Invited Paper

Downscaled Multi-model Superensemble and Probabilistic Forecasts of Seasonal Rains Over the Asian Monsoon Belt

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Abstract

This is a study on seasonal climate forecasts for the Asian Monsoon region. The unique aspect of this study is that it became possible to use the forecast results from as many as 16 state of the art coupled atmosphere-ocean models. A downscaling component, with respect to observed rainfall estimates uses data sets from TRMM and a dense rain gauge distriburion; this enables the forecasts of each model to be bias corrected to a common 25 km resolution. The downscaling statistics for each model, at each grid location is developed during a training phase of the model forecasts; the forecasts from all of the member models use the downscaling coefficients of the training phase. These forecasts are next used for the construction of a multimodel superensemble. A major result of this paper is on the climatology of the model rainfall. From the downscaled multimodel superensemble which shows a correlation of nearly 1.0 with respect to the observed climatology. This high skill is important for addressing the rainfall anomaly forecasts, which are defined in terms of departures from the observed (rather than a model based) climatology.

The second part of this study addresses seasonal climate forecasts of Asian monsoon precipitation anomalies. Seasonal climate forecasts over the larger monsoon Asia domain and over the regional belts are evaluated. The superensemble forecasts invariably carry the highest skill compared to the member models globally and regionally. This relates largely to the presence of large systematic errors in models that carry low seasonal prediction skills. Such models carry persistent signatures of systematic errors, and their errors are recognized by the multimodel superensemble. One of the conclusions of this study is that given the uncertainties in current modeling for seasonal rainfall forecasts, post processing of multimodel forecasts, using the superensemble methodology, seems to provide the most promising results for the rainfall anomaly forecasts.

1. Introduction

In part 1 of this paper, we addressed the prediction of monsoon rainfall climatology and anomalies using a suite of 16 Atmosphere Ocean global coupled models. This paper differs from a similar research effort that was carried out previously using 4 atmosphere ocean coupled models (Chakraborty and Krishnamurti 2009). The question of forecast sensitivity from increasing the number of member models and data lengths is also covered in this study. Our use of multimodel forecasts utilizes the cross validation method for forecast data sampling, (Krishnamurti et al. 2006). This is necessitated by the small lengths of forecast data strings that were presently available from multi models. We make forecasts covering the summer monsoon season for the years 1987 through 2001. The training phase includes all those seasons that are not being forecasted, thus successively the forecast of a given season excludes that season from the training phase. The training phase carries out a downscaling (Fig 1) of each monthly and seasonal forecast for each model. This is followed by the construction of multimodel superensemble forecasts (Fig 2), which provides weights for each grid location and is geographically distributed. Many of the details on resolution, data sets, downscaling and superensemble methodology are provided in this study, Kumar and Krishnamurti (2010). Due to the very high skill of the superensemble based rainfall climatology, we address rainfall anomalies with respect to the observed rainfall climatology. Some past model studies, Gadgil and Sajini (1998), defined observed rainfall anomalies with respect to the observed rainfall climatology, and the model based anomalies with respect to the model based climatology. That does

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not appear to be necessary in this study. This study also addresses the minimum number of years of forecasts that are needed for equilibrating the spin-up of the growth rate of precipitation during the downscaling and the forecast phases of the multimodel superensemble.

The present study addresses geographical distributions and skills of forecasts of seasonal rainfall anomalies. Those are first presented in terms of scatter diagrams. This paper measures the skills through RMS errors, the spatial correlations and the equitable threat scores are used for forecast evaluations. These skills are evaluated over a large monsoon Asia domain. The member models fair rather poorly in predicting such contrasting monsoon regimes. Several of those poor forecasts still carry persistent systematic errors; those are capitalized by the multimodel superensemble. The dry and wet spells carry opposite signs for the anomalies; the superensemble carries a collective bias removal to improve on such extremes compared to what is presently possible from the individual member models.

2. Coupled Models and Datasets:

Sixteen coupled atmosphere ocean global coupled model data sets are included in this study. These data sets were acquired from personal contacts with the data producers. In Table 1 some details on model resolution, physical parameterizations, description of the ocean modeling, years of model runs and relevant references are provided. This also includes the number of ensemble forecasts provided for each model run. The ensemble mean forecasts from a single model's several runs are also included in this study. These model forecasts are cast at a common horizontal resolution of $2.5^oX2.5^o$, for the construction of model ensembles. All data sets from multi-models were bi-linearly interpolated to this common resolution ($0.25^oX0.25^o$) prior to the construction of ensemble averaging. The observed rainfall data of APHRODITE is used in this study (Fig 3, Yatagai et al. 2009). Table 2 shows acronyms used in this study.

