Monsoon Monograph

(Volume 2)

Editors

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GOVERNMENT OF INDIA
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एयर वाईस मार्शल (डॉं) अजित त्यागी
मौसम विज्ञान विभाग के महानिदेशक

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Preface

Monsoon is traditionally defined as a seasonally reversing wind system accompanied by seasonal changes in atmospheric circulation and precipitation. A semi-annual reversal in the wind direction, a typical characteristic of monsoon, is caused due to differential heating of continents and oceans and the Coriolis force. The term was first used in English in the then British India and neighbouring countries, to refer to the large-scale seasonal winds blowing from the Bay of Bengal and Arabian Sea from southwesterly direction bringing heavy rainfall to the area. The monsoon rainfall is considered to be that which occurs in any region that receives most of its annual rain during a particular season. The English word '*monsoon' has* its origin in the Arabic word *mausim* ("season"). The definition includes major wind systems that change direction seasonally and allows other regions of the world to qualify as monsoon regions

The unique physiographic features of south Asia, with the vast Asian continent spread over equatorial to polar latitudes in the Northern Hemisphere contrasted by the extensive water surface of the Indian Ocean, spread over the equatorial to Antarctic latitudes in the Southern Hemisphere, primarily supports the development of intense thermal centres of action due to differential heating of land and oceans. The resultant pressure patterns and the meridional circulations in summer and winter are further accentuated by the presence of high mountain massifs (Himalayan and Tibetan Plateau) of south Asia, leading to the establishment of the South-West (SW) and the North-East (NE) monsoon, respectively.

The importance of the monsoons for India is manifold. Out of these two, the SW monsoon is more important as it accounts for over 75% of the annual rainfall in most parts of India, outside Tamil Nadu and Jammu and Kashmir. The economy of India is substantially dependent on its agriculture, which, in spite of development of irrigation facilities, is primarily and largely, rain-fed. It is thus dependent on the quantum and distribution of rainfall during the SW monsoon season. As such, the failure of SW monsoon, adversely affects the agricultural production in India and, in turn, the Indian economy. The SW monsoon, which is the main source of rainfall for India, is characterised by a high variability, both on spatial and temporal scales. This variability is a major feature and reason of the dependency of Indian agricultural economy on the SW monsoon rainfall

Due to its great socio-economic importance and its challenge as a complex scientific problem impacting on the global scale, there had been extensive research work on Indian Summer Monsoon in India and abroad, for almost over four centuries. An exhaustive summary of the research work on Indian Summer Monsoon, particularly carried out in India, was documented by Dr. Y. P. Rao, in 1976, in the form of a Meteorological Monograph (No. 1/1976), entitled 'South West Monsoon', which served as a

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principal reference document for research workers and operational weather forecasters for more than past thirty years.

During past few decades, there have been new developments in the understanding of Indian summer monsoon, particularly in the light of availability of extensive data sets, new research methodologies including modelling and field campaigns. Also, the issue of global warming has raised several questions about monsoon circulation and thus, has added a new dimension to it. In view of these developments, India Meteorological Department (IMD), which is the nodal agency for national meteorological services for India, has decided to bring out a comprehensive publication in the form of **'Meteorological Monograph on Monsoons'**.

Considering its wide scope, this publication will be brought out in two volumes. This volume contains the chapters on synoptic systems during monsoon season, monsoon variability on different temporal scales, tele-connections of monsoon, monsoon oceanic aspects, monsoon simulation, predictability of monsoon using coupled general circulation models, forecasting of monsoon in short; medium; extended range and long range time scales, and aspects of monsoon in relation to climate change. The second volume also includes a chapter on modeling of forecast sensitivity of progress of monsoon northward from southern tip of India during the onset and advance process.

The first volume contains chapters on scientific studies on monsoon, monsoons over other south Asian countries and elsewhere in the world, characteristics of Indian monsoon such as climatological aspects, onset; advance and withdrawal, components and semi-permanent systems of monsoon, operational procedures during monsoon as observed by IMD, observational aids used to monitor monsoon, orographic monsoon rainfall, extreme weather events related to monsoon, monsoon and agriculture, and northeast monsoon. The first volume also contains a chapter on Indian summer monsoon experiments.

All the contributors of this publication are eminent and experienced meteorologists from leading organizations in India and abroad of national and international repute. With its wide ranging scope and contents, this publication is intended to serve as a comprehensive reference publication for both, operational meteorologists and meteorological research scientists.

I take this opportunity to thank all the authors from India as well as from outside India including the authors from south Asian countries for their valuable contributions in making the monograph a comprehensive reference publication on monsoon over south Asian countries. I also thank other members of the editorial board viz., Prof. G. C. Asnani, Dr. U. S. De, Dr. H. R. Hatwar and Dr. A. B. Mazumadar for judiciously editing the publication. I also thank Dr. Medha Khole, IMD Pune and Dr. D. R. Pattanaik, IMD New Delhi in coordinating the work and bringing out the publications in time. Also I would like to thank Shri S. B. Gaonkar, and staff members of section of I & D of O/o DDGM (WF); Mr. Yogesh Visale and the staff members of the DTP unit of ADGM (R) Office, Pune for page setting and printing of the document.

New Delhi (Ajit Tyagi)

Dated

Director General of Meteorology
India Meteorological Department

CHAPTER 10

EXTENDED RANGE PREDICTION SYSTEM OF INDIAN SUMMER MONSOON

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10.1. Introduction:

Reliable high resolution weather forecasts are in increasing demand to the governments, industry, traffic, media, farming community and risk management departments of most of the countries worldwide (Majewski, 1997). The Indian Summer Monsoon Rainfall (ISMR) forecast for two weeks to one month in advance is one of the most challenging task to the scientific community due to complex interactions between land-air-sea and also small scale convective activities with large scale flow. The summer monsoon season (June to September) contributes more than 70% of the annual rainfall over India (Parthasarathy et al. 1994). The active equatorial intra-seasonal oscillations (ISO) enhanced the convective activity over the north Indian Ocean and moves northward to the Indian landmass. The onset of Indian Summer Monsoon (ISM) over the southern tip of Indian peninsula marks the beginning of rainfall season and ending of hot summer over the India. Though onset of ISM over Kerala on 1st June is considered the normal date for onset of ISMR according to India Meteorological Department (IMD), it generally occurs during end of May or early June. After the onset of ISM over Kerala, the monsoonal system marches towards the north associated with rainfall. One of the important features of monsoon is the monsoon trough, which, in general passes through the northern part of India such as Punjab, Rajasthan, Uttar Pradesh, Bihar, West Bengal & north of Bay of Bengal. The fluctuation of the ISMR mainly depends on the oscillation of the monsoon trough. In the active phase of monsoon the trough shifts to south of its mean position causing good amount of rainfall over the country; on the other hand when it shifts to foothills of Himalaya, the rainfall reduces over the central parts of the country and monsoon break occurs. In the second half of September strength of monsoonal westerlies gradually decreases leading to the withdrawal of southwest monsoon.

The Indian summer monsoon plays a crucial role for the agro economic country like India. Major parts of the Indian population (more than 70%) explicitly depend on the agriculture and their economies are highly dependant on the crop productions during the summer monsoon season. Though the monsoonal system is a regular phenomenon, but the Indian summer monsoon has a large abnormality in the global climate systems. This abnormality varies from region to region and time to time. The advance intimation of likely behavior of monthly and seasonal rainfall helps the farmer to avail the opportunities and to make decisions that could enhance the farm productivity and maximize returns or minimize the loss. Among various types of forecasts made for different temporal scales viz. short range, medium range and long or extended range, the extended range forecasts are highly valuable to the farming community, government, industry for long term planning, decision making, management and mitigation. The extended range prediction of monsoon rainfall over smaller regions such as met-subdivision scale (Parthasarathy et al. 1994) is one of the challenging tasks to the scientific communities.

The forecast products from General Circulation Models (GCMs) are being effectively used all over the world for generating seasonal forecasts. The GCMs are the important tools to simulate the atmospheric circulation. Present day, most of the GCMs are coupled with oceanic models to take into account the interactions between the oceans and the atmosphere. Although these numerical tools are required to understand complex interactions between land-ocean-atmosphere systems globally, they are computationally intensive and then, can only produce relatively low spatial resolution simulations which in turn provide data in coarse resolutions on model spatial grid. Therefore, direct application of GCMs output is often inadequate because of their limited representation of mesoscale atmospheric processes, topography and land sea distribution in GCMs (Cohen 1990; von Storch et al., 1993). Consequently, the performance of these model are poor in capturing small scale physical processes which drive some important local/regional surface variables and their high resolution properties such as precipitation (frequency of occurrence and intensity) and its strong variability (Wood et al, 2004). Also, it is difficult to compare GCMs output to local present observations (Vrac et al., 2007) and even more for extreme climate/weather events (Vrac and Naveau, 2007) due to coarse resolution of GCMs. However, comparison between local observations with the model simulation output is essential to understand physical and dynamical processes of the atmospheric circulation in local scale. In order to overcome these scale issues, it is important to reproduce information from GCMs output in higher resolutions for better understanding the regional/local weather/climatic phenomena though, this reproduced information for specific geographic location may not coincide with the model grid.

