2

CLIMATE & ENVIRONMENTAL MODELLING

Capacity to model and forecast climate and environmental processes at different spatio-temporal scales has the potential to revolutionize our approach and ability to address many issues that concern us closely. It was to address these issues in an integrated manner and to generate a capability for multiscale forecasting that CEMP was initiated.

INSIDE

CLIMATE MODELING AND SUSTAINABILITY ANALYSIS

2. 1 Climate Simulation with CSIR Climate Model (Version 1)

While dynamical climate models today offer an efficient, and essentially only, tool for studying climate change and generating future projections, these models need careful calibration and validation for application to a particular region or process. C-MMACS has developed a configuration for long-range dynamical forecasting of the monsoon based on a variable-resolution global circulation model (VR-GCM); it has been shown that the C-MMACS monsoon configuration has significant skill in forecasting the monsoon at different scales. As the next logical step, this configuration is being extended to develop a model of regional climate over India. This requires careful calibration for stability and validation.

To begin with, the model is being tested for high-resolution simulation at decadal scale. The variable resolution configuration was first integrated for 20 years with winter (January 1) and spring (May 1) initial conditions to examine the conservation properties and stability of the model for long integration at high spatial and temporal resolution. The annual cycle of area-averaged (75-85 o E, 8-28 o N) weekly precipitation from a winter (January 1) + spring (May 1) ensemble integration from the model for the 20-year period of 1981-1999 is compared with the

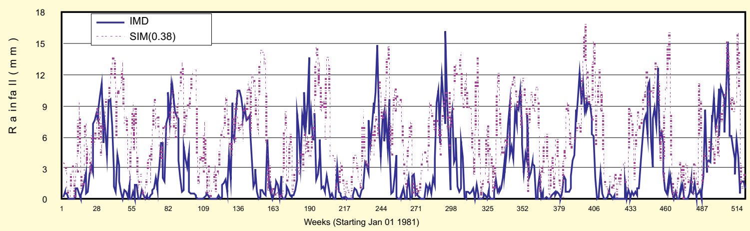
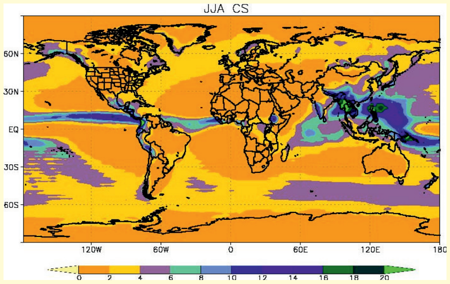


Figure 2.1 Annual Cycle of weekly average rainfall over India for Jan 1981- Dec 1990 (Ensemble of 1980 Jan 01 and May 01 Lead)

corresponding weekly Climatology from IMD (figure 2.1). It may be seen that the model simulations do not exhibit any significant drift; however, simulations show a significant positive bias with respect to observed rainfall.

Comparison of summer monsoon (JJA) rainfall climatology from the model with the corresponding observed climatology (CMAP) shows (Figure 2.2) good agreement in the distribution over India; similar conclusion also holds for the winter monsoon (not shown here).



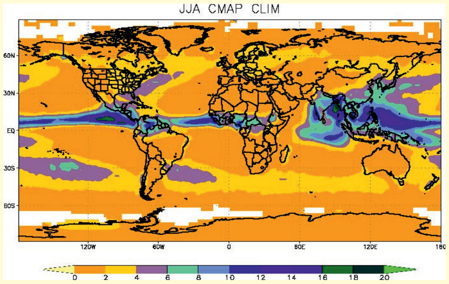


Figure 2.2 Comparison of global (Jun-Aug) rainfall climatology from CSIR Climate model and CMAP observation

The scope of model evaluation and inter comparison is very broad, and the results depend on the geographical region as the parameter for evaluation. The focus of the development of the CSIR climate model in the first phase is accurate simulation of rainfall over India. While the first results of long-term simulation of seasonal rainfall presented here are encouraging, the model will need multi-scale validation for its intended applications.

K C Gouda and P Goswami

2.2 Comparative Analysis of IPCC and CSIR Climate Simulations over India

The Fourth Assessment Report of the Intergovernmental Panel for Climate Change (IPCC AR4), climate modeling groups have performed a well coordinated set of pre-industrial, 20th and 21st century climate change experiments, including projections for the 22nd century. We have examined the pre-industrial (20th century) climate of the Indian summer monsoon simulated by 26 (23) IPCC AR4 models and compared with the climate simulations by CSIR climate model, along with observed rainfall over India. Aim of this exercise was to assess the ability of the CSIR climate model(Version 1.0) in simulating the observed mean and long-term variability of the Indian summer monsoon along with IPCC AR4 climate simulations. IPCC AR4 includes the state of the art coupled ocean-atmosphere models from various climate modeling groups around the world.

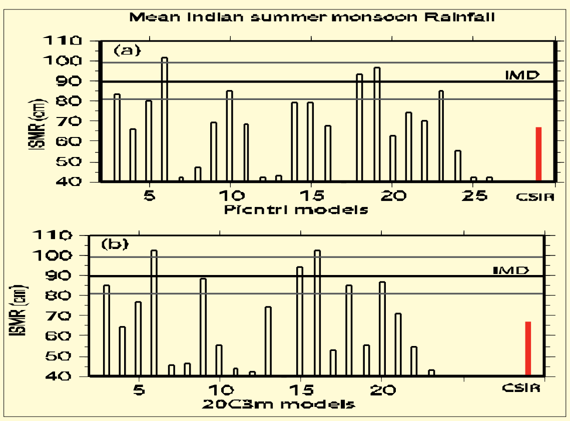


Figure 2.3 Seasonal mean rainfall (mm) from (a) pre-industrial and (b) 20th century simulations from IPCC AR4 over India is compared with observed mean rainfall from IMD (black thick line). The mean rainfall from the CSIR climate model (for 20-year simulation) is shown in red bars. The thin lines indicate ± 1 SD of observed rainfall. Out of 24 models from IPCC AR4, only 7 models are within one standard deviation of the observed (IMD) value.

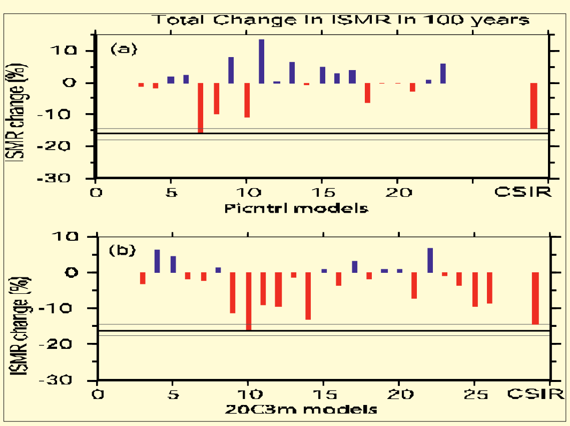


Figure 2.4 Total change in seasonal mean rainfall (%)from (a) pre-industrial and (b) 20th century simulations from IPCC AR4 over India is compared with observed mean rainfall from IMD (black thick line). Total change in rainfall from the CSIR climate model (for 20-year simulation) is shown in red bars. The thin lines indicate ± 10% of observed change.

Only six out of twenty six IPCC AR4 climate models simulated the mean seasonal rainfall within one standard deviation of the observed rainfall. A majority of the models produce a mean seasonal rainfall of about 70 cm; the CSIR climate model also produces a mean seasonal rainfall of a similar amount (figure 2.3) for the Pre-industrial simulations.

With respect to changes in the seasonal mean rainfall, only one model out of the 26 IPCC AR4 simulations produces results close to the observed (IMD) value (figure 2.4). It is quite interesting to note that the pre-industrial climate simulations indicate both positive and negative trends; while most of the 20C3m simulations show negative change in monsoon rainfall. The CSIR climate model has simulated the change in the monsoon rainfall close to the observed value. These comparative evaluations are essential for the identification of the appropriate model configuration for reliable simulation of regional climate change over the Indian region.

K V Ramesh , K C Gouda and P Goswami

2.3 Role of Observed Climate Change over India and its Implications on Regional Food Production

Food sustainability in the backdrop of increasing population and a changing climate is a growing concern. Agricultural sustainability is a complex function of many interacting variables, both natural and anthropogenic. Agricultural prospects, and in particular parameters like crop viability and irrigation requirement, critically depend upon the quantum as well as temporal distribution of rainfall. In the backdrop of a growing population, changing demand and impact of climate change, a careful and quantitative analysis of food sustainability for India is needed.

Epochal Change: food production & harvested area

Epoch	Total Food Prod (%)	FAO-Production (%) Rice	Wheat	Cereals,Other	WPI(food)	WPI	CPI
1961-1970	24.43	----	----	----	79.41	-------	------
1971-1980	29.67	25.41	108.83	9.69	104.17	------	------
1981-1990	33.06	34.74	61.12	8.6	118.5	118.6	121.5
1991-2000	26.08	31.05	42.77	2.11	149.5	149.5	211.7
2000-2009	11.20	10.13	13.6	12.66	40.22*	60.78	87.77

Epoch	Total Harvest (%)	FAO-Harvest (%) Rice	Wheat	Cereals,Other	Population
1961-1970	7.55	----	----	----	-----
1971-1980	5.01	7.42	43.6	-5.44	24.41
1981-1990	1.50	5.17	15.8	-8.43	25.19
1991-2000	-3.15	6.12	9.62	-19.68	22.65
2000-2009	-1.16	-0.20	4.89	-8.46	17.48*

Table2.1: Analysis of production and harvest of some major crops over the five decades 1961-1979 shows decrease in harvest in cereals since 1971; alarmingly the total harvest also shows negative trend since 1991.

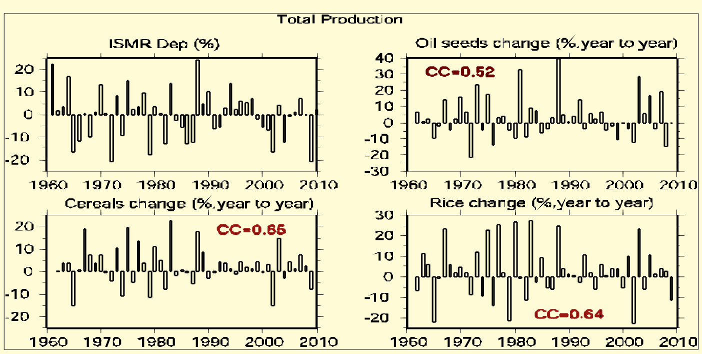


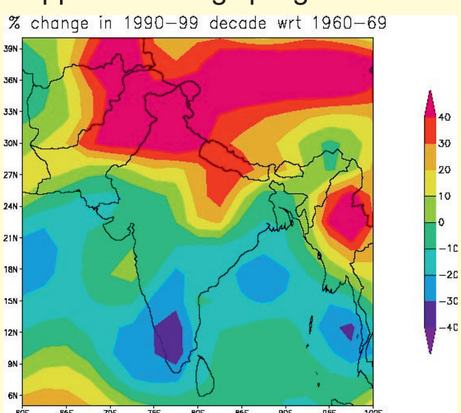
Figure 2.5: Inter annual variability in total production of oil seeds, sereals and rice for the period 1960-2010 show close association with Indian summer monsoon rainfall (ISMR), with significant correlation in each case

The change in agricultural production is a complex function of many variables. However, any change in monsoon rainfall is likely to have a major impact. It has been shown in earlier work at C-MMACS that the spatial and the temporal extents of the Indian summer monsoon are decreasing; such a change in the monsoon is likely to affect agricultural production significantly. However, given varying water requirements for the different crops, the impact of a changing monsoon are likely to be crop-dependent. An important requirement for an analysis of sustainability, therefore, is quantification of the association between rainfall and productions of various crops.

K V Ramesh , M V Sathish, M S Lavanya and P Goswami

2.4 Analysis of Change in Wind Energy Potential over The Indian Monsoon Region

For given turbine and height, power generated by wind energy is essentially a function of number of episodes of wind of sufficient strength. The nature of wind episodes, like given strength at a location and the locations with such episodes, however, are strong functions of circulation systems; for regions like the Indian summer monsoon for which the wind is strongly influenced by regional circulation systems like the seasonal reversal of wind with monsoon, sustainable wind energy is closely linked to changes in the wind regimes. There has been, however, very little information on the changes in the wind energy potential in a changing climate in general, and over the Indian region in particular. Decline in wind energy has significant indirect impact on the environment through increased CO_2 footprint of energy production. Comparison of the epochal climatology of wind strength over India, however, shows (figure 2.6) significant changes (both increase and decrease). It is necessary, therefore, to develop a simulation platform to aid decision support in setting up high-investment wind installations.