3. Forecast over monsoon Asia domain

3.1 Scatter plot of the rainfall over monsoon Asia

The superensmeble carries almost no scatter and all points fall along roughly the 45 degree slope line showing that a near perfect climatology is attainable from the construction of the downscaled multimodel superensemble (Fig. 4). Next we take all forecast grid points and show a scatter plot of the observed versus the predicted rain anomaly for the entire summer season (Fig 5). The correlations of the observed to the predicted season long rains for the 16 member models range from -0.10 to 0.65. The superensemble is able to elevate the correlation to 0.71. The combination of near perfect skills for the climatology, plus these high values for the rainfall anomalies from the multimodel superensemble makes it a valuable seasonal prediction product at this stage. The implication of these results are very significant, i.e. in an operational forecast environment, at the outset as a forecast is issued one might not know which single model might carry the best forecast for a coming season, since model forecast skills tend to vary a lot from one forecast to the next, however having a superensemble forecast of the rainfall anomaly provides one with some assurance of having the best available forecast.

3.2 Seasonal; forecast skill for precipitation over monsoon Asia

The histograms presented in Fig 6, carry a pair of diagrams for the RMS errors and for the correlations for the seasonal downscaled forecasts of rains with respect to the observed estimates at the 25km resolution. Also included are vertical bars for the downscaled ensemble mean, and for the downscaled multimodel superensemble. These pertain to skills for the summer monsoon months of June, July and August; the forecasts cover 15 years and are indicated along the abscissa. For the most part, the general conclusion that can be drawn is that the multimodel superensemble almost always carries the lowest RMS errors and the highest correlations. There are very few exceptions where it might carry a skill close to the best model. The errors for the ensemble mean are almost always somewhat larger compared to those of the superensemble. In a real-time framework one can place great reliance on the superensemble forecasts, since its performance is consistently better than all other models and the ensemble mean.

3.3 Seasonal rainfall anomaly forecasts for a dry monsoon rainfall season

From the sample of 15 years of seasonal forecasts, we selected forecasts for the year 1987 a dry monsoon year (Fig 7). Details of the monsoon from each of these two years were presented by Krishnamurti et al. (1989). The year 1987 was characterized by very deficient rains over northern India with 25 percent below normal rains. The different panels, from top left of fig 3 show the seasonal observed rainfall anomalies from the Yatagai et al. (2009) raingauge based data sets, and those from the 16 different model forecasts. These are all downscaled model forecasts for the rainfall anomalies during the forecasts phase of the multimodel super ensemble. The last two panels of this illustration show the results of rainfall anomaly forecasts from the downscaled ensemble mean and the downscaled multimodel superensemble. All of these anomalies were calculated with respect to the model mean minus the APHRODITE based observed rainfall anomalies. In each of these forecast panels on the top right we provide the pattern correlations, i.e. the anomaly correlations, and at the bottom right for each panel, the RMS error of the respective forecasts is presented. From an examination of these seasonal forecasts we note that many models carry rather low correlations, ranging from -0.05 to 0.39 (Fig. 3a). For the ensemble mean and the superensemble, these numbers were elevated to values 0.40 and 0.43 respectively. The superensemble also carried the lowest RMS error of 1.36; while these values were as high as 2.11 for one of the member models. The dryness revealed by the strongest negative values of the rainfall anomalies were present in the forecasts from the models NCEP, UH, UKMO, LODY, ECMW and GFDL. This was also reflected by the multimodel superensemble. The spatial distributions of low rains during the dry year 1987 were best reflected by the multimodel superensemble. Some prominent features in the seasonal rainfall over this larger monsoon domain include the below-normal rains over northern India extending north-northwestward from the east coast of India. Those dry features are best represented by the multimodel superensemble. The above normal rains over northeast China are somewhat underestimated by the multimodel superensemble, the GFDL model, and the FSU KOR model. Most other models fail to predict this feature. The above normal rains of Bangladesh were underestimated by most models, except by the BMRC and the FSU models ANR and KOR. Generally, the forecasts of individual member models were not consistent from one forecast to the next.

4. Single model based ensembles versus multimodel superensemble

Several of the single models that are included in our multimodel suite carry many forecasts for each start time. The data that were used from such single models, in our study, were the ensemble mean of several such runs. Generally such several runs for the same start time are generated by using perturbed initial states. In the seasonal climate context some of these different initial states are generated by having a lagged start by a few days that still can have data for the same start dates. A question is frequently asked, how the results from a single model compare with those of a multimodel superensemble. Based on several such comparisons we found that the multimodel superensemble is always much superior, in terms of performance skills, compared to a single model based ensembles. Fig 12 illustrates such results of RMS errors, where the results for models that included 10 or more ensemble members, are included. These seven models go by the names: ANR, BMRC, GFDL, KNR, KOR, NCEP and UH respectively.