A number of methods are used to convert GCMs output to required region. The simplest method is to consider the nearby model grid points as the representative points of the target region. This method often is not able to reproduce realistic features since the representative points are in general, far away from the targeted region and the surface characteristics of the representative points are also different. To improve the nearest point forecast, a number of procedures are present that fall in general calibration and downscaling techniques (Barnston and Smith, 1996; Goddard et al., 2001; Landman and Goddard, 2002; Stephenson et al., 2005). These downscaling techniques work as the bridge between climate forecasts and weather (Wilby and Wigley, 1997; Huth and Kysely, 2000). In other words, downscaling is a technique which links the state of some variables representing large space to the state of some variables representing a much smaller space (Benestad et al., 2008). The field of downscaling is divided into two approaches namely a) "Dynamical downscaling" based on nesting of high-resolution regional climate models (RCMs) to simulate finer scale physical processes consistent with large scale weather evaluation prescribed from a GCM (Giorgi et al., 2001; Mearns et al., 2004; Lim el al., 2007) and b) "Statistical downscaling" adopts statistical relationships between the regional climate and statistical characteristics of desired fields from the coarse resolution of GCM data (von Storch et al., 1993; Wilby et al., 2004; Goodess et al., 2007). The downscaled high resolution data can be used for forecast and as input into other types of numerical simulation tools such as hydrological, agricultural and ecological models. Therefore, use of proper downscaling techniques is the key issue for extended range prediction systems.

A brief overview has been given in 10.2 on the Extended Range Forecast System (ERFS) and its present status with skill evaluated by various scientists worldwide. Descriptions and methodologies of different downscaling techniques for ERFS have been discussed in 10.3. Preliminary efforts with some experimental results have been given in 10.4. Finally, the conclusions of this study have been presented in 10.5.

10.2. Extended Range Prediction System:

The forecasts are classified in various categories. These categories have mainly defined on the basis of temporal coverage of the forecasts viz. now cast, short range, medium range, extended range, seasonal scale and long range forecasts. The forecasting of the weather for the next six hours is generally referred as now casting. It is easier to forecast in the temporal range of now-casting than the other forecasts because possible occurrence of local weather features such as showers, thunderstorms, snowfall etc. can be predicted upto convincing accuracy by analyzing latest manual observations as well as the latest radar and satellite data sets. The forecasts delivered for a lead time of a day or three are called as short-range forecasts. Medium-range forecasts are made for periods covering 4 to 10 days ahead while the extended range forecasts are made for periods of two weeks to a month. Seasonal forecast refers the prediction of mean weather for seasonal scale. In the long range category, the time scale is more than a year. In short and medium range, local forecasts are most valuable for high impact weather phenomena such as cyclone, thunderstorm, tornado etc which may result in loss of life and property due to wide-spread/heavy rainfall and strong wind.

Present day numerical weather prediction models (NWP) are able to forecast short range atmospheric events with satisfactory accuracy due to improvement of model physics and dynamics and availability of high performance reliable computing systems. Seasonal and extended range forecasts are different from weather forecasts since it involves the prediction of the deviations from the seasonal climate. The skills of different scale of forecasts may be represented in a schematic diagram (based on inputs from various available published work on forecast skill over different temporal scales, researches and forecast application scientists) as Fig. 10.1. It is seen from the Fig.10.1 that though there is a good degree of predictability skill in short-range weather forecast, the skill is waning with time. The seasonal scale forecast which is mainly based on statistical methods has some predictability skills. The extended range prediction is one of the toughest tasks due to inherent complexity of low skill.

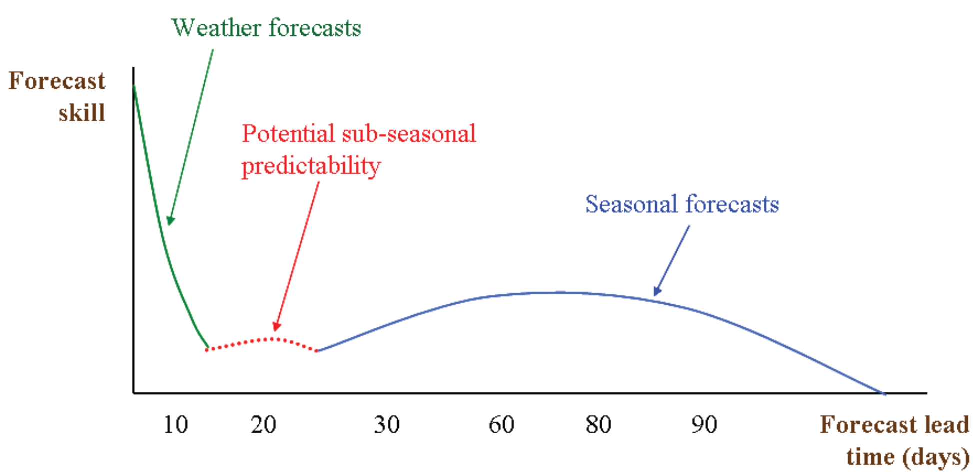

Fig. 10.1: Schematic diagram for skill of different scale forecasts with forecast lead time.

The first long range forecast for ISMR was provided by Blandford in 1886 based on the relationship between Himalayan snow cover and monsoon rainfall (Blandford, 1884). Long range forecasts during initial years were made through subjective and qualitative analysis. Sir Gilbert Walker in 1909 for the first time introduced an objective technique based on correlation and regression analysis (Walker, 1910, 1923, 1924). Walker discovered the link between Indian monsoon with the Southern Oscillation, which is see-saw of pressure between Darwin and Tahiti in the Pacific Ocean. The first model for long range weather forecast was developed by Walker and it was used for prediction of the Indian summer monsoon rainfall in 1909. He used a linear regression model based on four predictors namely i) Himalayan snow accumulation at the end of May, ii) South American pressure during March–May iii) Mauritius pressure of May and iv) Zanzibar rain in April and May. This was the most important step in the meteorological history for long range weather forecast. In the early and mid of 1930, C-G- Rossby and Jerome Namias had put efforts for long range forecast (Namias, 1955, 1968). Univariate time-series methods and multi-variate statistical and physical methods had been used in different centres for prediction of long range weather in late 60's. In the 70's and 80's research on probabilistic methods continued, and the Monte Carlo Method was developed in the 70's to improve the long range forecast. Till early 1970's, seasonal scale forecast was based mainly on simple regression equations. Along with these statistical techniques, dynamical approaches (using NWP models) were also in use (in R&D mode) for forecasting of weather and climate.

Vilhelm Bjerknes carried out an explicit analysis for weather prediction and divided the rational forecasting system broadly into two sections (Bjerknes, 1904); one is diagnostic section where the initial state of the atmosphere is determined using observations; and next is prognostic in which the state of the atmosphere and its changes can be calculated using the laws of motion. Richardson (Richardson, 1922) had tried to forecast on early 1920's by solving the governing equations numerically, but could not succeeded. In the mid 1930s von Neumann suggested that progress in dynamical forecasting would be greatly accelerated with the availability of faster computing systems that can solve the complex equations numerically. In the mid 1940's, the Institute for Advanced Study in Princeton was the setting for one of the major technological advances in atmospheric science with the advent of numerical prediction on the Eniac, the first high speed computer. The efforts of weather prediction through numerical weather prediction model in the early 1950's had been put forward by Charney and colleagues by solving the complex equations numerically by removing the gravity waves equations using Eniac computing systems. To generate 24 hours forecast using fastest computing system at that time, it took 24 hours! Moreover, the results were impressive and showed the scope of dynamical methods for numerical weather predictions. With the increase in efficiency of computers and improvements of model physics, the first dynamical seasonal prediction came into picture in the early 1970's using a general circulation model (GCM). Efforts for reliable forecast in extended range weather using dynamical models was taken by European Centre for Medium-Range Weather Forecast (ECMWF) in the mid of 1980's. The improvements of model physics and dynamics, assimilation techniques, more observational data and increase of efficiency of computation systems with time, the skill of seasonal scale predictions have been improved (van den Dool, 1994; Palmer et al 1990) and a number of organizations had started to issue seasonal scale forecast in the late 1990's. In long range forecast, both the statistical techniques and dynamical approaches have similar skills.

In the evolving of seasonal scale prediction which is mainly based on statistical methods, the forecast has some predictability skills over a larger domain. Since the life cycle of a crop is almost completed within a season and evolve through different phases which have two weeks to one month time for each, thus, this seasonal scale prediction of rainfall is not sufficient to the agricultural communities. Therefore, prediction in the scale of two weeks to one month which is known as extended range is highly needed to the farming communities and also for policy planning for agro-economic country India. The short and medium range prediction systems have advanced a great success with the accuracy level nearly 80% for forecast of atmospheric events. This success comes since short and medium range atmospheric events depend largely on its initial values and also with the improvements of observational data sets in higher density. While, the seasonal scale events are mainly governed by seasonal scale features specifically by some large scale features, slowly varying land surface parameters and some semi permanent features, therefore, prediction of seasonal scale events using these features through statistical techniques has some predictability skill. In the context of ERFS programme in India, the predictions of monsoonal rainfall is set for different temporal (two weeks to a month) and spatial (India as a whole, homogeneous and met-subdivision) scales. Earlier studies found that the predictability skill for forecast of surface air temperature have positive value beyond day 9 (Fig.10.2) and for other weather variables such as total precipitation, surface wind speed etc., the skills are decreasing faster than temperature in the long range forecast. It is also clear from fig.10.1 that extended range prediction has very low skill and that is probably due to characteristics of inherent nature of the prediction systems.