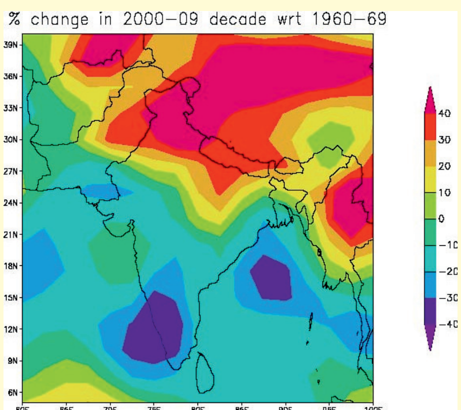


Figure 2.6: Epochal changes in wind strength over the Indian monsoon region between 1970-2009 with respect to 1960-1969 based on NCEP Reanalysis. While some areas show negative trends, there are areas with growing potential.

An essential tool for a quantitative and reliable projection of wind energy is a climate simulation platform validated for regional circulation. We have used the CSIR Climate model (Version 1.0) to show that an optimized configuration represents well the variability as well structure of the

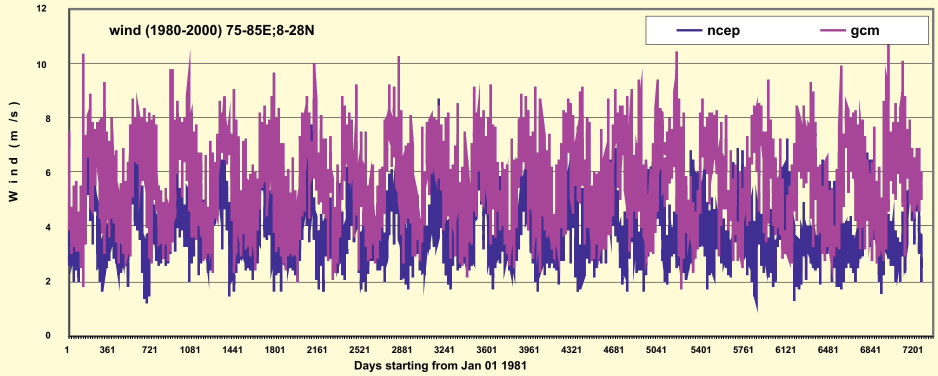


Figure 2.7 Area averaged daily wind from 20-year GCM simulation compared with NCEP Reanalysis .

wind over the Indian monsoon region.

The model was integrated for a period of 20 years to examine the simulated wind field compared against NCEP Reanalysis. Area averaged near-surface wind at weekly scale compares well (figure 2.7) with the corresponding NCEP data. The model has a positive bias, which is systematic and hence can be removed.

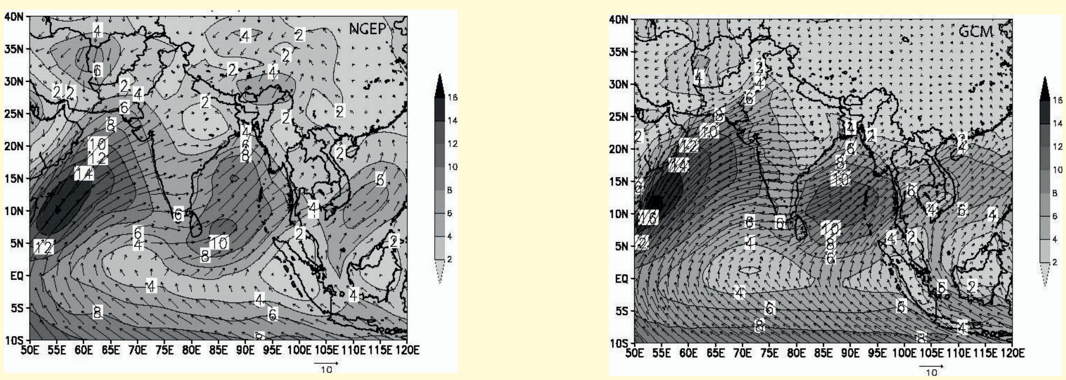


Figure 2.8 Comparison of seasonal (JJA) wind climatology (1980-1992) from NCEP Reanalysis (left panels) and CSIR Climate model simulations (right panels).

The simulations also capture the spatial structures of the seasonal wind over the Indian monsoon region (figure 2.8). As the NCEP Reanalysis is on a coarse grid, the bias in the high resolution simulations from the CSIR Climate model needs to be investigated against observations at high resolution.

2.5 A Dynamical Model for Agricultural Self–Sustainability over India

Food security in the backdrop of increasing population and a changing climate is a growing concern; the total food produced against the minimum food required is a good measure of the state of a community or a people. The actual demand for food needs to take into account variety, nutritional requirements as well as a number of other factors. Similarly, the available food depends on not only domestic production from various sources but also on import and reserve. However, agricultural self-sustainability, defined as a condition in which the entire minimum food requirement of a people is produced from agriculture, can provide a good and quantitative measure of the state of a nation; agricultural self-sustainability, taken more comprehensively to include marine products, is going to be increasingly more relevant for a people as external sources become increasingly less effective due to world-wide saturation in arable land and productivity.

The food requirement of a people itself is a complex function, with varying requirements of different food type depending on the people. However, an equivalent agricultural production may be defined to represent the total food requirement. The available food depends on the total agricultural production as well as on minimum resources (seed, land, fertilizers, irrigation and machinery). To examine a scenario of agricultural self-sustainability, we define an index in term of the total food produced and the total food demand at a given time t (year) as

$$S(t) = \frac{F_A(t)}{F_D(t)}$$

Where $F_A(t)$ represents the equivalent amount of food available for distribution (not including import) while $F_D(t)$ represents the total food demand.

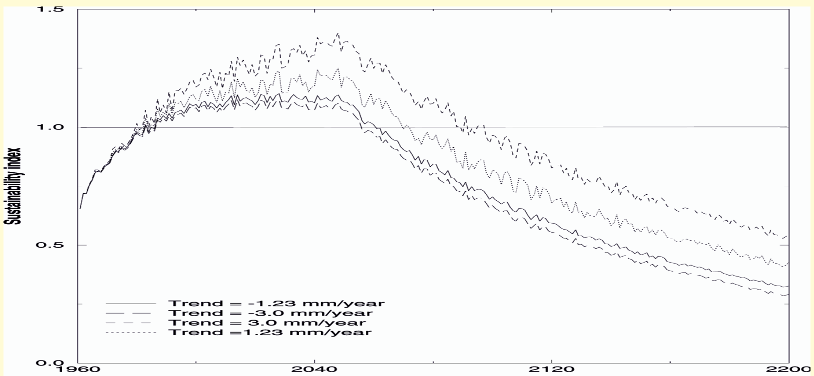


Figure 2.9 Agricultural sustainability index for India in different scenarios of surface water (annual rainfall) trend from year 1961 to 2000.

We have developed a dynamical model to investigate agricultural self-sustainability in different scenarios where the production changes due to natural and anthropogenic factors such as trends in surface water, population and aridification of land area due to climate change. The supply is considered in terms of food producible and the demand is considered in terms of minimum per capita food requirement for the population.

The dynamics of sustainability from the model shows the present era to be very different from that in the past. Our model validated with multi-source data shows that India's agricultural sustainability has nearly reached a plateau and is now in a declining stage. While this decline can be much faster with a negative trend in the surface water (annual rainfall), the sustainability index is still projected to fall below 1 (critical value for loss of self-sustainability) even with a positive trend in the surface water (figure 2.9) in a few decades from now. In addition to regional impact of climate change, this decline is caused by decrease in agricultural area due to habitat, industries and use in other non-agricultural purpose and increase in population.

P Goswami and Shiv Narayan Nishad

HEALTH

2.6 A Model of Malaria Over Arunachal Pradesh

Quantitative relation between climate variables and vector population can aid generation of projections of vulnerability for decision support. As malaria is a vector (mosquito) borne disease, vulnerability to malaria depends both on exposure and the population of mosquitoes carrying the parasites. As the malaria vector requires specific ranges of environmental variables like temperature, humidity and rainfall for genesis and development, vulnerability to malaria is expected to strongly depend on climate change; new areas are thus likely to become endemic while some other areas may become non-conducive for vector genesis. In general, only a fraction of the total mosquito population will affect the incidental host (human), and of that only a small fraction will carry either of the parasites to infect the host; however, an increase in total vector population is likely to result in increased infection.

A model for malaria, combining effects of weather, exposure and transmission, has been developed at C-MMACS under the CSIR Network project “Integrated Analysis for Impact, Mitigation and Sustainability”. The model has been applied to Arunachal Pradesh, a state known to be endemic to malaria. The primary data is number of blood samples collected (BSC) from reportings at Primary Health Centers (PHC); the BSC is subjected to detection tests to determine blood samples positive (BSP) if the parasite is detected.

To begin with, the number as well as the structure of the annual cycle of malaria cases exhibit strong inter annual variability (figure 2.10). Although the peak occurs generally in the monsoon months (June-September) for most of the twelve districts, there are significant variations from year to year (figure 2.10).

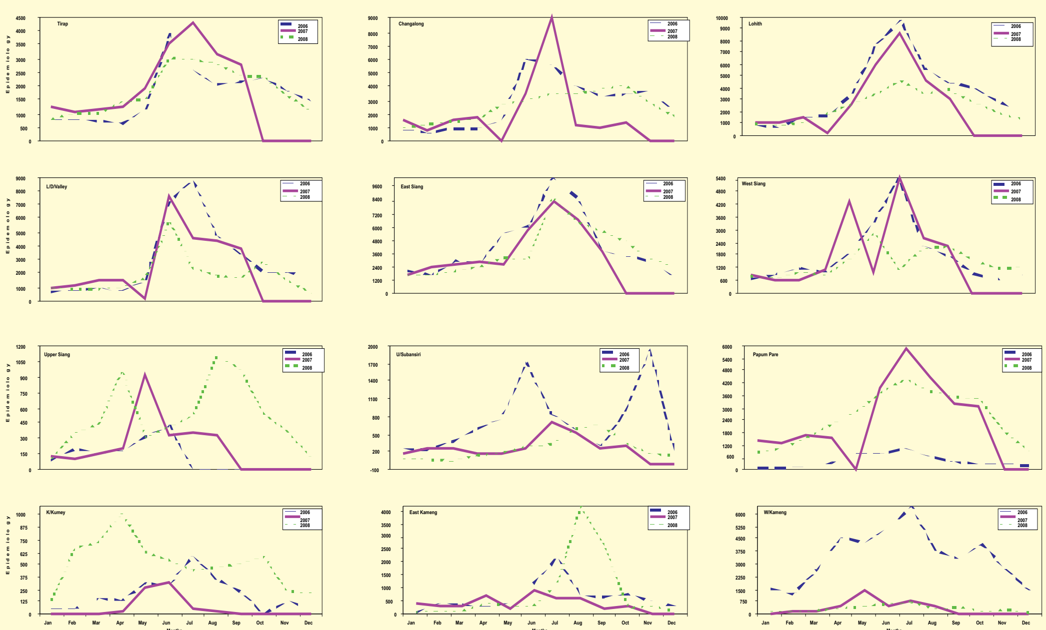


Figure 2.10 Internal- annual variability in epidemiology (Blood Sample Positive) for the years 2006(thick solid line), 2007(thin solid line) and 2008(dash line) for the twelve districts in Arunachal Pradesh.

