalysis project. Bull. Am.Meteorol. Soc. 773, 437471.

[7] Kannan, S., Ghosh, S. (2013). “A non parametric kernel regression model for downscaling multisite daily precipitation in Mahanadi Basin”. *Water Resource Research, 49,* 1360-1385

[8] of Indian summer monsoon rainfall differ from those of CMIP3? Atmosp. Sci. Lett.. http://dx.doi.org/10.1002/asl2.466, 10.1002

[9] Parthasarathy, B., Munot, A.A., Kothawale, D.R., 1996. Monthly and Seasonal Rainfall Series for All-India Homogeneous Regions and Meteorological Subdivisions. Indian Institute of Tropical Meteorology, Pune, India, pp. 1871–1994.

[10] Salvi, K., Kannan, S., Ghosh, S. (2013). “High-resolution multisite daily rainfall projections in India with statistical downscaling for climate change impact assessment”. *J.Geophys.Res.Atmos, 118,* 3557-3578

[11] Shashikanth, et al (2014) ., “Comparing statistically downscaled simulations of Indian monsoon at different spatial resolutions” ,*Journal of Hydrology, 2014.10.042*.

[12] Shashikanth, K., Kaustubh, S., Ghosh, S., Rajendran, K., 2013. Do CMIP5 simulations of Indian summer monsoon rainfall differ from those of CMIP3? Atmosp. Sci.Lett.. http://dx.doi.org/10.1002/asl2.466, 10.1002.

[13] Wilby, R., et al., 2004. Guidelines for use of climate scenarios developed fromstatistical downscaling methods. <http://www.narccap.ucar.edu/doc/tgicaguidance-2004.pdf> (accessed 719 10.08.13).

[14] Wilby, R.L., Wigley, T.M.L., 1997. Downscaling general circulation model output: a review of methods and limitations. Prog. Phys. Geogr. 21, 530–548.

[15] Yatagai, A. et al., 2012. APHRODITE: constructing a long-term daily gridded precipitation dataset for Asia based on a dense network of rain gauges. Bull. Am. Meteor. Soc. 939 (1401–1415), 727. http://dx.doi.org/10.1175/BAMS-D-11-00122.1.