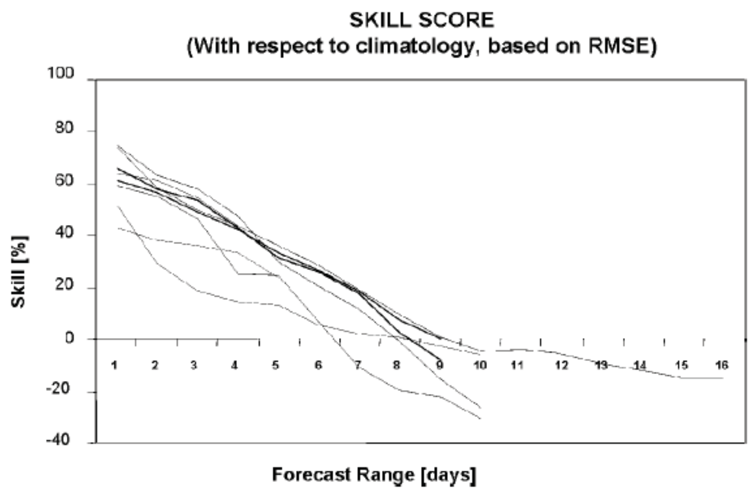

Fig. 10.2 : Skill scores of a set of eight competing forecast of the daily average temperature at London Heathrow. Positive (negative) skill scores indicate that the forecasts are more (less) accurate than long-term climatology. Accuracy was measured by calculating root mean squad errors (RMSE). After Mailer (2010)

10.2.1. Status of Extended Range Forecast:

10.2.1.1. **International**

Present day, a number of organizations/institutes including almost all eminent meteorological organizations such as European Centre for Medium Range Weather Forecast (ECMWF), National Centre for Atmospheric Research (NCAR) (Hack et. al, 1998; Hurrell et. al, 1998 and Kiehl et. al, 1998), UK Met. Office, National Centre for Environment Prediction - Climate Forecast System (NCEP-CFS) (Saha et. al., 2006) , USA, International Research Institute for Climate and Society (IRI) (Li and Goddard, 2005; van den Dool, 1994; Delworth et. al, 2006; Anderson and coauthors, 2005), USA, Japan Agency for Marine-Earth Science and Technology (JAMSTEC) and APEC Climate Centre (APCC) Korea etc. are issuing a monthly to seasonal scale global forecasts using both dynamical models and statistical techniques. These centres are running coupled (semi or fully) general circulation models and integrations are carried out for several months to generate dynamical output to prepare monthly and seasonal forecasts. The forecasts are mainly generated for precipitation and temperature and issued in each month.

10.2.2.2. National:

As mentioned in earlier section, Blanford (1884), then chief of newly formed India Meteorological Department, was the pioneer in the long range prediction based on inverse relationship between Indian Summer Monsoon Rainfall (ISMR) and preceding winter snow cover over Himalayan region. This relationship was used during the early 1880's for prediction of ISMR in seasonal scale till the discovery of tele-connections with 3 large scale horizontal see-saw oscillations with ISMR by Sir Gilbert Walker (1923, 1924). These pressure oscillations are called the Southern, the North Pacific and the North Atlantic oscillations. Based on this relationship, he made simple regression equation to predict the ISMR in seasonal scale. Further, Sir Gilbert Walker found in-homogeneity in rainfall over India, and divided India as two homogeneous rainfall regions namely North West India and Peninsular India based on the correlation with the predictors and ISMR used for study. This classification on homogeneous region of rainfall was used till 1987 (Gadgil et al, 2005). Till late 1990's, the operational forecasts were generated mainly based on statistical techniques. For this purpose, lot of efforts have been made to find out suitable predictors to improve the seasonal scale forecast (e.g. Walker, 1910, 1923, 1924; Hahn & Shukla, 1976; Banerjee et al., 1978; Shukla and Paolino Jr., 1983; Thapliyal, 1984, 1997; Verma et al., 1985; Bhalme et al., 1987; Hastenrath, 1987; Parthasarathy et al., 1988, 1990). With this, attempt had also been made to develop different forecast techniques (Thapliyal, 1982, 1986; Gowariker et al., 1989). Review on the development of forecasts techniques can be found in some useful literatures (Jagannathan, 1960; Das, 1986; Thapliyal, 1987; Shukla, 1987; Thapliyal &

Kulshrestha, 1992). The developed new models such as Parametric, Power regressions, multiple-regression and Dynamic Stocashtic Transfer etc., have been used since mid 1980's for long range forecasts (LRF). Details of different operational models being used for seasonal forecast of ISMR and methodologies for preparation of forecast over India can be found in Thapliyal (1997). Xavier and Goswami (2007) have developed a OLR based model to predict the monsoon activity (active and dry spells) over India up to 3 weeks. With the development of regional climate models (RCM), an extensive research is going on to downscale coarse resolution coupled general circulation model for forecast in monthly to seasonal scale.

10.3. Methodologies for ERFS

In the last two decades, dynamical numerical models have improved considerably in terms of prediction skill of seasonal scale mean forecast of rainfall over some regions such as over central Pacific; however, not much breakthrough has taken place in improving the prediction skill of Indian summer monsoon rainfall. In recent years, dynamical (with high resolution, improved parameterizations scheme, data assimilation, observed land surface parameters insertion etc.) and statistical (bias corrections, model output statistics, canonical correlation analysis, multi-model ensemble, Bayesian techniques, etc) techniques have shown that the monsoon variability in the tropics can be resolved with reasonable skill in monthly as well as seasonal scale. An extensive research work on dynamical and statistical techniques is required for extended range prediction of rainfall over homogeneous or met-subdivision regions for India.

Present day coupled GCMs produce forecast of atmospheric variables in coarse resolution over grid points, which is insufficient for forecast over smaller regions in extended range prediction. Improvement of forecast in extended range can be made by reproducing global model forecasts in local scale using downscaling techniques. Forecasting of these downscaled variables can be more useful to the application sectors such as agricultural section, hydrology section etc. for planning and management. There are mainly two kinds of downscaling methods i) Statistical downscaling and ii) Dynamical downscaling which are used to reproduce coupled GCMs data in higher resolutions for extended range prediction.

10.3.1. A review on performances of both techniques over different region worldwide

There are a number of application related criteria that contribute to an appropriate choice of downscaling method in a particular context (Mearns et al., 2004; Wilby et al., 2004). But there are assumptions involved in both techniques (Giorgi et al., 2001) which are difficult to verify a priori and contribute to the uncertainty results. Though statistical downscaling has an advantage over dynamical downscaling for long range forecast, it is not clear which method provides better prediction of localized climate (Benestad et al., 2008). The limitation of statistical methods is that downscaled variables might not guarantee physical consistency between them because it may not be possible fully to include the complex physical processes encompassing nonlinearity in the methods.

Several studies have been carried out to compare dynamical and statistical downscaling methods for various atmospheric phenomena over different regions worldwide. Kidson and Thompson (1998) studied present day climate over stations in New Zealand with the help of a regression-based statistical model and a RCM integration and found that both statistical and dynamical methods gave similar levels of skill in the representation of observed temperature and precipitation anomalies. Similarly, Murphy (1999) found that a regression model for monthly temperature and precipitation anomalies has a comparable performance to a RCM for stations in Europe, but scenarios developed from statistical and dynamical methods differed significantly (Murphy, 2000). Schmidli et al (2007) tested statistical and dynamical methods over European Alps region and stated that none of these methods is superior and performance varies significantly from region to region and season to season. It is also observed from experiments that performance is better for the indices related to the precipitation occurrence than to the indices related to precipitation intensity. Large differences were also found in precipitation scenarios between a RCM and a multivariate regression model in Scandinavia (Hellström et al., 2001). Charles et al (1999) have studied the stationary of statistical downscaling methods using RCM climate change integration and concluded that a relative humidity predictor is required for the reproduction of RCM simulated changes in precipitation occurrence in global warming scenario. Several inter-comparison studies have adopted dynamical and statistical downscaling for hydrological impact models and significant differences are found between downscaling methods (Hay and Clark, 2003; Wood et al., 2004). Finally, it is accepted that both the statistical and dynamical downscaling methods are capable to capture well the mesoscale atmospheric features that are not captured in GCMs (Schmidli et al., 2007).

10.3.2. Statistical

The basic approach used for application of extended range forecast is tailoring of GCM forecasts in time and space, this approach is often referred as downscaling. These downscaling techniques work as the bridge between Climate forecasts and weather (Wilby and Wigley, 1997; Huth and Kysely, 2000). One of the important techniques for downscaling is statistical downscaling that includes a large number of methods, ranging from simple interpolations to eigen techniques, regression methods (such as Multiple Linear Regression, Principal Component Regression, Stepwise regression etc.), stochastic time series models (Markov Models), artificial neural networks, genetic algorithms etc. (Hewitson and Crane, 1996; Ji and Vernekar, 1997; Wilks 1999; Fuentes and Heimann, 2000; Huth and Kysely, 2000; Huth, 2002; Widmann et al., 2003; Rabiner and Juang, 1986; Zucchini and Guttorp, 1991; Robertson et al., 2004; Kioutsioukis et al., 2008; Feddersen and Andersen, 2005; Coulibaly et al., 2005). These methods are based on finding statistical relationships between sets of predictors and predictands. Usually, predictors are selected from the Global Model output while the predictands are the observed variables for the training period.

The success of downscaling techniques depends on the accuracy of Global Circulation Model's fields. Therefore, Model Output Statistics (MOS) techniques (e.g. Bias Correction, Multi Model Ensemble etc.) must be applied on the model products before applying the downscaling methods.

10.3.2.1. Bias Correction Methods

The term Bias is used to explain an inclination towards a particular perspective or result. Any tendency to favour a certain set of values naturally lead to an uneven dispensation of judgment. Regarding model forecast at a particular time the bias is the difference between estimated parameter and the true value of the parameter. All statistical methods are generally developed with the assumption that errors generated are random in nature and the mean is zero (unbiased estimations). But forecast models have systematic errors. These errors can result in biased forecasts. That means if we have number of simultaneous model simulations and observations then it is essential to check whether the model is biased towards particular range of values, i.e. the model may predict low values of the parameter/s better than high values or vice versa. Then it is very important to remove the bias for the improvement in the quality of the forecast. The best way to handle the issue of bias in forecasts is first estimate the bias and then correct it, before using the data for analysis.

In the case of rainfall there are two characteristics, one is duration/frequency and another is its intensity. Model forecast may be biased for both. In such situations the bias can be corrected in two steps (Ines and Hansen, 2005) viz. frequency correction and intensity correction.