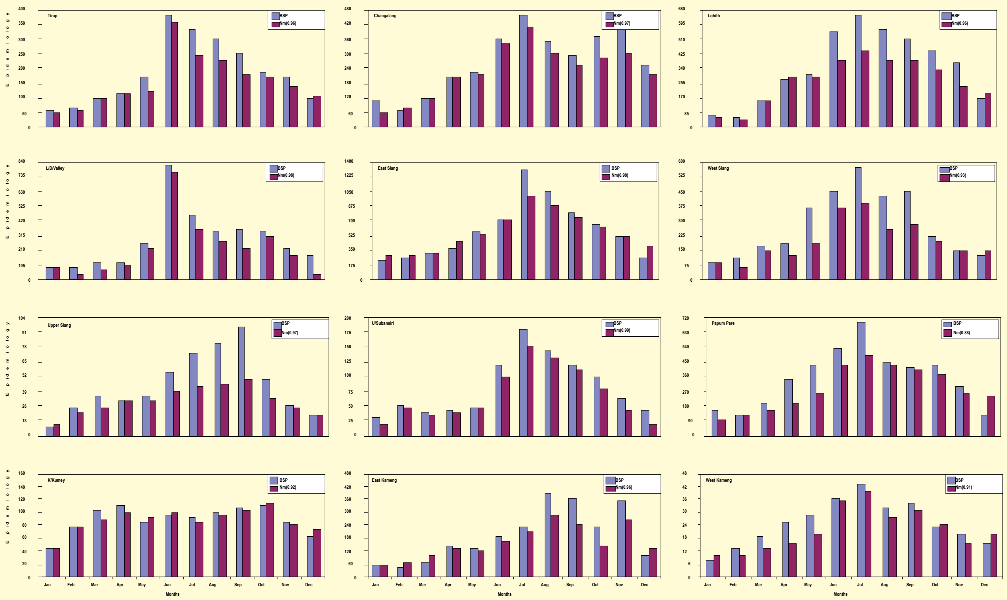


Figure 2.11 Monthly climatology (2006-08) of observed and computed malaria counts for the twelve districts.

The ability of the dynamical vector model to capture these district-specific seasonal cycles of malaria (Figure 2.11) makes it a potential tool for pro-active mitigation (through advance identification of abundance peaks) and assessment of impact of climate change on vulnerability.

P Goswami1, U Suryanarayana Murty, M Srinivasa Rao & K Avinash

2.7 Model of Air Pollution over Delhi : Simulation with GCM Driven Fields

The massive growth in the size and the population of cities over the past few decades has led to serious deterioration in the quality of air. Species like SPM, RSPM, SO2 and NO2 not only act as atmospheric pollutants but also affect long-term climate. The spatio-temporal variations in these species depend on both meteorological processes and various natural as well as anthropogenic sources and sinks. An air pollution model validated for a given air basin and interfaced to high-resolution weather forecast model can be used to provide advisories and traffic planning; interfaced to a global circulation model, it can be a valuable tool for impact assessment and policy planning. C-MMACS has developed and validated an air pollution model for the Delhi air basins this Report highlights efforts to interface this model to global circulation model as a part of the efforts to develop a comprehensive CSIR Climate Model.

While the basic conservation equations and the meteorological fields are common to all the four pollutants, the sources and sinks for each are modeled in a species-specific manner to obtain maximum skill. In line with our current objective, the meteorological fields are obtained as forecasts from C-MMACS monsoon model.

A comparison of climatology (2000-2005) of daily values of SPM, RSPM, SO2 and NO2 over Delhi from observation (CPCB) and model simulations for the four species shows (Figure 2.12) that the model simulations follow the observed features quite closely, as reflected by a correlation coefficient of above 0.6, significant at 99% confidence level for the degrees of freedom involved. Except for NO2, the observed annual cycles of SPM, RSPM and SO2 have two maxima: January-February and October-November. The winter maxima (especially during January-February) appear to be significantly controlled by domestic sources. This is consistent with the fact that during May-June, the winds over Delhi turn westerlies, bringing the dust from Thar Desert and arid regions to the west of Delhi. The relatively high values of SPM in the pre-monsoon periods especially after March are attributed to the strengthening of winds associated with the monsoon currents and the resulting dust storms. Consistent with our finding of significant negative correlation between precipitation and SPM, there is a steep fall in SPM in the monsoon months. The sharp fall in SPM in the monsoon season shows the effect of rain on clearing the atmosphere (Figure 2.12, top left panel). On the other hand, the observed annual cycle of NO2 is nearly flat (Figure 2.12, bottom right panel), indicating no significant correlation with precipitation.

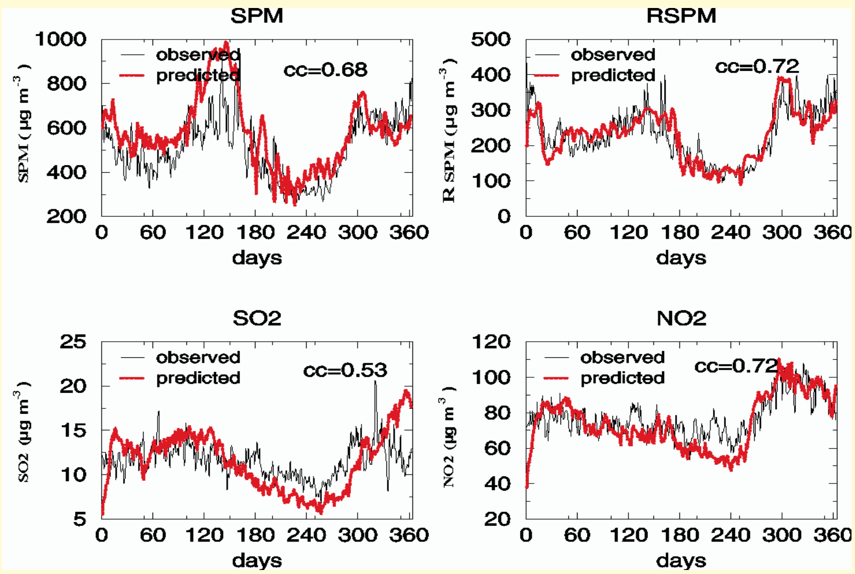


Figure 2.12 Climatology (2000-2005) of observed (black line) and simulated (red line) values for different pollutants over Delhi as indicated. The meteorological variables have been taken from debiased prediction of gridded GCM output at at 77° E and 28° N (Delhi). The observed data is from CPCB.

The ability of the air pollution model to simulate the observed features with GCM driven fields is the first requirement for it to serve as a tool for long-term projections and impact assessment as a climate model.

P Goswami and J Baruah

MESO-SCALE AND STATION SCALE FORECASTS: APPLICATIONS OF COMoN

2.8 Objective Bias Correction for Improved Skill in Forecasting Temperature Over India: The Winter Case

Station-scale forecasts are necessary for many applications related to health (such as vector borne disease), agriculture (such as germination potential) and industry (such as power requirements), where the diurnal cycle of temperature plays a critical role. Such station-scale forecasts from dynamical models have to be necessarily obtained through a procedure of downscaling. Similarly, while typical climate simulations generate fields averaged over thousands of square kilometers, many applications require meteorological filed at local scale. While generic improvement in model skill requires parallel and comprehensive development in model and other forecast methodology, one way of achieving skill in station scale forecasts without (effort-intensive) calibration of model is to implement an objective bias correction. The main goals of the present work had been to assess an objective debiasing methodology to obtain significant skill in 24-hour forecasts of diurnal cycle of surface temperature.

It has been shown earlier that a non-linear objective debiasing can transform zero-skill forecasts from a meso-scale model (MM5) to forecasts with significant skill for temperature over 12 urban locations over India in different geographical conditions. The present Report complements the earlier results by considering the same 12 locations during November-February, 2009-2010. The model MM5 was integrated for 24 hours with initial conditions from [global gridded analysis (FNL)] of the National Centers for Environmental Prediction Global Forecast System (Final) for each of the days of November-February, 2009-2010 in a completely operational setting. It is shown that for all the locations and the four months, the skill of the debiased forecast is significant against essentially zero skill of raw forecasts.

The model simulations were tested for the (monthly) average diurnal cycle for November 2009 to February 2010 at each location (Figure 2.13). From a steep diurnal cycle over locations like Amritsar and Ahmadabad to rather flat diurnal cycles over coastal locations like Chennai and Mumbai, the debiased forecasts capture them well for all the four months.

Table 2.2. A comparison of the performance of raw forecast (RF) and debiased forecast (DFR) in terms of Mean Absolute Error (MAE), Bias Error (BE) and Root Mean Square Error (RMSE) in maximum (Tmax) and minimum (Tmin) temperature by different methods. For RF and DFR all parameters are calculated out of 120 days and 80 days respectively from November to February, 2009-2010.

Model	MAE (^{0}C)	BE (^{0}C)	MAE (%) < 1^0	RMSE in T_{max}	RMSE in T_{min}
ETA *	2.6	0.9	26	__	__
ETAKF *	1.9	0.0	37	__	__
ETA7DBR*	1.8	0.0	37	__	__
ETAMOS *	1.5	0.1	42	__	__
RF$^+$	3.0	-1.3	40	1.8	1.7
RMER$^+$	1.6	-0.9	60	__	__
DFR$^+$	0.9	0.4	72	0.9	0.8
GCM (NCMRWF)†				2.2	1.4

* June – August, 2004, + November-February, 2009-2010; average over 12 stations, † June – September, 1997-2000; average over 12 stations.

A comparison of the skill of the present method with a number of other methods [like the Eta Model (ETA) which was renamed the North American Meso (NAM) model in 2005, model output statistics with ETA model (ETAMOS), the Kalman filter with ETA model (ETAKF) and a 7-day running mean bias removal with ETA model (ETA7DBR)] for debiasing shows (Table 2.2) the present method to have generally better skill.

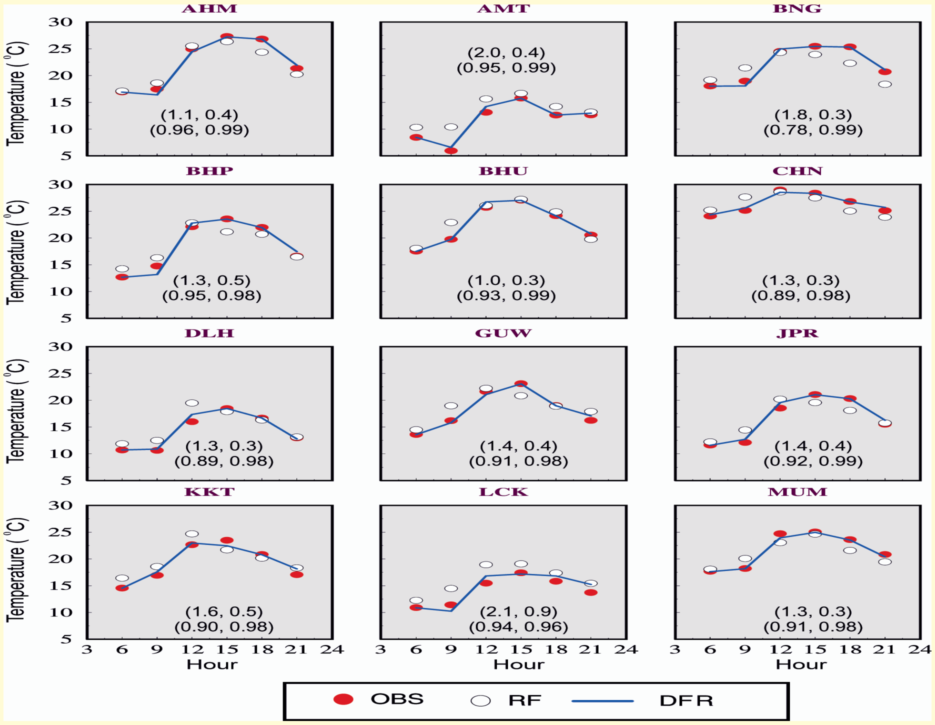


Figure 2.13 Average diurnal cycle for the 12 stations for the month of January 2010; the red circle and white circle respectively, represent observed and raw forecasts beginning from 0600 UTC and ending at 2100 UTC, while the continuous lines represent debiased forecasts downscaled to station location. The first two numbers in the bracket in each panel represent average error (0C) while the second set of two numbers represent correlation with respect to observation (OBS) for raw (RF) and non-linear realizable (DFR) debiased forecasts, respectively.

Along with our earlier results for the summer case, the present results show the ability of the algorithm to generate skillful forecasts at station scale. This is important to make weather informatics and forecasts reliable for agricultural and industrial applications.

It is possible that the degree of improvement due to debiasing will depend on model configuration and horizontal as well as vertical resolution; however, while this issue is particularly important for operational applications it is unlikely to change our conclusions qualitatively. While higher resolution may improve the raw forecasts, the importance of objective debiasing will remain as long as the raw forecasts are not bias-free.

S Mallick and P Goswami

2.9 Analysis of Meso-Scale Structure of Weather over Delhi Using CSIR Climate Observation and Modelling Network (CSIR COMoN)

A large city with its complex combination of structures and surface characteristics presents a unique challenge in terms of its weather. It is important to know the meso-scale structure of a city's weather to determine aspects like vulnerability and energy demand. However, knowledge of such meso-scale structure requires an observational network with sufficiently high density, which has been essentially missing. In early 2009, recognizing the need of mesoscale observations of weather in urban areas like Delhi, CSIR, in collaboration with the Indian Air Force (IAF), has established a Mesoscale Observation Network for Urban Systems (MONUS) covering the National Capital Region (NCR) with meteorological profilers over four locations. Out of these four locations, NPL (CSIR National Physical Laboratory) is essentially in central Delhi; the other three are at Narela (NAR), Hindon (HIN) and Rajokri (RAJ) at the periphery of the city at sites provided by IAF.

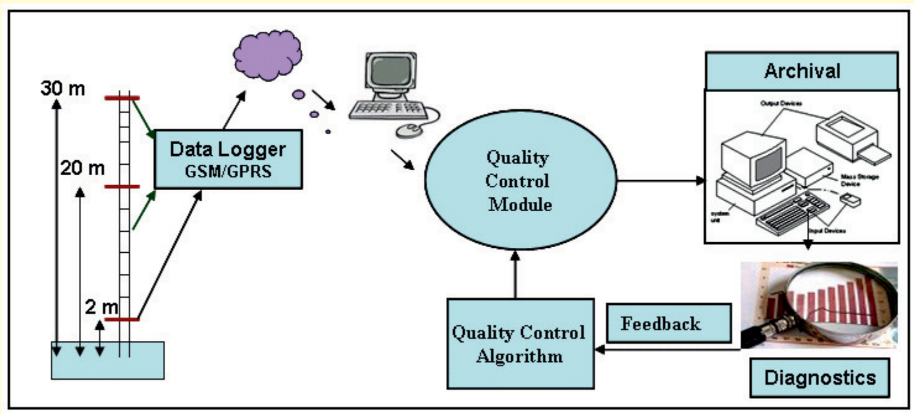


Figure 2.14 A schematic of the 30-meter meteorological profiler, and the associated measurements, at each location & telemetry.

The meteorological profiler at each location is a 30-meter tall tower instrumented with sensors for wind speed, wind direction, temperature and humidity at three levels: 2-meter, 20-meter and 30-meter. In addition, there are also sensors for sub-surface measurements of soil moisture and soil temperature. The data from each tower is received telemetrically at C-MMACS, where it passes through quality control software before archival for analysis (Figure 2.14); the data is also made available near real time to IAF. Monus is a part of a Climate Observation and Monitoring Network (COMoN).

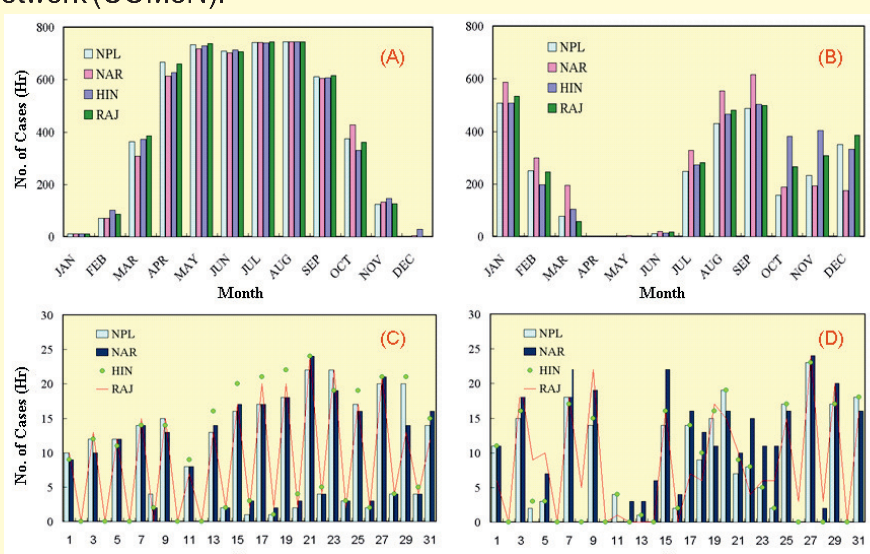


Fig.2.15 (A) Number of cases (Hr) in each month with temperature above 24 0C, (B) Number of cases (Hr) in each months with relative humidity above 80%, (C) Number of cases (Hr) in each day of the month January 2010 with wind chill less than 10 0C and (D) Number of cases (Hr) in each day of the month July 2010 with heat index greater than 32 0C for the four location.

This is the first such analysis of multi-level meso-scale weather over a major city of India. It is shown that the four stations at National Capital Region (NCR) of Delhi show significant differences in variables like maximum and minimum daily temperature, wind as well as rainfall, implying the need for such meso-scale observation network over urban locations. Further, there is also considerable difference in temporal structures of near-surface (2-meter) and upper level (30-meter) variables; thus multi-level observations are necessary for a comprehensive understanding of the meso-scale weather of a city. As a measure of meso-scale de-coherence (or diversity), we consider differences in the variables from those at a reference location, taken as NPL(Figure 2.15).

In spite of their societal, strategic and industrial importance, our knowledge of meso-scale structures of weather regimes over a city like Delhi has been essentially nil; the establishment of COMoN-MONUS provides us the first glimpse of this fascinating phenomenon. To begin with, the variability in the urban weather, even at such horizontal scales, is significant to make practical differences. These findings are being used to validate and improve models of processes like fog and other high-impact weather.

P Goswami, S Mallick and G K Patra

2.10 A High-Resolution Regional Atmospheric Analysis (HiRRAA) over India from NCEP Reanalysis through Objective Bias Correction.

High-resolution long-term analyses of variables like temperature and wind are critical for many applications like regional climate analysis and assessment. Reanalysis data, like those from National Center for Environmental Prediction (NCEP), provide a versatile, and sometimes only, long-term, multi-variable data at a location. However, reanalysis data, besides their coarse resolution, are known to contain significant biases that depend on geographical location. It has been shown earlier at C-MMACS that NCEP Reanalysis could be used through an appropriate algorithm to generate good representation of high-resolution distribution of precipitation.

Under a CSIR project “High-resolution Regional Atmospheric Ananlysis (HiRRAA)” to create a long-term, reliable, atmospheric analysis at high resolution, we have developed and tested an algorithm for creation of station level analysis from coarse-resolution NCEP Reanalysis over India. The basic method is an objective bias correction algorithm applied to NCEP reanalysis for multiple locations over India. It is shown that objective bias correction can effectively improve quality of such analysis at station-scale. Downscaling of reanalysis data to arrive at station scale values will remain a necessary step for many applications.

The observations were taken from 3-hourly data from India Meteorology Department (IMD) for each of the days of January to June 2010. It was found that significant differences exist among the variables from these twelve stations. It is shown that for all the 12 locations the skill of the debiased forecast is significant against the skill of raw reanalysis data and significantly higher than that of a 7-day running mean difference removal (null hypothesis).

The objective bias correction method were tested for(monthly) average absolute difference of daily averaged temperature, daily maximum temperature and daily minimum temperature in ^{o}C between IMD observed data and raw NCEP data (UN), 7-day running mean difference (RMD), bias corrected NCEP data (DFR) from January to June 2010 at each location. In terms of percentage of days (out of 181 days for UN, 139 days for RMD and 121 days for DFR from January to June 2009) for which daily averaged temperature is in the error bin -1 to 1° C shows (Figure 2.16) it is found to be generally below 35% for the UN, while for debiasing forecast (DFR)

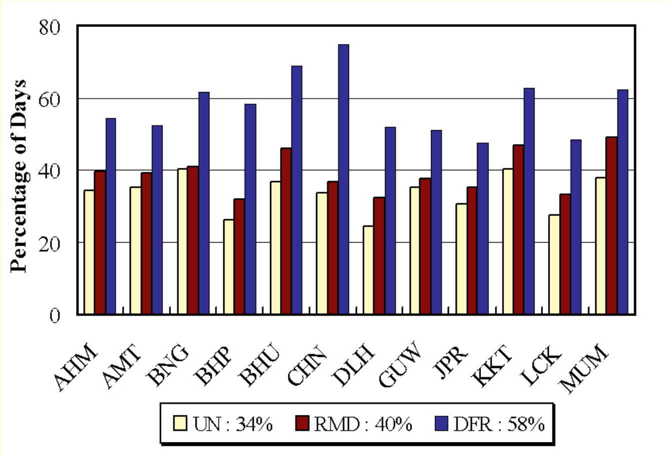


Figure 2.16 Percentage of days (out of 181 days for UN, 139 days for RMD and 121 days for DFR) for which daily averaged temperature is in the error bin -1 to 1 0C from January to June 2010 for each station. The average of all station is given with the legends.

this number is generally above 50%; for RMD, the skill is below the DFR but higher than UN. In terms of monthly averaged error in daily maximum and daily minimum temperature, non-linear debiasing can potentially reduce the error by more than 50% for all the stations (Table 2.3) in daily averaged temperature. The improvement for RMD is less compare to that for DFR (Table 2.3).

Table 2.3 Average absolute difference for daily maximum and daily minimum temperature in degree Celsius for different type of bias corrected forecasts for all 12 stations for the month January to June 2010.

Month	Average over 12 stations.					
	Daily Maximum Temperature (°C)			Daily Minimum Temperature (°C)		
	UN	RMD	DFR	UN	RMD	DFR
JAN	2.71	2.29	1.53	3.04	2.41	1.68
FEB	2.51	2.16	1.23	2.75	2.28	1.92
MAR	2.05	1.91	1.38	2.12	1.74	1.67
APR	2.37	1.97	1.66	2.31	1.88	1.79
MAY	2.67	2.04	1.59	2.37	2.14	1.71
JUN	2.62	2.18	1.42	2.25	1.95	1.71
Average	2.49	2.09	1.46	2.47	2.06	1.75

The two critical components in developing a HiRRAA from NCEP are validated algorithms for downscaling/debiasing and local observations for validation. The first requirement has now been addressed to a degree through development and validation of algorithms for station-scale analysis. The second critical component of local observations is being addressed through CSIR Climate Observation and Monitoring Network (COMoN), comprising of meteorological profilers at various locations over India through an inter-agency research alliance.

S Mallick and P Goswami

2.11 Dynamical Soil Moisture Model for the Indian Region; Validation with CSIR-COMON Data

Dynamics of soil moisture is a critical input for agricultural activation to determine sowing schedule, irrigation requirements, ground water recharge, and flood forecasting. Soil moisture is a key component that affects large scale circulation patterns due to its role in evapotransipiration. Modeling efforts have shown that different land surface models interact differently with atmospheric circulations to create a range of climate sensitivities to latent heat fluxes. Even with the same atmospheric forcing, the simulation of soil moisture by land surface models still has considerable scatter.

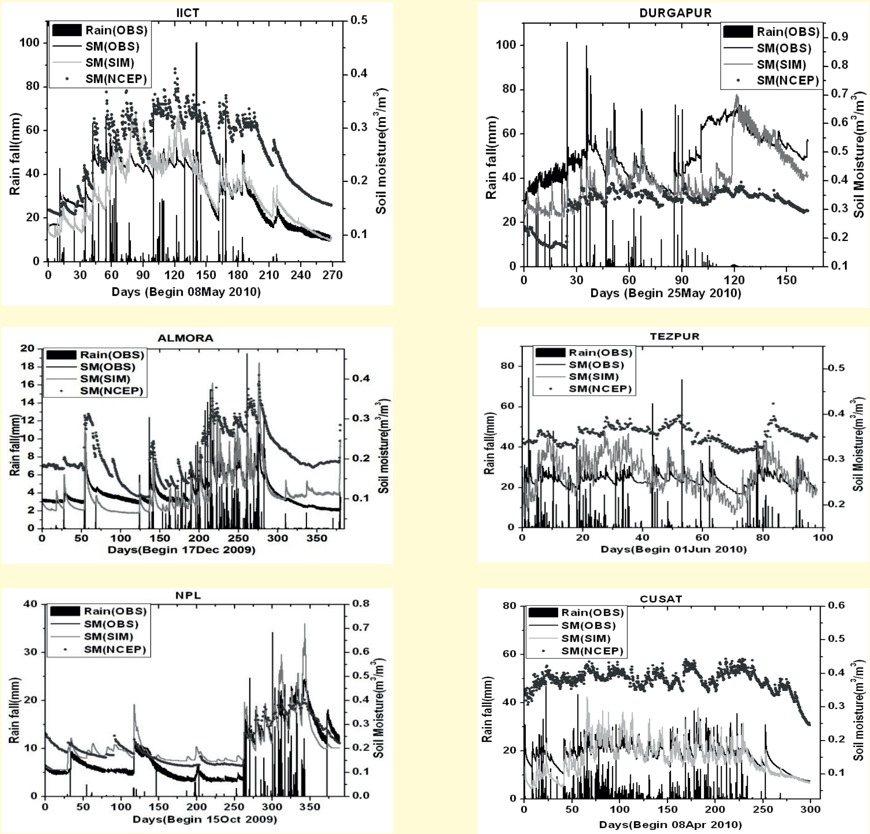


Figure 2.17 Comparison of observed soil moisture (1cm) with C-MMACS Soil moisture model simulations and NCEP data over 6 locations in India.