There are two different definitions for the model forecast bias.

According to Wilks (1995)-

Bias is the ratio of number of "yes" forecasts to the number of "yes" observations. That is, if number of "yes" forecast is 'a', while number of "yes" observations is 'c' then the bias B can be given by following ratio.

$$B = \frac{a}{c}$$

It indicates that if B is 1 then the forecast is unbiased. If B>1 then the forecast is over-estimated and if B<1 then the forecast is under-estimated.

According to Dee and Da Silva (1998)-

A forecast is said to be biased if the mean of forecast error is non-zero. It (the mean of forecast error) is the forecast bias (Dee and Da Silva, 1998). So, forecast bias can be estimated by comparing forecasts with Observations, i.e. from observed-minus-forecast residuals. In such situations we have to assume that observation is the true state of atmosphere.

Some methods for bias correction are given below. Generally bias is corrected by transformation of model output into the corrected one. This correction can also be done without use of transformation functions. In the without transformation methods, the bias is estimated and then corrected but while using transformation methods bias is not calculated explicitly.

Method 1 (without transform):

If F_T is model forecast at time T and O_T is observation at the same time then the model error ε_T will be.

$$\varepsilon_T = O_T - F_T$$

Then the Bias B can be defined as follows.

$$B = \langle \varepsilon_T \rangle$$

Thus, using this definition we can find and remove the general model forecast bias.

i.e. corrected Model forecast = $B + F_T$

But what if the model has different biases for different in range of forecast. In such situation we can find the forecast biases for the different categories of forecast. This technique has been illustrated in following steps.

The model output can be divided into various classes, created using quantiles.

For each and every class, model error and bias can be calculated.

Then the biases may be removed from the respective classes of model output.

One can also fit an equation to find out corrected Model forecast CF_T as follows:

$$CF_T = a_0 + a_1 F_T$$

One way of finding values of a_0 and a_1 is given earlier i.e. substitute a_1=1 and a_0 = $\langle \varepsilon_T \rangle$, this method is also referred as bias corrected individual forecast (Kharin and Zwiers, 2002).

In another technique which is called as regression corrected individual forecast, the coefficients are calculated as following ways:

$$a_1 = \mathrm{Cov}(O_T, F_T)/\mathrm{Var}(F_T) \text{ and } a_0 = \langle O_T \rangle - a_1 \langle X_T \rangle$$

According to Kharin and Zwiers (2002) the regression coefficient a_1 rescales the forecast to correct systematic errors in simulating the atmospheric response to the lower boundary conditions and to minimize the effect of climate noise in the model forecast on error variance. The intercept a_0 removes the bias from the rescaled forecast.

Quantile-Quantile (Q-Q) Mapping Method:

In the quantile mapping method empirical probability distributions of observed and forecasted values are used. The transformed/bias corrected output is inverse of cumulative distribution function (CDF) of observed values at probability corresponds to the model output CDF at the particular value. In quantile mapping method the bias is not calculated explicitly. Suppose we have CDFs, F_o for observed data and F_f for model forecast. Then for a model output X the bias corrected value Y will be as follows:

$$Y = F_o^{-1}(F_f(X))$$

Here F^{-1} is an inverse of CDF. Thus, the quantile mapping procedure is transformation between two CDFs. This method is used and well explained by Wood et al. (2002), Hashino et al. (2006). The steps that can be followed for this purpose are given as follows. Find empirical probability distribution of the observed as well as model output data. This can be done using simply fitting their histogram and then dividing the frequency of each class by the total number of observations. But for this purpose number of classes created should be large or at least sufficient enough.

This will give us set of probabilities falling in each class say P(xi) where the suffix i =1, ….,n, where n is the number of classes. Now the cumulative distribution function (CDF) will be as follows:

Mathematically we have to write the CDF equation as $C(x_i) = \int f(t)dt$ where f(t) is the probability density function. If we replace the integration sign by summation for the discrete data then it is easier to understand and the function looks as follows.

$$C_i = \sum_{j=1}^{i} P(x_i), \quad i = 1,2,3......n \qquad \text{-----------------------(1)}$$

Its easy to understand that ∑Ci =1. Also Ci will give us the fraction of total number of data points below the given value i.e. the quantile of the particular class. The inverse of CDF will give us the value at a particular probability. The inverse of CDF is also called as quantile function.

Now one can use the equation (1) written above for getting the bias corrected value of model output. The working of the model output quantile function's mapping on the CDF of observed data can be shown by following fig. 10.3.

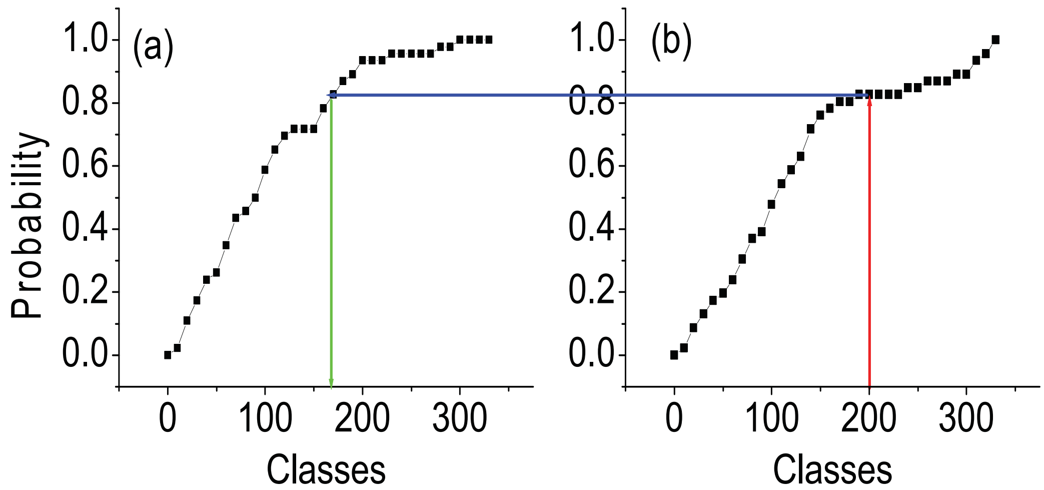

Fig.10.3 : Illustration of quantile mapping for virtual data sets.
The CDF from sub plot (b) is mapped on the CDF of subplot (a)

From the Fig. 10.3 we can easily understand the equation 1 and quantile mapping. In the above Fig.10.3, suppose that Fig. 10.3 (b) is plot of CDF of model output F_f. And Fig. 10.3(a) is the plot of CDF of observed data F_o. Lets consider that the model output is 200 then the from equation 1 F_f (200) ≈ 0.83 (i.e. 0.83 is the probability or 200 is q0.83) and $F_o^{-1}(0.83) \approx 160$. Thus the bias corrected value of model output 200 will be 160.

Regression method:

A regression model is an estimation of expected value. Fitting a regression model is the generally implemented option for the transformation. The regression model is estimated using the observed and simulated datasets from the historical records, i.e. a regression equation is fitted for model output as dependable variable and observed data set as independent variable. In this method the bias is not calculated directly instead, removed indirectly. The regression may be fitted using Locally Weighted Least Square regression approach.

Locally weighted least square method:

If the form of the function f(X,β) is complicated or unknown, then locally weighted least square method can be used. It is also known as LOESS or LOWESS (LOcally WEighted Scatterplot Smoothing). Cleveland (1979) has explained this method in detail. LOESS combines the simplicity of liner least squares and flexibility of nonlinear regression. In this approach, a simple regression equation is fitted to localized subset of the data. First, the data are divided into various subsets and then at each point of the subset, a simple polynomial is fitted using weighted least square technique. Using the response from variables in the neighborhood of the particular point, the weights are calculated i.e. more weightage is given to points near the point and less weightage is given to points which are away. The beauty of this method is user need not specify any particular global function of any form to fit the entire data.
The steps followed in this technique are as follows.

Sub setting the data: it is done by taking the data points close to each other. Actually this can be done by sequential shifting of data points. It means if we have 100 data points, then first we may select 1 to 30 then 2 to 31 till 71 to 100 for fitting the local regression equation.

Then the weightage is given to each point according to the scaled distance.
Weight function (W(x)) as selected. (in general tri-cub). It has following properties

$$W(x) = \begin{cases} (1-|x|^3)^3 & \text{for } |x| < 1 \\ 0 & \text{for } |x| \geq 1 \end{cases}$$

Here, x is the scaled distance.

Then a simple regression equation is fitted using weighted least square method taking W(x) as the weight matrix.

10.3.2.2. Multi Model Ensemble

The skill of climate predictions is limited because of internal atmospheric variability, which is largely unpredictable beyond the deterministic predictability limit of about two weeks (Kharin and Zwiers, 2002). This variability induces noise in model predictions. Generally model forecasts initiated from different initial conditions as well as different models are averaged using different techniques to reduce this noise in model predictions. This approach is called as ensemble. There are two ways to solve this problem viz. deterministic and probabilistic. The simplest technique is just linearly averaging the model forecasts. Krishnamurti et al., 1999, 2000 have introduced the concept of superensemble approach. This approach has been used by Kar et al. 2010 for precipitation forecast for July month over Indian domain. This approach is briefly discussed below:

Super ensemble:

$$S_t = \overline{O} + \sum_{i=1}^{n} a_i \left(F_{i,t} - \overline{F}_i \right)$$

Where,

St = Super ensemble prediction at time = t.

$\overline{O}$ = Observed monthly mean over the training period.

$\overline{F}_i$ = climatology of the ith model forecast over the training period.

$F_{i,t}$ = ith model forecast for time t.

ai = Regression coefficient (obtained during the training period.)

n = No. of models.

The knack in employing this approach is the estimation of a_i.

The simplest way to do it is ai = 1/n this approach is also known as Simple Composite MME. Another method to calculate ai is singular value decomposition discussed as below.

A covariance matrix is built from the forecast anomalies.

$$C_{i,j} = \sum_{t=0}^{Train} F'_{i,t} \, F'_{j,t}$$

Where,

Train = Training period.

i = ith model forecast.

j = jth model forecast.

F´ = Forecast anomaly

An assumption can be made from the above two equations as O´ = C A. Here A is the column vector containing a_i values.

The matrix C can be written using SVD as C = UWVT. C is a square matrix hence; it is easy to understand that U and V are equal. And a little calculation gives us the vector A.

$$A = V.\left[diag\left(\frac{1}{W}\right)\right].\left(U^T.\tilde{O}\right)$$

Where $\tilde{O} = O' - F'$ while $O' = O - \overline{O}$

Kharin and Zwiers (2002) have applied a slightly different approach called as mutimodel linear regression. These methods can also be used to remove systematic bias from model products. It is given as follows.

$$S_t = a_0 + \sum_{i=1}^{n} a_i F_{i,t}$$

In this approach the main trick is to find out the regression coefficients. It can be done by covariance analysis.

Another technique suggested is, synthetic multi model ensemble. In this technique firstly a synthetic dataset is generated using spatial correlation between model forecast and observational data set analysis by principal component analysis and then the MME is performed on the synthetic dataset Yun et al (2005).

10.3.2.2. Probabilistic forecasting

Extended-range prediction is inherently probabilistic. For climate risk management, it is essential that uncertainties in predictions are communicated to user agencies. There are two main approaches for probabilistic forecasting, one is non-parametric and another is parametric. In non-parametric method, one can just count the number of ensemble members falling in each category and divide them with total number of members to get the probabilities of each category. In parametric method, some distribution is assumed for estimating the probabilities. Here onwards, the discussion is made for the parametric method. In general, the forecast is delivered in three categories (generally terciles) viz. Above Normal, Near Normal and Below Normal. These categories are decided using distribution of observed data in the hind cast period. Afterwards, when the forecast for a particular year will be available, then mean and spread of the forecast distribution is computed using various methods. Once the forecast distribution is known, then chance (probability) of falling the mean of forecast distribution in a particular category is computed. If we have multiple numbers of GCMs then the mean of forecast distribution may be just simple ensemble of all the models while the spread can be computed using the correlation between mean of forecast distribution and observed time series (Tippett et al. 2006).

Downscaling

As mentioned earlier, downscaling is a procedure to find relation between variables at larger spatial and temporal scales to those at smaller scales. The simplest technique is fitting linear regression. In this technique if we choose more than one predictor then it is called as multiple linear regression (MLR). If Y is the predictand and X is set of predictors i.e. model products then

$Y=a_0 + a_1 x + a_2 x + \ldots\ldots\ldots.+a_n x$

The coefficients (a_0, a_1,….etc) can be calculated using simplest least square technique. Selection of the best regression equation is the main problem in MLR. Various approaches to select best regression equation can be found in Draper and Smith (1966).

Principal Component Regression (PCR) & Canonical Correlation Analysis CCA:

Principal Component Regression (PCR): If there is very high correlation among the independent variables (predictors) of a regression equation (problem of multicollinearity), then it may lead to unstable regression, in that case, it is essential to remove the correlation among them. This can be done using the Principal Component Analysis (PCA). Some times PCA is also called as Empirical Orthogonal Function (EOF) analysis. Principal components of the independent variables can be used in the regression equation instead of directly using the independent variables. This technique is called as principal component regression. One more advantage of PCR is to reduce the dimension of the independent variables to a large extent which simplify the computation. The steps followed in this procedure are as follows:

Principal component analysis is applied on the set of predictors and the PC's are generated. These PCs are ranked by order of explained variance. This means that the first PCs represent significant variance (which explains the maximum variability among the predictors), and the last unwanted variance or noise. These last PCs are eliminated without losing important information from the data and a new set of independent predictors are generated say 'P'. Afterwards MLR is fitted for 'Y' using 'P' as predictors. Though there doesn't exists any fixed rule to fix the number of PCs to be used, the screen plot of eigen values may be used to identify the number of significant modes.

Canonical Correlation Analysis (CCA): Canonical Correlation Analysis (CCA) is a statistical technique having some similarity with the PCA (Principal Component Analysis). This approach picks out a sequence of pairs of patterns in two multivariate data sets, and constructs sets of transformed variables by projecting the original data onto these patterns. Canonical correlation analysis can also be viewed as an extension of multiple regression (Wilks (1995)) as a multi-component predictors are linearly related to multi-component predictands where, the correlation structure is explained with each successive CCA modes. In CCA, original data sets X (independent) and Y (dependant) are transformed into new set of variables V_m and W_m respectively, called as canonical variables. These variables are defined as follows

V_m = A X

W_m = BY

Calculation of A and B called as a canonical vector is similar to that of the Principal component analysis.

Then we can write

$W_m = \beta V_m$

It can be easily proved that β = Rc, where Rc is the diagonal matrix of the canonical correlations. Thus Y can be easily found out using the relation Y = $B^{-1} W_m$

Hidden Markov models:

The climate forecasts can also be downscaled to station level using Hidden Markov models. These models have emerged from the Markov processes, in which we assume that the next value in a series is solely depends on its earlier value. But in some cases, the weather patterns that we wish to find out are not completely explained by Markov processes. It means, we don't have all the observations, some of the atmospheric states are hidden (assumed from observations). For example: a person sitting in the house observes that his friend has come to meet him with a wet umbrella, so in this case the hidden state is, it is raining outside. Another example can be given for it as follows: State of a day may be sunny, cloudy or rainy and our observations are dry, slight dry, slight humid, humid. In such cases use of Markov process only based on observations will produce incorrect results. In such situations the observed sequence of states is probabilistically related to the hidden process; and these processes are modeled using a hidden Markov model, in which the underlying hidden Markov process changing over time, and a set of observable states which are related somehow to the hidden states. These Hidden Markov models are further broadly divided into two groups viz. homogenous HMM (referred hereafter as HMM) and Non homogenous HMM (referred hereafter as NHHM), where HMM is spatial case of NHMM (Hughes and Guttorp 1994).

The development of HMM is explained in detail by Zucchini and Guttorp (1991). In this model the atmospheric states (not observed) are estimated from observations such as rainfall and then these states are verified by plotting some general atmospheric variables. The HMMs are useful for analyzing the multisite sequences of atmospheric variables (generally rainfall). The need of prediction or tailoring of GCM products to station level can be accessed by NHHMs. In NHHM, a relation between atmospheric circulation and a given regional process (GCM product) is worked out to simulate the space-time relation of the regional processes with a particular sequence of atmospheric data. The development of NHMM is explained in detail by Hughes and Guttorp 1994.

Chaos theory (Lorenz model):

A number of attempts have been made for the extended range predictions with the use of the Lorenz model (Lorenz 1963, 1965, 1975) in which the state vector of barotropic model evolves with two characteristic time scales—an oscillation time around the regime centroid, and a residence time within a regime (Palmer 1993). Regime structure in low-order baroclinic models has also been noted (Reinhold and Pierrehumbert 1982, Legras and Ghil, 1985 and Schneider et al., 1991) and it is found that in such models, the faster time scale can be associated with baroclinic instability. Observational studies give some support to this view of the atmosphere. The Lorenz model gave a clear conceptual understanding of results from numerical weather prediction experiments that time averaging alone is of limited value, while ensemble forecasting has greater potential, enabling predictable and unpredictable regime transitions to be recognized a priori. The extended Lorenz model was used to provide a conceptual framework to understand the potentially conflicting GCM results. It is noted that sea surface temperature anomalies can have a statistically significant response in the extended range predictions and the magnitude of low-frequency variability in long integrations with climatological and interannually varying SST are very similar. Results from the extended range model also indicated that the time-mean response to SST anomalies should have a strong projection onto a preexisting weather regime. The SST anomalies in the extended range model had a strong effect on the probability of residence within these regimes; in practice, estimation of these probabilities can be realized only through ensembles of integrations.

Palmer (1993) has discussed elaborately the physical basis underlying extended-range prediction based primarily on three premises. Firstly, observational (Namias 1955) behavior of synoptic-scale secondly, the definition of deterministic limit finally the slowly varying surface parameters. It is observed that time averages are inherently more predictable than instantaneous fields, that predictability depends very strongly on initial conditions, and that underlying anomalies in the tropical sea surface temperature impart extra predictability to the large-scale extratropical flow. On the one hand, cluster analysis of long hemispheric records of geopotential height indicate the existence of weather regimes (Mo and Ghil 1988; Molteni et al. 1990, 1993; Cheng and Wallace 1993), though they are not as distinct as in the Lorenz model. On the other hand, the nonlinear balance associated with quasi-stationary states in the atmosphere, and the nonlinear interaction between large and synoptic scales, has been very well established from observations (Shutts 1986; White 1990). However, the most important property of the Lorenz model, relevant to the discussion of all three premises for extended-range prediction, is associated with the fact that its local predictability properties vary substantially with position on the attractor; associated with this, phase-space regions where predictability is small are distinct from regions where the flow is quasi-stationary.