Soil moisture dynamics can vary both in time and space, and depends on a number of climatic & soil factors. Climatic factors include precipitation data containing rainfall intensity, storm duration, interstorm period, temperature of soil surface, relative humidity, radiation, evaporation, and evapotranspiraton. The soil factors include soil matrix potential and water content relationship, hydraulic conductivity and water content relationship of the soil, saturated hydraulic conductivity, and effective medium porosity. Beside these factors, information about the depth of water table is also required.

The model is based on numerical solution to Richard's equation and the hydraulic conductivity of the unsaturated soil is defined as product of a non-linear function of the effective saturation, and hydraulic conductivity at saturation. The hydraulic conductivity decreases strongly as the moisture content decreases from saturation. Model inputs (rainfall, radiation, wind speed, relative humidity) are collected from half-hourly in-situ observation from CSIR COMoN. The evapotransipiration was calculated from penman-monteith evapotranspiration equation.

The formulation and code development were done in-house for configuration of the model for different locations in India. The simulated the soil moisture over different locations in India was validated against observations from CSIR-COMON soil moisture measured in 4 vertical levels (1cm, 15cm, 50cm, 100cm) with half-hourly interval.

Comparison of half-hourly soil moisture(1cm) over six locations in India shows (figure 2.17) the simulations to be in good agreement with observations; the results also show that spatio-temporal variation of soil moisture strongly depends on soil texture and rainfall.

Kantha Rao Bhimala and P Goswami

2.12 Relation Between Meteorological Variables and Visibility Over Delhi: Analysis with Multi-level Comon-Monus Observations

Fog is a high-impact weather event, especially for road and air transport. Over airports, fog can cause disruption in air traffic, delays and significant financial losses; the disruptions affect a large cross section of the population, especially those travelling for medical purposes. Fog is a persistent winter phenomenon in the national capital region of Delhi and, in particular, over the Indira Gandhi International Airport (IGI). Accurate forecast of fog can enable pro-active mitigation, with significant societal and economic benefit.

Both large-scale systems like the western disturbances, and local circulation and surface features, are important in the formation and dynamics of fog. During winter, the entire northern India, especially the Indo-Gangetic plains are influenced by western disturbances which move from west to east, often leading to intense haze and fog in the region. The widespread fog extends over a stretch of ~1500 km in length and ~400 km in width. The low topography of the Indo-Gangetic plains and fine mode aerosols also contribute significantly to the widespread formation of fog.

A dynamical fog forecast model was developed at C-MMACS, and transferred to India Meteorological Department (IMD) for induction into the national weather services under a collaborative framework. However, there is need for continuous evaluation and improvement in terms of accuracy and scope; experimental forecasts have been generated for each fog season since 2005 that are communicated to various agencies including IMD for post-forecast evaluation. Equally important, however, is to understand the dynamical processes that govern genesis and evolution of fog over Delhi.

Until recently, absence of multi-level meteorological observations at sufficiently high frequency had been a major obstacle in investigating relationships between the meteorological variables and formation of fog over Delhi. The establishment of CSIR Climate Observation and Monitoring Network (COMoN), with four 32-meter meteorological profilers in the national capital region of

Delhi under the Meso-scale Observation Network for Urban Systems (MONUS), established in collaboration with the India Air Force (IAF), has provided the first opportunity for examining relationship between dynamical meteorological variables and occurrence of fog over Delhi. Here we highlight some interesting relationships between the meteorological parameters and visibility over Delhi based on observations during winter (December 2010 to January, 2011) that included several severe fog episodes.

One of the four stations under MONUS is located at the campus of CSIR National Physical Laboratories (NPL), while the other three are located at three IAF sites NARELA, RAJOUKRI and HINDON covering the national capital region of Delhi (27-29N,76-78E). The profilers have been designed to provide high frequency data (30 minutes interval) on the state of the surface boundary layer with

- Temperature, Relative humidity , Wind speed and direction at 2m, 20m and 30m level
- Net Radiative fluxes at 2m level
- Soil temperature and soil moisture at the surface, -10cm, -20cm and -30cm level.

The fog data consists of hourly visibility over IGI Airport (77.5E, 27N), Delhi, provided by IMD.

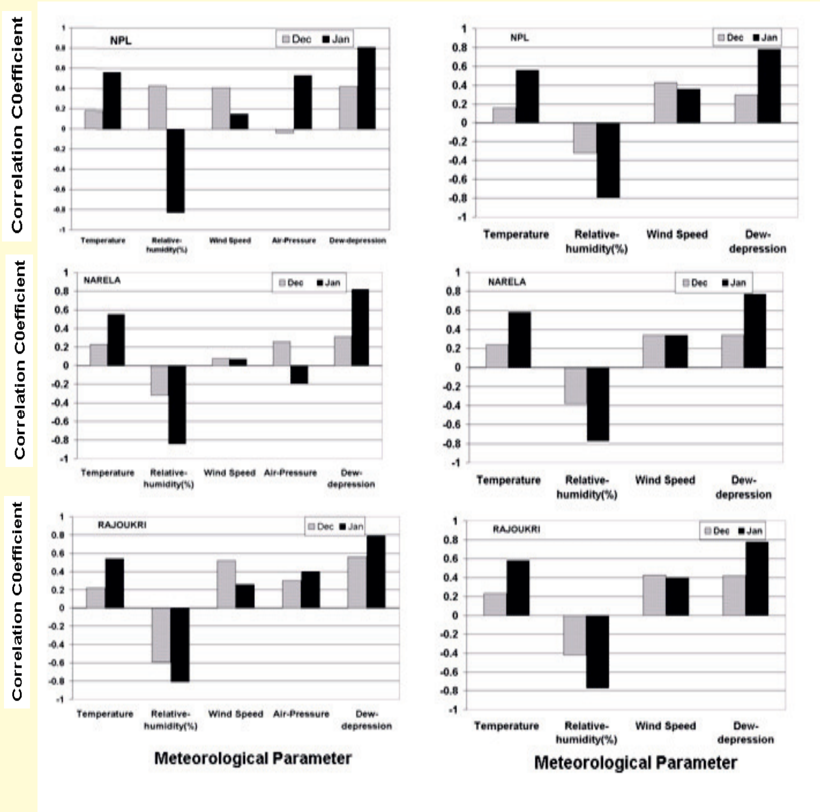


Figure 2.18: Correlation between daily averaged Meteorological parameters (X-axis) observed over 3 stations (NPL, NARELA, and RAJOUKRI) and visibility obtained from IGI Airport Delhi for December 2009-January 2010. Left panel shows correlation with 2m level data and Right panel shows correlation with 20m level data.

It was found that daily averaged visibility showed significant correlation with temperature and relative humidity at both 2m and 20m level. However, the correlation between visibility and wind speed was much more significant (figure 2.18) at 20-meter level than that at at 2-meter level. These findings can improve the model performance through use of appropriate dynamical variables.

P Goswami and S Sarkar

2.13 Improved Intensity Forecasting of Tropical Cyclone through Bias Correction

The damage potential of a tropical cyclone is proportional to a power (generally greater than one) of intensity, which demands high accuracy in forecasting intensity for managing this natural disaster. However, the current skill in forecasting cyclone intensity is rather limited, especially over the north Indian Ocean, with very little improvement over the years. We present a methodology for objective non-linear debiasing to generate intensity forecasts with enhanced reliability from raw forecasts.

The intensity forecast is generated using an optimized configuration of a variable resolution Global Circulation Model (VR-GCM) that combines the advantages of a limited area model and a global model. The hindcasts were carried out in a completely operational setting, that is, without assuming any observed information beyond the day of the initial condition. The VR-GCM and a non-linear debiasing were found to provide skill (Skill Score ~ 0.5) in forecasting tropical cyclone intensity 2-7 days (variable depending on event) in advance for the thirty-six cases including storms and cyclones representing different locations, seasons and years (1990-2009) over the north Indian Ocean. It is shown that while skill scores without debiasing are only marginally better than a climatological forecast (null hypothesis); the skill score with a non-linear debiasing is appreciable. The climatological forecast has zero skill score, a mean absolute error is 12.9 m s-1 and 20% of the cases in the error bin -5 to +5 m s-1; the corresponding numbers for debiased forecasts for realizable skill are 0.65, 6.4 m s-1 and 57%. It is further shown that the non-linear debiasing is also effective in improving forecast of (3-hourly) intensity change.

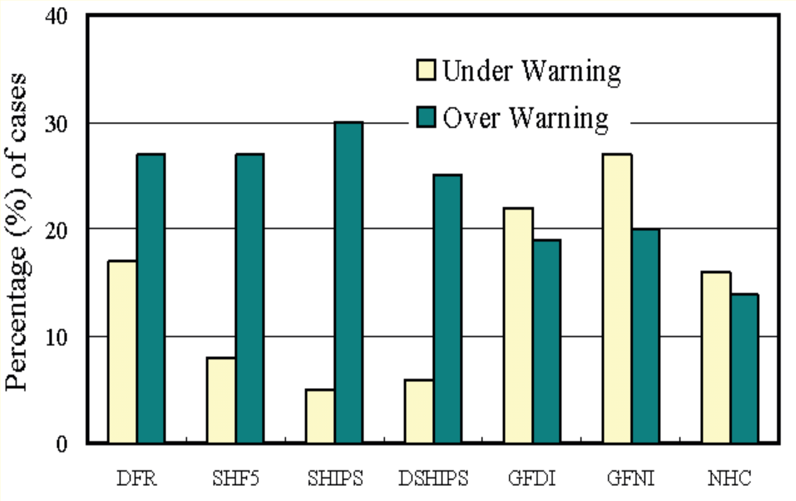


Fig.1 A comparison of skill in terms of under warning and over warning of the non-linear debiasing (DFR) with six other methods including 5-day Statistical Hurricane Intensity Forecast model (SHF5), Statistical Hurricane Intensity Prediction Scheme (SHIPS), Decay SHIPS (DSHIPS), Interpolated Geophysical Fluid Dynamics Laboratory model (GFDI), Interpolated Navy version of Geophysical Fluid Dynamics Laboratory model (GFNI) and the National Hurricane Center (NHC; United States).

While a strict comparison of skill with other methods require experiments is yet to be carried out for the same events, a comparison of the skill of other methods and over different ocean basins based on available data shows the present method to have comparable skill. A comparison of skill in terms of under warning and over warning of the non-linear debiasing (DFR) with six other methods including SHIF5, SHIPS, DSHIPS, GFDI and NHC data shows the skill of the presented method to be comparable in some cases but not superior; in general, a distinct pattern does not emerge (Figure 2.19). It should be emphasized, however, that a comparison of skill over the Bay of Bengal with that over the Atlantic or the Pacific is not strictly valid as the tropical cyclones over these basins have quite different characteristics. In particular, the cyclones over the Bay of Bengal and those over the Pacific have different seasonality and thus different mean background states (like steering current).

The simulation of tropical cyclones with the variable-resolution GCM is a part of the overall goal to develop a CSIR climate model through multi-scale evaluation. The skill of the debiased forecast with the GCM-derived fields show that the model is a potential candidate for assessing impact on tropical cyclone intensity due to change in regional climate.

P Goswami, S Mallick and K C Gouda

2.14 Improvement in Forecasting of Tropical Cyclones Over The North Indian Ocean Using Regional Background Error Statistics

While there has been significant progress in modeling and forecasting of cyclones over the past decades, the progress over the north Indian Ocean has been relatively low. Although the dynamical forecasting techniques such as meso-scale model and data assimilation are quite generic, there are issues that need a regional approach for improving forecast skill; the choice of background error statistics (BES) in data assimilation is one such.

While the quality of background error statistics (BES) is recognized as one of the key components of assimilation, considerable uncertainties exist in prescribing BES, especially since the prescription and impact of BES can also depend on the weather regime and geographical location. In this backdrop, it is necessary to quantify the impact of different BES for particular weather systems; this is particularly true for cyclones over the north Indian Ocean which has characteristics different from those over the Atlantic and the Pacific. The objective of this work is to assess the relative improvement in forecasting tropical cyclone track and intensity due to different BES.