10.3.3. Dynamical:

The efforts have been initiated for monthly to seasonal scale prediction more than five decades ago (Namias 1955) and the use of dynamical models for predictions of Asian summer monsoon was initiated around four decades ago (Krishnamurti, 1969). Atmospheric General Circulation Models (AGCM), Global Coupled GCMs (CGCMs) and coupled Atmosphere Ocean GCMs (AOGCMs) are the main tools for dynamical seasonal scale prediction. Numerous groups in USA, Japan, Australia, China and Europe have made major contributions in the area of research and operational practice on Numerical Weather Prediction (NWP). Shukla (1981) has discussed a physical basis for the prediction of monthly means and Miyakoda et al (1983) have represented a skillful dynamical prediction for 30days in early 80's. During last decades, major progresses have been occurred in data quality (those from surface, upper air, automatic weather stations, aircraft and space based) and assimilation techniques which in turn, improved the forecast using NWP models. In recent years, improvement of NWP modeling systems have taken place in terms of resolution, better representation of orography, improvement in physical parameterizations of shallow and deep convection, radiative transfer (treatments of clouds, details of diurnal changes and surface energy balance), surface and planetary boundary layer physics for the fluxes of heat, moisture and momentum, and the inclusion of land surface processes. With the improvements of NWP modeling systems, the forecast skills have also been gradually improving with time. The skill of forecast in case of nowcasting and short range is satisfactory with the use of present day dynamical models and the skill scores has improved by 10 to 30 percent for medium range forecast with the help of multi-model and super ensemble methodology using a number of present day lead models simulations (Krishnamurti et al 1999, 2000a, 2000b, 2001, 2002). Both high-resolution global and very high-resolution regional non-hydrostatic microphysical models have been developed by a number of scientists to address the issues of monsoon life cycle and precipitation which is one challenging concern to the scientific community till date. The scientific basis of dynamical seasonal forecasting is that, in tropics, the lower-boundary forcing (sea surface temperature (SST), sea-ice cover, land-surface temperature and albedo, vegetation cover and type, soil moisture and snow cover etc.), which evolve on a slower time-scale than that of the weather systems themselves, can give rise to significant predictability of statistical characteristics of large-scale atmospheric events (Charney and Shukla, 1981). Several observational and modelling studies (Charney and Shukla, 1981; Palmer and Anderson, 1994; Shukla et al., 2000b) provide evidence that boundary forcing in the tropics contribute significantly to the internal variability of the tropical and monsoon circulations. A number of experiments have been carried out using a frequency filter (at the initial state to remove all high frequency motions) within a low-resolution global model (Krishnamurti et al., 1982, 1990c, 1992) and simulation results can be used to provide some guidance for the occurrence of the wet and dry spells of the monsoon roughly a month in advance. Impact of resolutions of global models have been studied and improvements have been noticed in the location of monsoon depressions, in the monsoon circulations included distribution of organized convection of mesoscale precipitating rain elements (Krishnamurti, 1990a; Krishnamurti et al., 1998a). It is recognized that the atmosphere is fundamentally chaotic (Houghton 1991) and its evolution is extremely sensitive to initial conditions. By prescribing realistic initial moisture field (from INSAT IR data) over the Bay of Bengal and Arabian Seas, the skill of the precipitation forecast associated with movements of monsoon depression was improved considerably (Rao et al., 2001). Though in dynamical model, significant improvement has been made through the improvement of the model physics and dynamics, but present day AGCM are yet not able to simulate mean and interannual variability of Indian summer monsoon very successfully (Gadgil and Sajani, 1998; Kang et al., 2002). Researches have been carried out using limited area model at low resolution to simulate precipitation during monsoon season over Indian region and results indicate that the orographic rainfall associated with the Western Ghat Mountains is under-predicted, though summer monsoon rainfall in short range is captured well (Roy Bhowmik and Prasad, 2001). With enhanced resolution, the model could capture the heavy rainfall belt along the Western Ghats as well. It is seen that when the orographic rain decreases and the rainfall belt moves to peninsular India, the skill of this model is found to be much higher.

A major emphasis regarding the improvement of extended range predictions is that to identify and finally rectify those aspects of a GCMs climate that deviate significantly from observed climate (i.e. model climate drift). Miyakoda et al (1986) have indicated that most of the error seen in time averaged extended range forecasts is the result of systematic model biases rather than random errors. It is found during mid 80's that significant amount of the systematic errors in GCMs due to probably inaccuracies treatment of convection, cloud -radiation interaction, surface boundary forcing and orography. A lot of efforts have been made to improve atmospheric GCMs through the development and improvement of parameterizations of these physical processes. Forecast skill of the GCMs has improved after inclusion of improved parameterization schemes for orographic gravity waves (Stern and Pierrehumbert, 1988) as well as increase in the model resolutions (Miller and Palmer, 1987).

RCMs are a first approach to develop downscaling methods to generate realistic local time series from large-scale model outputs. For a number of regions of the world, efforts are made to improve regional climate models which can provide monthly to seasonal scale forecasts. Developed nations have put huge resources for real-time regional NWP models for extended range forecast. With availability of enhanced computing and communication resources, efforts on regional numerical prediction for monsoon also have increased in Asia. Basically, regional climate models (RCMs) are limited area models that are driven at their lateral boundaries by reanalysis or GCMs output data (Giorgi 1990). In other way, RCMs can be understood as regional GCMs, i.e., model solving equations of the smaller scale atmosphere dynamics for given regions (Liang et al., 2006). It is accepted that in a RCM model run, the integration time is approximately more than two weeks, so that the sensitivity to initial atmospheric conditions is lost (Jacob and Podzum, 1997). Although, it is found that if the variability of synoptic/large scale features is underestimated or there is a consistent bias in the larger model (i.e. in GCMs), no increased skill would be gained by dynamical downscaling for large scale, but at the same time it is also demonstrated that the RCMs could able to capture better small scale features which have a greater dependence on the surface boundary (Christopher et al., 2005).

A number of RCMs have been developed in different organizations / institutes / centres that can be used as reliable tools for dynamical downscaling (or regionalization) of large-scale climate change signals forced by global climate models (GCMs), to finer, regional scales. For example ARPEGE (Gibelin and Déqué 2003), CHRM (Vidale et al, 2003), CLM (Steppeler et al., 2003), HadRM3H (Buonomo et al., 2006), HIRHAM (Christensen et al., 1996), RACMO (Lenderink et al., 2003), RCAO (Döscher et al., 2002, Jones et al., 2004, Meier et al., 2003), RegCM (Giorgi and Mearns 1999), REMO (Jacob, 2001) and PROMES (Castro et al., 1993) have been used to study the regional scale climate events. Climate version of PSU/NCAR mesoscale model MM5 has been used widely for regional scale simulation (Singh et al 2007). Though Nested Regional Climate Model (NRCM) (Climate version of Weather and Forecast Research model) is under development stage, but NRCM is using by climate scientists for its better performance in finer scale simulation of regional scale events.

The regional climate model Providing Regional Climates for Impacts Studies (PRECIS) is developed by the Hadley Centre of United Kingdom (Simmons and Burridge, 1981; Simon et al., 2004) and has been evaluated its performance through regional scale simulation over various regions such as European region and South Asian region. Regional Spectral Model (RSM) developed at National Centre for Environment Prediction (NCEP) also one important tools for regional scale simulation. Attempts have been made to coupling atmospheric regional climate models with the regional ocean climate models to enhance the performance of the regional climate models (Ratnam et al 2009). Intercomparison of different RCMs (Jacob et al 2007) indicated that most of the models have warm bias in simulation of temperature but precipitation is well simulated in regional scale. Efforts have been made to develop methodologies for the assessment of the quality of a RCM system in the presence of limited predictability (Vidale et al 2003).

Simulation of Indian monsoon carried out by nesting the regional model to the global model indicate that the onset and progress of monsoon and associated rainfall distribution is better in the regional nested model simulation (Kanamitsu and Juang, 1994; Ji and Vernekar, 1997). A number of experiments have also been conducted to simulate monsoon system using non-hydrostatic mesoscale model (Das, 2002) and it is noticed that the skill of the model is increased if surface parameters/characteristics are represented more realistic in the model (Singh et al, 2007). In India, National Centre for Medium Range Weather Forecast (NCMRWF) is using mesoscale Eta model for medium range forecast (Rajagopal and Iyenger, 2002).

Regional climate models (RCMs) are one of the robust tools to downscale coarse resolution GCMs output. The RCM has three basic components: i) Pre-processing of data ii) main code and iii) post processing of model output. In the pre-processing component, a user has to set the domain and resolutions of their interest first. After completing this, interpolation of geophysical data from geological survey, surface data and basic atmospheric fields from GCMs over the each grid point of user's specific domain are carried out. Then vertical interpolation and transformations from pressure co-ordinate to model coordinate (generally sigma or eta coordinate) is performed to prepare the data as input for main model. The main code consists the model dynamics and physics which govern the atmospheric motions and it has a number of different parameterizations schemes such as land surface parameterization schemes, planetary boundary layer schemes, cumulus schemes, radiation schemes, etc. with various options in each schemes. A number of combinations between each scheme have to be tested to tune the model and the results of each combination of the schemes are verified with the observations/verification analysis. Based on the results, the best combination is used to reproduce GCM output to get better simulated results. Optimization of the model can be made through the tuning of scheme so that the efficiency of the model increases. The main code reproduces outputs from the GCMs using the input prepared by Pre-processing component. In the post processing, the output is converted from model coordinates to pressure coordinates for operational applications.

10.3.4. Some empirical methods:

Extensive studies on periodic oscillations between active spells of plentiful rain and break spells of insufficient rain which are one important characteristics during the Indian summer monsoon season have been carried out by many scientists (Rao, 1976; Ramamurthy, 1969; Webster et al., 1998; Goswami and Ajayamohan, 2001; Waliser et al., 2003; Goswami, 2005; Waliser et al., 2009) that can be helpful for the predictions of abundant rain (frequent/prolonged breaks) leading to flood (drought) conditions. Since production of agricultural yields is highly related with the active or break phase of monsoon rainfall, therefore, skillful and timely forecasts of the duration of active/break spells could be of enormous value for agriculture planning, disaster and water resource management. Researches in recent years have exploited the large-scale quasi-periodic character of the monsoon ISOs to develop empirical models for extended range prediction of the Indian summer monsoon ISOs (Goswami and Xavier, 2003; Webster and Hoyos, 2004) and Dwivedi et al (2006) have attempted to develop an empirical technique for extended range prediction of the duration of monsoon breaks from the concept of rules of regime transitions and the duration of regimes in some idealized two-regime dynamical systems such as the Lorenz model (Lorenz, 1963; Evans et al., 2004; Yadav et al., 2005).