The assimilation was carried out using the WRF three-dimensional variational data assimilation (3D-Var) assimilation scheme. A set of three experiments were conducted for each cyclone: one control (CNT; no assimilation) and two assimilation experiments (GBES & RBES) that differ in their prescription of background error statistics. While global BES (GBES) is inbuilt with WRF 3D-Var system, RBES is domain specific; in the present case the RBES was generated from WRF short range forecasts by applying NMC method. The results with the assimilations were tested against a control experiment with no assimilation which served as baseline for a comparative assessment of impact of GBES and RBES. The observational data included both conventional (radiosondes and SHIP) as well as satellite (QSCAT and SSM/I) data. We have used ± 1 hour window to assimilate the QSCAT & SSM/I observations for all the experiments.

We have also compared our results for track and intensity prediction with those from several operational agencies like India Meteorological Department (IMD), National Hurricane Center (NHC), Japanese Meteorological Agency (JMA), UK Met Office (UKMO), Climatology and Persistence (CLIPER) model, Statistical Hurricane Intensity Prediction (SHIP) and Logistic

Table 2.4 The mean absolute track errors (Km) from different experiments averaged over all the cyclones along with the errors from various operational agencies.

Forecast source	Day 1 error	Day 2 error	Day 3 error	Remark
WRF -CNT	140	176	205	
WRF -GBES	137	168	188	
WRF -RBES	102	119	121	
CLIPER	136	270	626	
+IMD	138	214	341	**Mean error for 11 year period 1998-2008 from the India Meteorological Department (IMD) operational model QLM over the north basin**
*NHC	99	179	266	**Mean error of (NHC) official forecast for the five year Period 2004-2008 and is the average value over the and North Pacific basin**
@UKMO	150	220	330	**Mean error of Met Office (UKMO) operational forecast for the five year period 2004-2008 over the north basin**
#JMA	156.5	165	200	**Mean error of the Japanese Meteorological Agencies (JMA) operational forecast for the years 2008 and 2009 over the north basin**

Growth Equation Model (LGEM). A comparison of the mean errors in track prediction from the present study with those from these agencies showed (Table 2.4) the skill with RBES to be comparable or better than that from most of the forecast agencies. The results from the present work should be thus considered as indicative of potential improvement in forecast skill due to RBES. Generation BESs form other methods such as time lagged NMC or ensemble perturbation and its impact will be attempted as future directions of the present study.

V Rakesh & P Goswami

2.15 Improved Simulation of Heavy Rain Events Over The Indian Region Using Regional Background Error Statistics in WRF 3D-Var.

A major source of errors in numerical weather prediction (NWP), especially for short-range, is the initial state prescribed for model integration. A large number of studies in recent past have shown the positive impact of assimilation of observational data in numerical models. However, many challenges remain. In particular, certain aspects of the assimilation system require careful, region-specific design. An important issue is the background error statistics (BES) which determines the amount and propagation of observation information in data assimilation system; this is also an aspect that requires a region-specific consideration.

The quality of background error statistics (BES) is one of the key components for successful assimilation of observations in a numerical model. Considerable uncertainties and non-uniqueness exist, however, in prescribing BES; in particular, the prescription and impact of BES can also depend on the weather regime. However, not much is known in this regard over the Indian region.

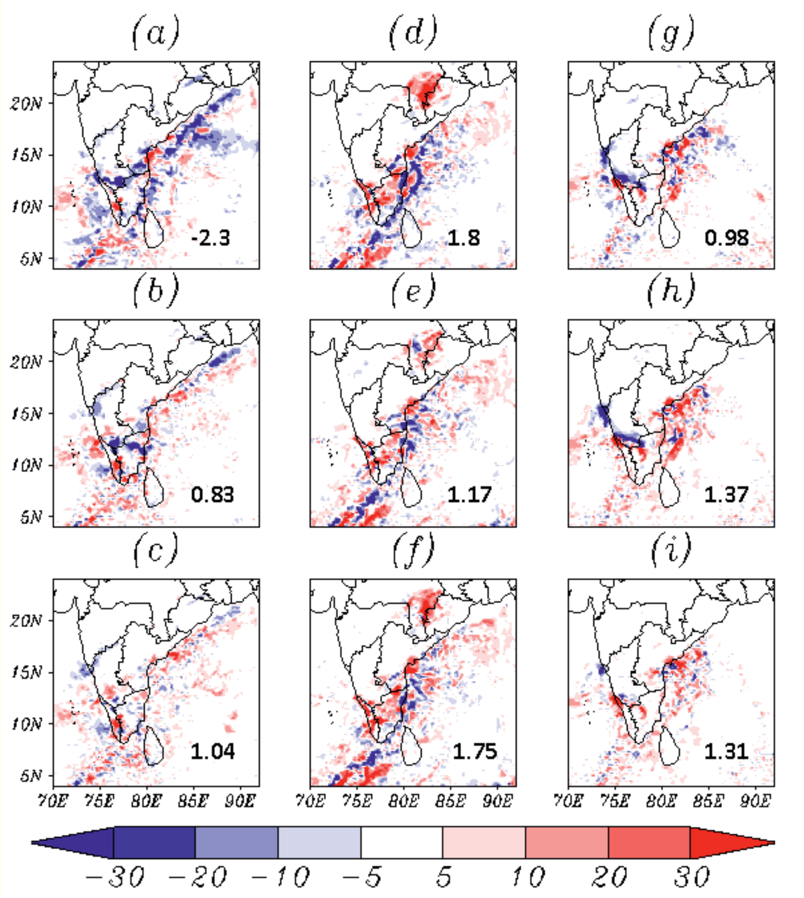


Figure 2.20 Forecast impact (FI) in day1 (first 24 hour) rainfall prediction (cm) for the assimilation experiments; using global BES (top panel; a, d, and g); using regional BES from NMC method (middle panel; b, e, and h), using regional BES from ENS method (bottom panel; c, f, and i), for EXP1 (left panel), EXP2 (center panel), EXP3 (right panel). The number in each panel represents domain averaged FI for the respective case.

A set of assimilation experiments have been conducted with WRF 3D-Var to study the impact of different background error statistics (BES) in simulating the meteorological features associated with a high impact weather system that affected south east peninsular India. The three different BESs included a global BES (GBES) inbuilt with WRF 3D-Var system and two regional BES (RBES) generated using NMC and ENS method. A control experiment (CNT) was also conducted to serve as baseline in assessing the impact of assimilation. The forecasts were verified against NCEP analysis, conventional and satellite observations.

Significant differences in wind, temperature and humidity fields were noticed over Bay of Bengal, Arabian sea and north west part of India between the 3D-Var analysis using GBES and RBES. The assimilation of observations improved the spatial distribution of 24-h forecasted wind speed, temperature and humidity as compared to those from CNT; the improvement was found to be significantly higher in experiments using RBES as compared to that using GBES(figure 2.20) . Similarly, the vertical structures of wind, temperature and humidity were better simulated with RBES. The rainfall prediction was found to improve with assimilation in general: once again, higher improvement was seen with RBES.

V Rakesh & P Goswami

2.16 Simulation of Rainfall Due to Cloud Burst Over Leh During August 2010 Using a Non Hydrostatic Model (NHM)

The cloud burst that occurred near Leh in Jammu and Kashmir around 0130-0200 hours IST on 6th August, 2010 leading to flash flood and mud slides, brought home sharply the vulnerability of people to such hydro-meteorological events. The sudden downpour and flash floods swept away houses and killed at least 103 peoples. Needless to emphasize, advance and accurate early warning can significantly reduce the impact of such events.

Meso-scale atmospheric models provide an effective tool for generating forecasts of such high-impact weather events. However, while the basic principles and the formulations of meso-scale models are quite generic, the forecast models suffer from significant variations due to non-uniqueness representation of physical processes through parameterization. For effective application, a meso-scale model needs to be calibrated for a specific location.

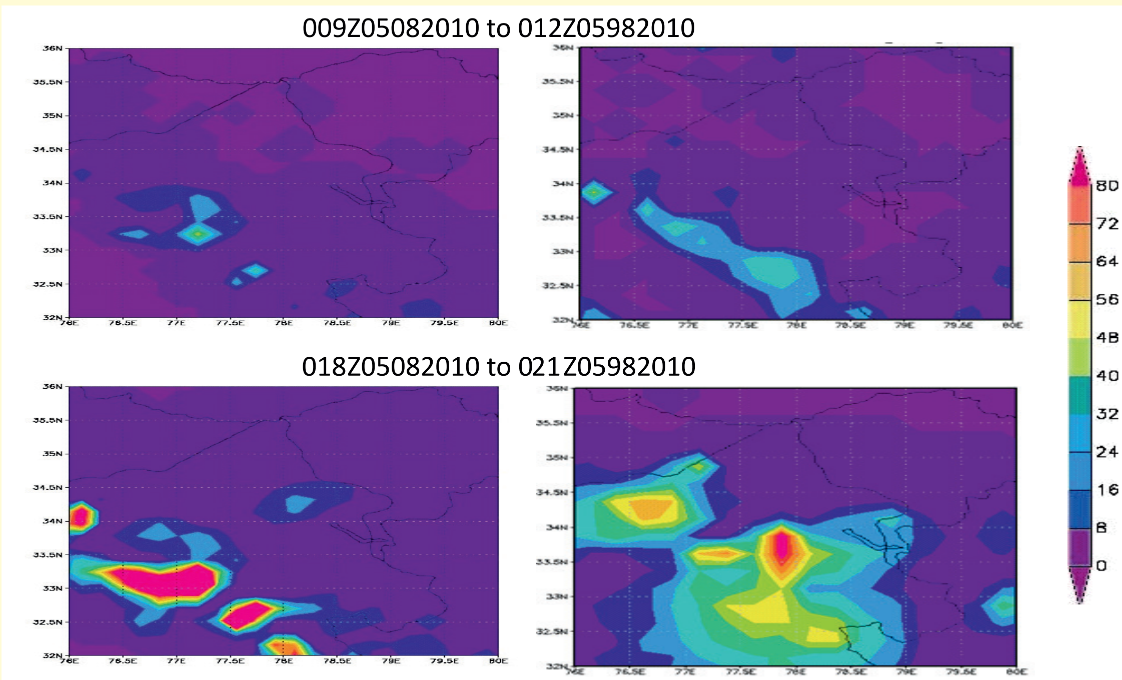


Figure 2.21 Comparison of C-MMACS simulation (left panels) and analysis of TRMM rainfall (right panels) for 09-12Z (top panels) and 18-21Z (bottom panels) on 5th August 2011.

C-MMACS has over the years developed principles as well as methodology for calibration of meso-scale models. In the present case, a non-hydrostatic meso-scale model, adopted from Meteorological Research Institute, Japan (MRI), was employed to hindcast the Leh event. Because the intense convective system developed in the easterly current associated with monsoon conditions over the region, it was expected that NHM with a finer resolution of 5km grid interval would reproduce the rainfall system. The simulations could capture the detail structure of the cloud and heavy rainfall associated with cloud burst (Figure 2.21).

These results indicate potential of a well calibrated meso-scale model for use in pro-active disaster mitigation. The positional error evident in figure 2.21 could likely be reduced with still higher resolution. Besides, a systematic bias, if found in multi-event simulations, can be removed using an objective method.

K C Gouda G N Mohapatra and P Goswami

OUTREACH AND INDUSTRIALIZATION

2.17 Long-Range, High-Resolution Forecast of Summer Monsoon 2010

While the potential of atmospheric General Circulation models (AGCM) for diagnostics and prediction of monsoon was recognized quite early, the skill of most AGCM has proved inadequate even to properly simulate the area-averaged and climatological features of Indian Summer Monsoon (ISM). On the other hand, forecasts need to be at scale and lead that meet user demands. Recognizing a critical gap in long-range forecasting of monsoon, C-MMACS had maintained a sustained effort over the last decade to improve skill in long-range forecasting of monsoon at high resolution. For an objective evaluation of the methodology, C-MMACS complements its results published in scientific journals by generating long-range forecasts that are communicated to a number of agencies, including India Meteorological Department (IMD). The generation of forecasts for 2010 monsoon has been a part of this outreach effort.

Forecast of Date of Onset: The C-MMACS forecast of an early onset around 29th May 2010 was realized according to the criteria of sustained, significant and large-scale rainfall in the model simulation. The announced DOM according to IMD is May 31, 2010.

Forecast of Monthly and Seasonal Anomalies: C-MMACS uses its monsoon ensemble to generate a long range forecast. The monthly anomalies are computed with respect to 25 year model mean for each ensemble. The ensemble average is then determined as an average over the members of the ensembles with equal weight. The monthly and seasonal anomalies are expressed as percentage of the model mean.