A number of methodologies have been developed to predict the 30 to 60 days oscillations of monsoonal Intra-Seasonal Oscillations (ISO) and Madden Julian Oscillations (MJO) (Krishnamurti et al., 1982, 1990c, 1992; Waliser et al 2009, Sperber and Waliser 2008). It is found that ISO has a relation to the dry and wet spells of the monsoon. Therefore, signal of ISO captured by atmospheric models can be useful to predict the dry and wet spells of monsoon. Krishnamurti et al. (1998b) noted a marked predictability for the ISO on a one-month time scale in their integration using atmospheric global model, and concluded that it is possible to address the issues of monsoonal dry and wet spells one month in advance. Goswami and Xavier (2003) noted from an analysis of historical data sets that there is a possible potential predictability exits through almost 20 days in advance for break periods of the monsoon. The potential predictability of active spells is only of the order of 10 days. The former appears to have large-scale controls (Krishnan and Kasture, 1996), whereas the latter seems to have thermodynamic control as well. Using several different indices of the Indian summer monsoon ISOs, it is noticed that the peak anomaly in an active regime can be used as a predictor for the duration of the following break spell and the stochastically forced Lorenz model may be a useful tool to study some of the salient dynamical properties of the Indian summer monsoon intra seasonal oscillations (Dwivedi et al 2006).

10.4. Preliminary efforts for prediction of Indian summer monsoon:

The Indian summer monsoon is the largest seasonal abnormality of the global climate system. Therefore, the extended range forecast from monthly to seasonal scale in tropics is one of the most challenging tasks in atmospheric sciences. Demand for high-resolution meteorological information is increasing with the increase of economic activity especially in the monsoon region. The climate forecasting of precipitation in monthly to seasonal scale has significant implication in policy planning and national economy for the agro-economic country like India.

India Meteorological Department (IMD) is issuing seasonal scale forecast based on statistical techniques for whole India. Efforts are being made with the use of some statistical methodologies mentioned in previous section to forecast monsoon rainfall in monthly as well as seasonal scale for India and met-subdivisions. Use and development of dynamical methods are in progress.

Development and Application of Extended Range Forecast System for Climate Risk Management in Agriculture (ERFS) – a multi-institutional/organizational project in India has been initiated after the severe drought during 2002 to prevail over the gap between medium range and long range forecast in weather and climate forecast system. In 2002, the deficiency of July was severest for more than a century and had crossed the recorded deficiency occurred during 1877 (-49%). This deficiency had a great impact on the farm productions and need of extended range forecast was realized. A flow chart of the ERFS programme for extended range prediction of monsoon over India has been shown in fig. 10.4. For this purpose, different Atmospheric GCMs (AGCM) and coupled GCMs (CGCM) outputs from various national and international organizations such as NCMRWF, IRI, ECMWF and NCEP etc. are obtained. Using precipitation and temperature data from IMD surface observational network, model systematic biases are estimated and removed to use as input for statistical and dynamical downscaling. Different methodologies described earlier are being used for predictions of rainfall and temperature in monthly as well as seasonal scale. Final forecast can be generated through probabilistic approaches with the predictions of rainfall/temperature by different statistical and dynamical methodologies.

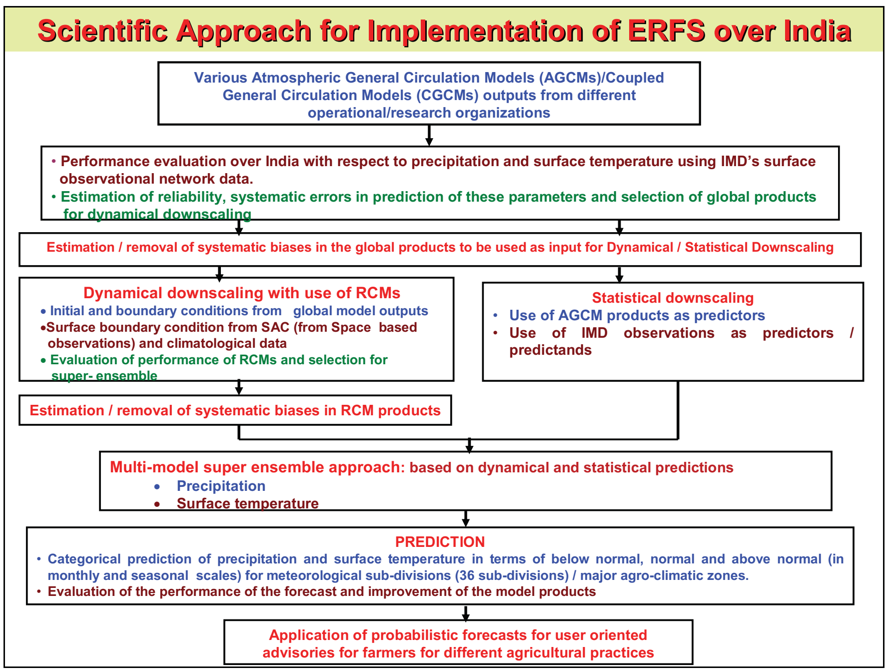

Fig. 10.4: Flow chart of scientific programme for implementation of ERFS project over India.

Experimental test forecast using different techniques for 2010 summer monsoon precipitation and discussions are presented in the next section.

i) Multi Model Ensemble (MME) based model:

An experimental forecast for summer monsoon 2010 (JJAS) is made at each grid point using super ensemble MME approach and given in Fig.10.5. Precipitation forecast from five global models (May start) viz. ECHAM4p5 (2–tier), ECHAM4p5-GML (semi-coupled), ECHAM4p5-MOM3 (1–tier), SINTEXF1 (1–tier) (from Japan Meteorological society) and NCEP-CFS (1–tier) for the period of 1982-2008 are used to generate this forecast. The observed data set used is IMD's 1^0 X 1^0 rainfall. SINTEXF1 is being run at Japan Agency For Marine-Earth Science And Technology (JAMSTEC), Japan and NCEP-CFS model is being run at NCEP, USA while other models run at International Research Institute (IRI) for Climate and Society, USA .

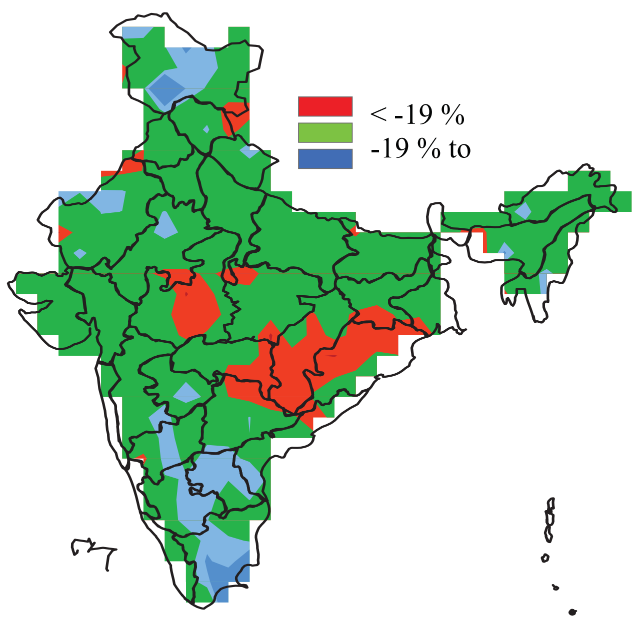

Fig. 10.5: Experimental monsoon rainfall forecast (in % departure) for 2010 using the SVD based multi-model ensemble scheme.

ii) Probablistic Approaches:

Same models (May start) which have been used in the MME scheme also used for probabilistic forecast for summer monsoon (JJAS) 2010 rainfall. The observed data set used is IMD's 1^0 X 1^0 rainfall. The model and observed data sets are normalized to have zero mean and one standard deviation before subjecting to any analysis. As the mean is shifted to zero and standard deviation changed to unity the bounds for the categories become as follows.

Below Normal category: $-\infty$ to -0.43

Near Normal category: -0.43 to 0.43

Above normal category: 0.43 to ∞

The yellow-red colors tell the probabilities of getting below normal rainfall while the shades in gray tells the probabilities for normal rainfall and the shades in blue to pink give the chances of occurring above normal rainfall. It can be observed from the fig. 10.6 that entire Bihar, West Bengal, some part of Uttar Pradesh, Haryana and Uttarakhand may get below normal rainfall, while there are more chances that the southern parts of country will receive above normal rainfall. But over the white region the forecast doesn't have any skill.

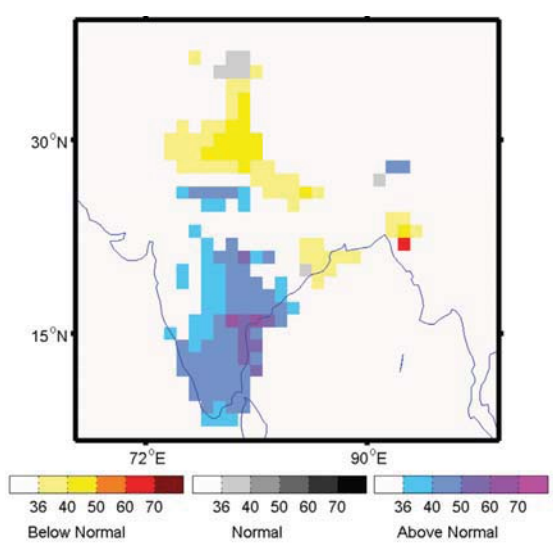

Fig. 10.6 : Experimental Probabilistic forecast for 2010 Monsoon.

iii) Supervised Principal Component Regression (PCR) based model:

In this methodology, the precipitation products from the models used in the earlier method for probabilistic forecasting are considered as predictors (independent variables). These predictors are screened according to their correlation with the observation in hind cast period. After screening, the pool of predictors are gone through the principal component analysis procedure where these variables are made orthogonal to each other. First three principal components are selected on the basis of their correlation with observation. These selected principal components will finally used in the stepwise regression model to generate the forecast. The precipitation forecast generated by this method for 2010 monsoon season is given in fig.10.7. The fig.10.7 indicates that the southern part of country having four subdivisions viz. Tamilnadu, south interior Karnataka, Rayalseema and coastal Andhra Pradesh may get excess rainfall while remaining part of the country may get normal rainfall.