A Comparison of distribution of anomalies in seasonal rainfall of (JJA) 2010 from NOAA CAMS Analysis (left panel) and C-MMACS long range forecasting (right panel) shows good agreement (figure 2.22) both over land and ocean.

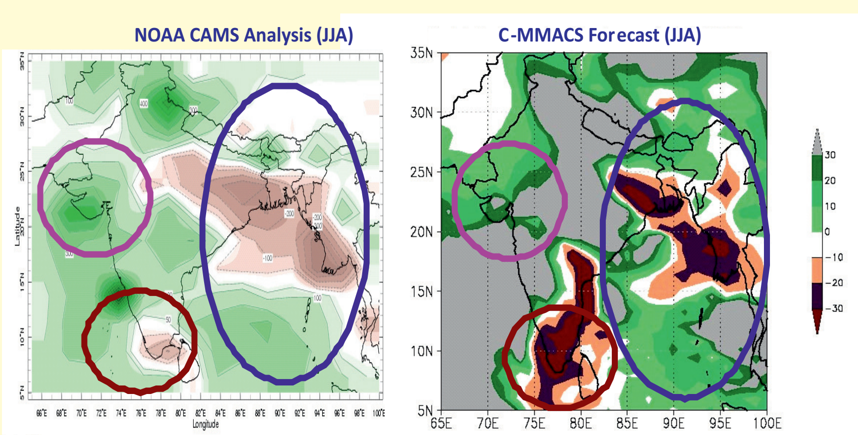


Figure 2.22. Comparison of distribution of rainfall anomalies of (JJA) 2010 from NOAA analysis (left panel) and C-MMACS long range forecasting (right panel).

These results are a part of C-MMACS' efforts to develop a platform for dynamical long-range forecasting of monsoon through validation in a completely operational setting. As the forecasts are communicated well ahead of the season, the post-forecast validation is completely objective. Along with the novel ensemble methodology and forecast configuration developed at C-MMACS, these sustained, objective validations build up reliability of the forecast platform.

K C Gouda and P Goswami

2.18 Quantitative Rainfall Forecasts at Hobli- Level Over Karnataka State: Evaluation for the Winter Monsoon, 2010

Advance and accurate forecasts of rainfall can aid many sectors, from agriculture to disaster mitigation. However, for effective application, such forecasts must be at relevant spatial scales; given the tremendous spatial variability of rainfall, the forecasts need to be at hobli level. Recognizing dynamical meso-scale forecasting as an emerging but promising technology, C-MMACS, in collaboration with Karnataka State Natural Disaster Monitoring Centre (KSNDMC), has initiated a project to usher in dynamical hobli-level forecasts over Karnataka state.

While the basic formulation of the dynamical (meso-scale) models is quite generic, the models based on the formulation vary from one another in many respects. World over, dynamical meso-scale forecasting is an evolving technology, with many challenges. The challenges grow as the spatial scale of the forecast is reduced. However, careful calibration of model configuration and forecast methodology can significantly improve simulation skill, as has been shown by research at C-MMACS. Statistical evaluation of forecasted rainfall at hobli-level is carried out by comparing with the rain gauge observations from KSNDMC.

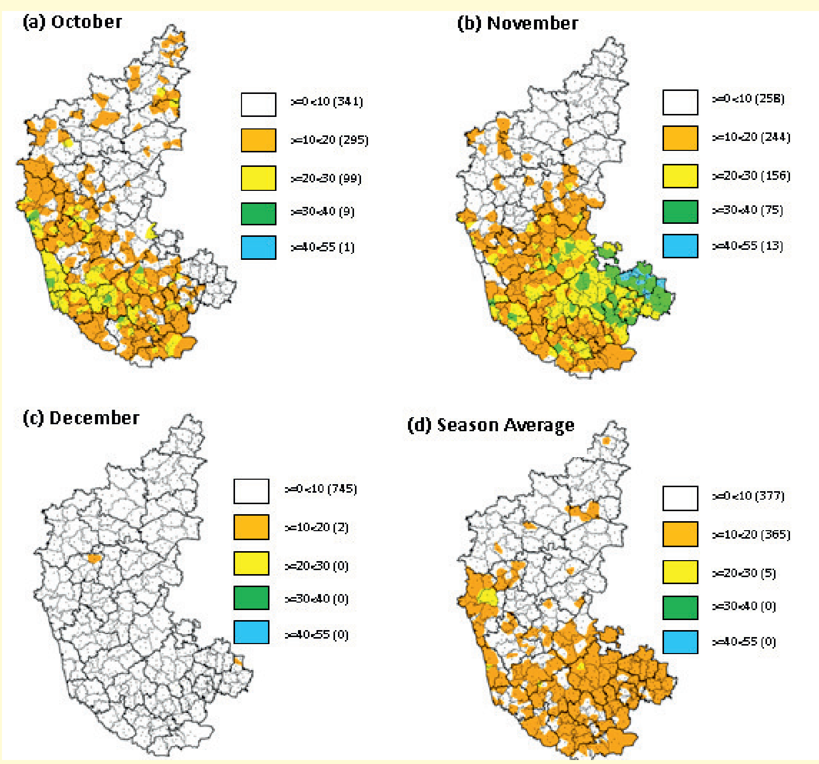


Figure 2.23: Root mean square error (mm/day) in daily rainfall prediction for (a) October, (b) November, (c) December, and (d) Average for the winter monsoon season. The numbers in bracket show the number of hoblies in each error category.

The Root Mean Square Error (RMSE) in forecast for the season is less than 2mm for most of the cases (Figure 2.23). The forecasted rainfall is significantly correlated with observed rainfall particularly for October and November when significant rainfall activities were observed. While the forecasts show significant skill of the model in simulating the spatio-temporal variability of rainfall over Karnataka, there are some areas such as southern Karnataka where the skill is poor. It is expected that the assimilation of more observations such as from the CSIR COMoN will improve skill over these areas.

This work is a part of a collaborative and resource-sharing research programme between CSIR C-MMACS and KSNDMC; the forecasts issued twice daily are communicated to KSNDMC by the Industrial Partner of C-MMACS, M/S Frontier Pusher. Dissemination of forecasts, with necessary value addition, is carried out by KSNDMC.

V Rakesh & P Goswami

PROCESS STUDIES

2.19 Simulation of High Impact Weather Events: Comparative Analysis of Three Heavy Rainfall Events

Episodes of heavy rainfall, although relatively rare, significantly contribute to the hydrological cycle due to the large quantum of rainfall in a short span of time. An important requirement for pro-active management of disaster related to such extreme rainfall events is advance and accurate forecast with sufficient precision. It has been earlier shown that careful calibration of model configuration can lead to significant improvement of simulation of such events. Accurate simulation of such extreme rainfall events (ERE) therefore is an important benchmark for a model.

It has been shown at C-MMACS that the geographical coverage of the model domain plays a major role in the quality of the simulation. To understand the physical processes involved in such localized convective events, simulations have been carried out at high resolution (2 km) to resolve orographic features and land-ocean gradients over the event locations. The simulations were carried out with the meso-scale model MM5 with a 3-nest, 2-way configuration. In all the experiments, the model was run for 3-days with one initial condition (FNL 1ox1o data); 0000UTC 25th July 2005,(Mumbai), 0000UTC 21st October 2005 (Bangalore) and 0000UTC 25th October 2005(Chennai) respectively.

Comparison of observed and simulated rain (Figure 2.24) shows that the model configuration could capture the intensity of the event quite well but not the event location for Mumbai. In the case of the Bangalore event, high intensity convective cells were captured, howevere overall distribution was not simulated well. In the case of the Chennai event; both intensity and location were simulated well, except that rain over the oceanic part was overestimated.

Thermodynamic stability indices prevalent at the beginning of the event window computed over the event locations were found to be close to threshold values even at the beginning of the event time window, indicating (unstable) atmospheric conditions which are precursor for high intensity convective storms like heavy rainfall. Higher values of CAPE and K-index for Mumbai event that occurred during summer monsoon, in particular, indicate greater degree of atmospheric instability. Bangalore and Chennai events which occurred during winter have shown relatively lower values of CAPE and K-index.

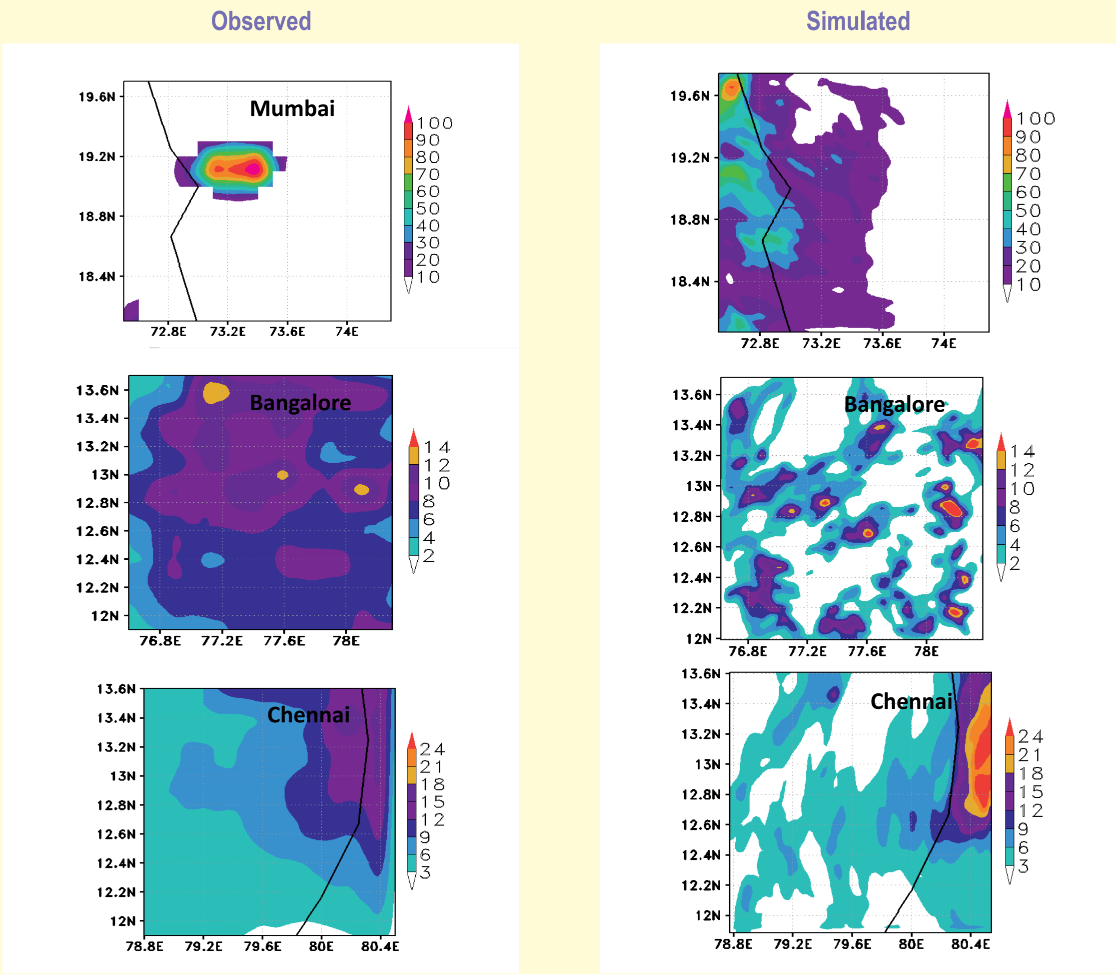


Figure 2.34. Comparison of the distribution of (24-hour accumulated) of simulated rain (right panels) with 10-km resolution satellite data (left panels) for three events as seen in domain D3. The time windows are; 0300UTC 26th July – 0300UTC 27th July 2005 (Mumbai), 1500 UTC 22nd Oct -1500UTC 23 Oct 2005 (Bangalore), 0600UTC 26th Oct – 0600 UTC 27th Oct 2005 (Chennai)

These results show that a very high relative humidity, Low-Level Convergence (LLC), convective instability in terms of Equivalent Potential Temperature (EPT), high vertical velocity, smaller mixing ratio at low level and higher mixing ratio at upper level essentially dominated and sustained the convective dynamics in all the three events. It is interesting to note that while all the parameters fulfill threshold conditions for instability for the Mumbai event, only KI and CIN meet threshold conditions for all the three events, indicating them as perhaps the optimum set of parameters for precursors.

S Himesh and P Goswami

2.20 A Comparative Evaluation of Impact of Domain Size and Parameterization Scheme on Simulation of Tropical Cyclones

Numerical weather prediction (NWP) models, like meso-scale atmospheric models, have emerged as powerful tools for simulating and forecasting high-impact events like tropical cyclones. A large number of processes and factors control the quality of simulations with a NWP model, and especially with a meso-scale model. Identification and optimization of these processes are critical for improving forecast skill. The importance of cumulus parameterization schemes in simulation of tropical cyclones was recognized early, and a large number of studies have addressed this issue. However, many other processes also have critical roles. In particular, unlike simulation with a global circulation model (GCM), a meso-scale simulation is characterized by a limited domain and hence inhomogeneous lateral boundary conditions.

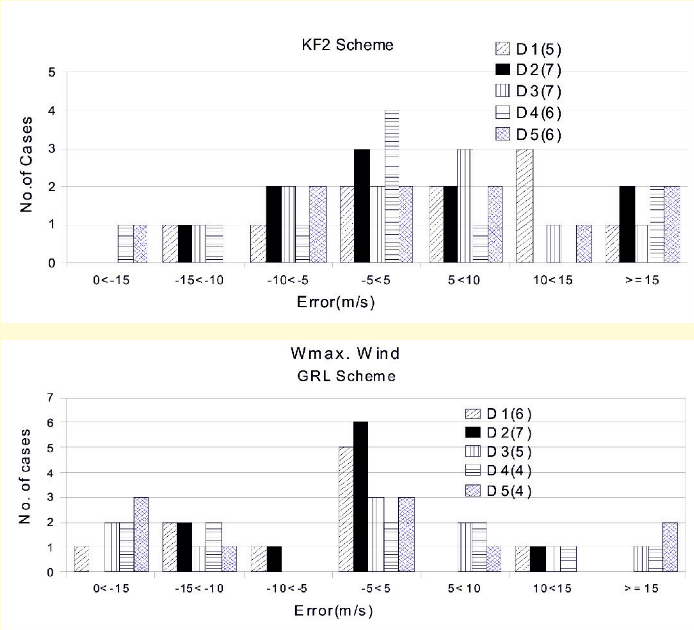


Figure 2.25 Histogram of errors in simulated maximum intensity (during event durations over inner most domain) for different domains for GRL(top panel)and KF2(bottom panel) parameterization schemes. The number in the bracket represents the number of cases with absolute error between -10 to +10 m/s for the respective domain.

The limited domain introduces several issues in a mesoscale simulation as there is no unique choice of the extent and geographical coverage of the integration domain. In this work we investigate the relative impact of size of the model domain and CPS on simulation of ten cyclones over the Bay of Bengal during the period 1999-2009 using the mesoscale model MM5. For five domains with different spatial extents, simulations were carried out for three different cumulus parameterization schemes for each of the 10 events. Our results show (Figure 2.25) that along with the cumulus parameterization, variation in domain size introduces differences in maximum intensity as well as spatial structure of the simulations; the impact of domain size is not linear, and neither the largest nor the smallest domain provides the best simulation. However, there is consistency in the sense that a single domain emerges as best among the five considered. While the conclusions may depend with the scale and the location of the events, our study points at the necessity for adopting an objective methodology for selectin the domain size for meso-scale simulations.

G N Mohapatra and P Goswami

2.21 Effect of Multi-scale Dynamics on Predictability Experiments with Lorenz Systems : Effect of Background Processes

It has long been recognized that predictability of the atmospheric flows is affected by the chaotic nature of the dynamics. In particular, small errors in the initial condition or in the model used to make a prediction will eventually lead to a loss of predictability in a sense that no information will be retained in the forecast regarding the initial conditions. The loss of predictability, however, is not uniform in space and time.

The initial concept as well as measures of predictability in the atmospheric dynamics arose from the analogy to the Lorenz system. To bring out the differences between the Lorenz system and a natural system like the monsoon, we introduce the concept of embedding dynamics. An embedding dynamics is a multi-scale flow with no point of rest (no special initial state). Our null hypothesis is an ensemble created from the standard initial conditions with an added noise. We then compare errors in simulation from the two ensembles to test our hypothesis.

The system of equations (Lorenz equations) was solved numerically and tested against known standard results.The Lorenz system exhibits different dynamical regimes based on the values of

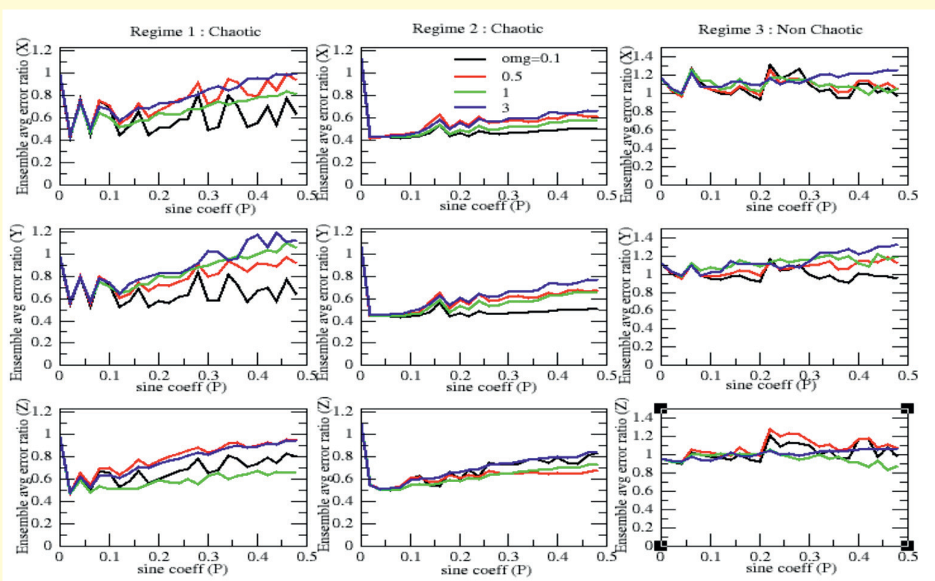


Figure 2.26. Impact of a background dynamical process on the predictability of the Lorenz system. The impact is quantified in terms of ensemble (100) average ratio of time averaged errors from control and test simulations. The control simulations are characterized by standard initial conditions (x0=2, y0=5, z0=20) with a random perturbation; the test simulations are initiated from initial conditions extracted from observations that contain both Lorenz dynamical and and the background processes (in the form of sinusoidal wave). The x-axis shows frequency of the background process as a fraction of (inverse of) characteristic time scale $T_c=1/\beta$ of the Lorenz system. A value of $\varepsilon < 1$ (y-axis) implies less error in test simulation (with embedding) than in the control simulation. The three curves in each panel represent three amplitudes (as fraction of the dynamical variable) of the background process.

parameters (σ, ρ and β); we have considered three different cases for chaotic and non chaotic regimes.

It was found that the presence of a background process can significantly affect the error growth in the system(Figure 2.26); these results provide clues to improve predictability of atmospheric systems. These finding are being applied to improve long range forecasting of monsoon.

P Goswami and Preeti Wagh

2.22 Simulation of Response of Cloud over Western Ghats to Prescribed Seeding

Applications like forecasting of high-impact weather and cloud seeding require reliable and high-resolution simulation of clouds. In particular, simulation of spatio-temporal distribution of orographic cloud over India is a critical component of the ambitious CSIR project on Precipitation enhancement through ground-based cloud seeding, being implemented as a Network project between C-MMACS and CSIR National Aerospace Laboratories. A major challenge has been to calibrate and validate a 3-dimensional dynamical cloud model capable of multiple applications.

A non hydrostatic model (NHM) was installed and integrated into the C-MMACS Multi-scale forecasting platform under a collaborative effort with Japan Meteorological Agency (JMA). The JMA-NHM explicitly calculates the microphysical processes of liquid and solid water substances like cloud water, rain, cloud ice etc.

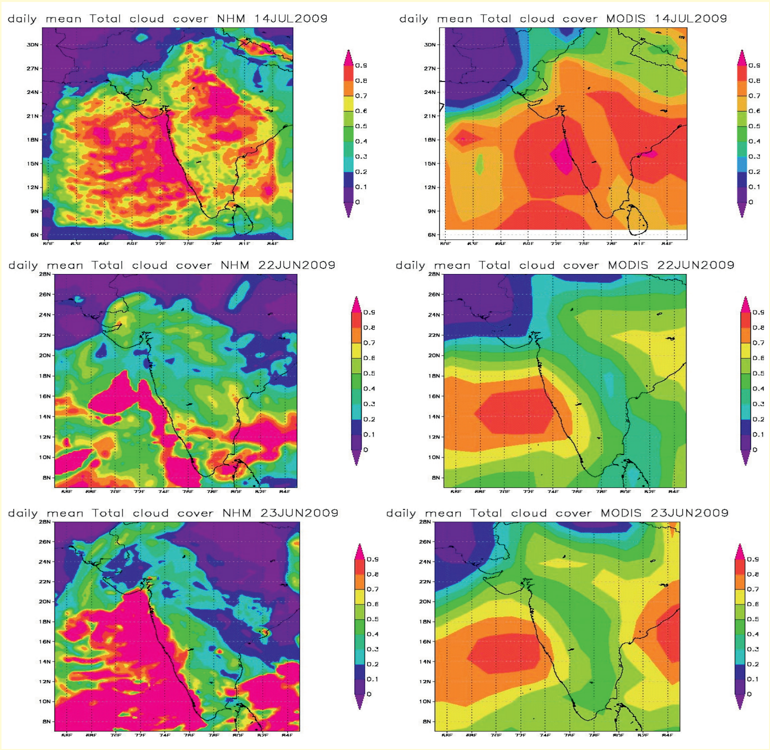


Figure 2.27 Comparison of model simulated (left panels) and satellite observed (right panels; MODIS) daily mean total cloud cover over a few days over India for selected day.

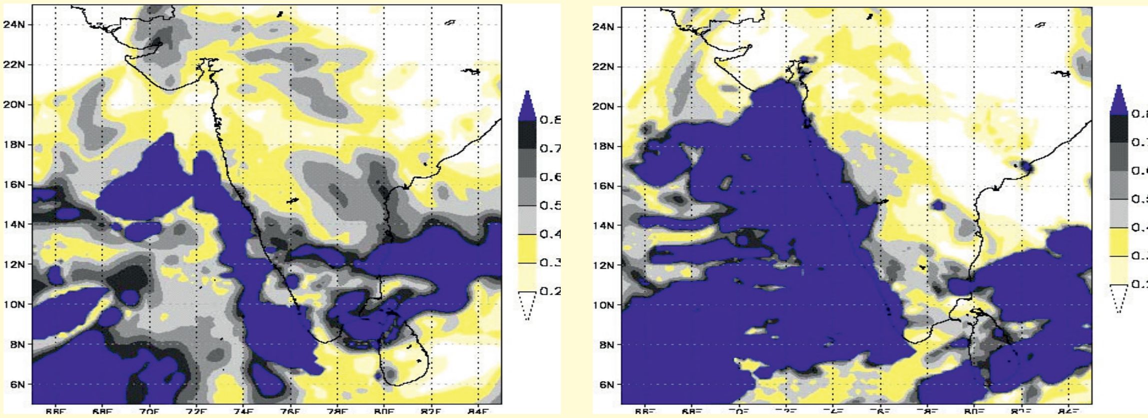


Figure 2.28: Comparison of effect of seeding by varying the cloud droplet size (left panel represents the size of 550cm-3 and right panel is with 400cm-3) in the distribution of base cloud.

The model has been subsequently configured and calibrated for simulation of cloud cover over the Western Ghats, a potential area for ground-based cloud seeding. Subsequently it has now been tested over much wider domain. The simulation domain of 5km- resolution has an area 2500kmX2000km covering India. The top height of the model domain is about 22km. Around 40 variable vertical layers are employed in the model.

A potential application of a 3-dimensional dynamical cloud simulation model is to assess the possible impact of cloud seeding through simulation, such as choice of cloud condensation nuclei (CCN). A series of simulations (control: seeding with small CCN and Test with proper seeding) were carried out to quantitatively investigate possible impact of seeding on clouds over the Western Ghats. Comparison of cloud cover from simulations with different size of droplet was carried out to mimic the effect of seeding.

A comparison of Control and Test simulations (figure 2.28) shows that the cloud cover can significantly enhance and move landward due to appropriate seeding. These results indicate potential applications of the model for diverse applications, and, in particular, to design of cloud seeding for targeted enhancement of precipitation.

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