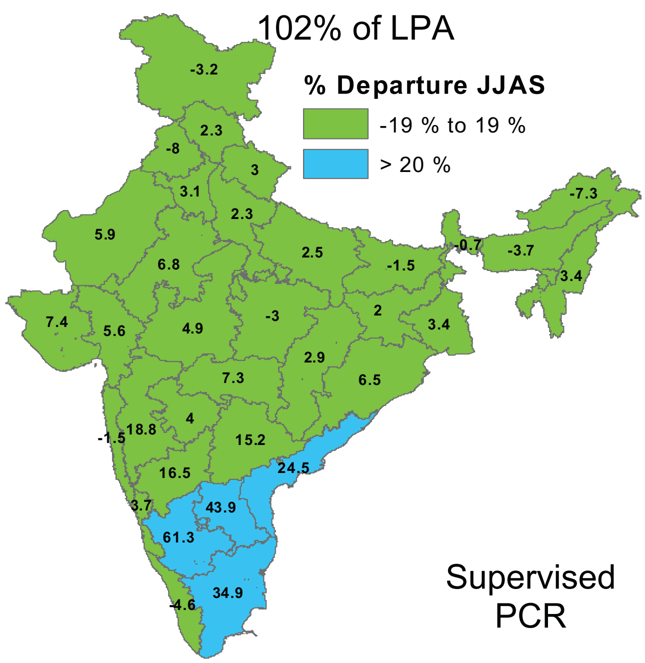

Fig. 10.7: Forecast for 2010 summer monsoon rainfall over different met- subdivisions using supervised PCR

iv) Canonical Correlation Analysis (CCA) based model

JAMSTEC SINTEXF1 model outputs (June start) have been used for experimental forecast of seasonal monsoon rainfall using CCA techniques. Here, model outputs (June start) are considered as predictors to forecast June–September 2010 rainfall over India. Out of all variables of the model output, seven variables (in different regions) are considered as suitable predictors for CCA analysis. These predictors are selected on the basis of the correlation map between predictors and predictand over different domains. The domains and predictors are presented in fig.10.8. It can be noticed from the figure that following seven predictors have been selected. These are:

i) Precipitation (domain1)
ii) Vertically Integrated All Liquid Water Content (domain2)
iii) Specific humidity at 850 hPa (domain2)
iv) Specific humidity at 850 hPa (domain3)
v) Zonal Wind at 850 hPa (domain3)
vi) Meridional Wind at 850 hPa (domain3)
vii) Meridional Wind at 200 hPa (domain2)

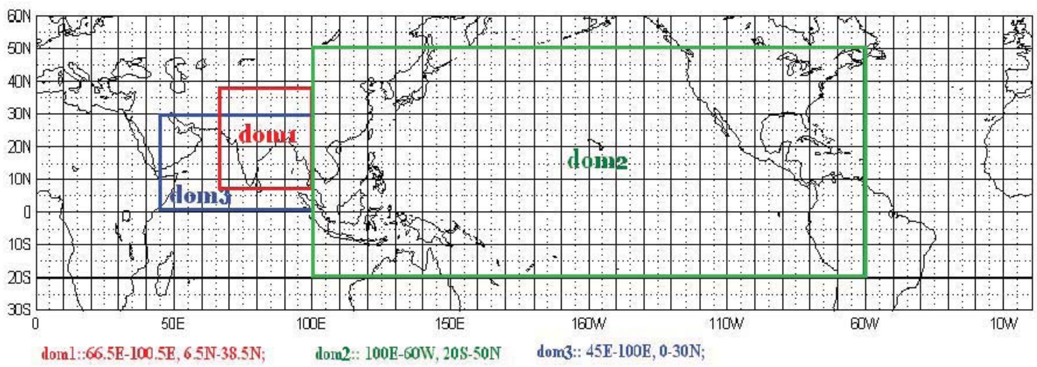

Fig. 10.8: Domains of different predictors for MOS approaches using CCA techniques.

Training period for building up regression equations is considered from 1982-2008 with zero lead (June start time) and IMD rainfall data (1° x 1°) is used as predictand. The data has been normalized before analysis and a composite forecast has been produced using the seven predictors. Experimental test forecast using CCA techniques based on the selected predictors are shown in fig. 10.9. In fig.10.9, forecasted standardized rainfall anomaly for JJAS 2010 over each grid point has been shown. Results indicate that east part of central India viz. west Bengal, Orissa, Bihar, Uttar Pradesh may get deficient rainfall (seasonal) while North West India (Rajasthan, Gujrat), northern India (Delhi, Himachal Pradesh, some parts of Jammu and Kashmir), north of peninsular India may get excess rainfall.

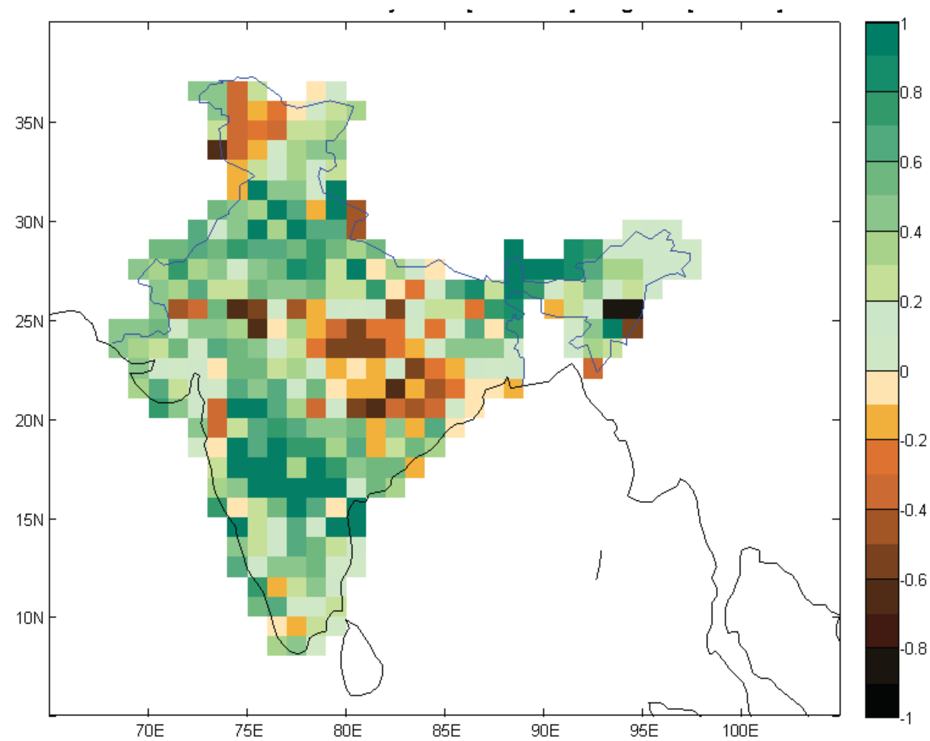

Fig. 10.9 : Forecasted standardized rainfall anomaly for summer monsoon of 2010 using canonical correlation analysis

10.5. Conclusions:

The importance of reliable high resolution forecast and its impact on various sectors of economic activities (especially agriculture) is followed by a broad review of extended range forecast system (not yet comprehensive) and their methodologies are presented. The forecast methodologies are mainly classified into three approaches, statistical, dynamical and dynamical-statistical. Statistical and dynamical downscaling tools on bias corrected GCMs data could able to capture the monthly to seasonal scale features on regional scale and dynamical-statistical approaches have shown better performance over individual statistical or dynamical methods for prediction of extended range forecast.

The present-day monthly to seasonal prediction has shown some promising features with the advancement of observational network, dynamics and physics of CGCMs/AGCMs, improvement of model initial conditions using data assimilation techniques and availability of high performance computing systems. However, till date, the skill of the Asian summer monsoon rainfall forecast (in particular over Indian sub-continent) sharply decreases after 3-4 days time period. None of the deterministic method could able to improve forecast skill of rainfall remarkably in the medium/extended range time scale over Indian region as compared with the skill of medium/extended range forecast over other regions. Moreover, deterministic forecast is a single value forecast therefore if it fails, it becomes totally wrong. In such circumstances if the accuracy of the forecast is conveyed to user with some confidence then it will be more useful than a single value. This can be achieved using probabilistic forecast. In this study some parametric methods are mentioned, that can be used for probabilistic forecast in tercile categories. This forecast can also be issued in the categories of users' interest. One can use some other parametric as well as non parametric methods for this purpose. In addition to that the Bayesian approach can also be used to generate the probabilistic forecast. In Bayesian approach previous knowledge of the system is used along with some type of linear/non linear models.

Hence, the limitation of the deterministic extended range forecast leads to the greater focus in the development of appropriate probabilistic forecast of different categories of precipitation such as excess, normal, deficient, scanty and so on instead of the location specific and magnitude of rainfall forecast. It is a challenging task and needs concentrated efforts on the improvements of observations as well as the proposed approaches discussed above.

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