In Fig 8 we show the RMS errors, along ordinate) for these 7 models (shown as vertical bars), as a function of the 15 years of forecasts along the abscissa. Also shown, in the far right are the results from the ensemble mean of all 7 models and for the superensemble. The results that stand out are that the multimodel superensemble carries less error for seasonal forecasts of summer monsoon rains over the large Asia domain as compared to the single model based ensembles and their joint ensemble means (shown in the last set of bars in the far right). Clearly the superensemble benefits from the diversity of physical parameterizations, resolutions, different ocean model formulations, different initial states and the different land surface physics.

5. Conclusion

The forecast of seasonal rainfall anomalies, a season in advance, is a major scientific challenge for the monsoon world. Known for large droughts, floods and its need for advance information for agriculture, many scientific efforts to provide the best of such precipitation forecasts have been made e.g., Rajeevan et al. (2006). That progress largely came from a statistical multiple regression approach that included a number of predictands. A mix of multimodel based seasonal forecasts and a comprehensive downscaling and the construction of superensemble from model outputs is the approach followed in this study.

Much further improvement comes from the construction of the superensemble using the cross validation principle, with almost a lack of scatter between the observed and the model climatology; and the correlation reaches a value of nearly 1.0. That is not necessary since it is now possible to derive a downscaled superensemble based rainfall anomaly with respect to the observed climatology; the superensemble based rainfall climatology is very close to the observed climatology. Roughly 11 years of past seasonal forecast data sets were needed during the training phase of the downscaling and superensemble construction for the stabilization of the statistical weights. We also find that further improvements of results, presented in this paper, may be possible if a larger number of forecasts are carried out by each member model, in which case lower errors could be achieved from the use of a larger number of member models. For a given data length, an optimal number of model forecasts provide the least errors, using more models than the optimal number appears to degrade the results. We have also included a normalized rainfall anomaly based metric that shows the uniquely large improvements for the correlations and RMS errors of the observed versus the modeled rainfall anomalies from the superensemble. This study points to the presence of large systematic errors in many models that carry poor skills; persistence of such errors enables the superensemble to benefit from this feature. Further research on post processing of model results would be quite helpful to extract more information from model forecasts and their errors.

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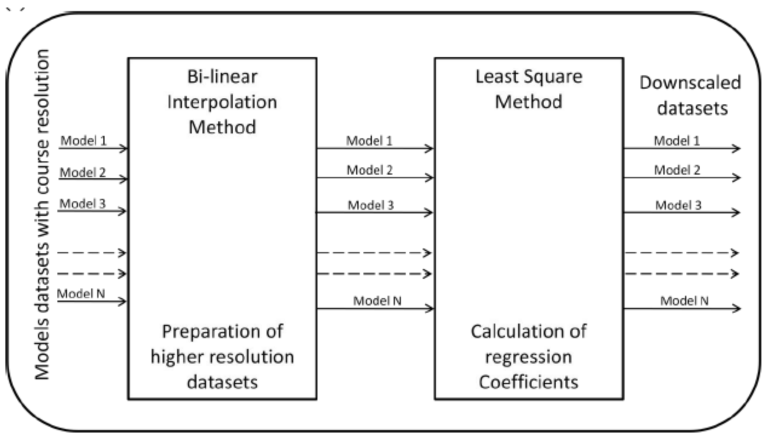

Fig. 1: Schematic shows the steps involved in Downscaling methodology

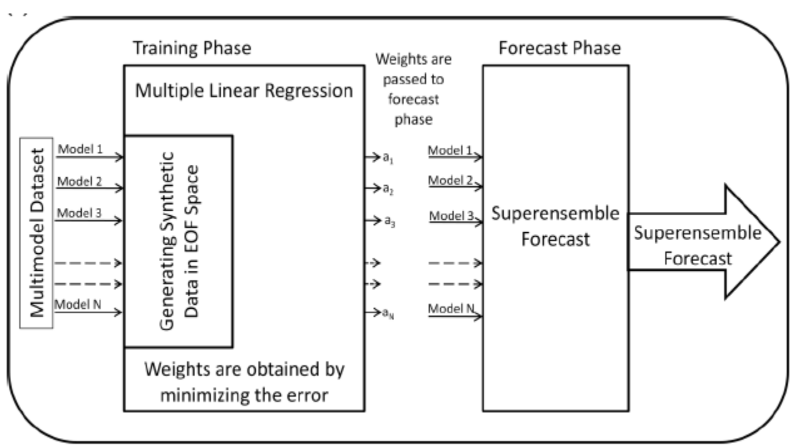

Fig. 2: Schematic shows the steps involved in Synthetic Superensemble forecasts.

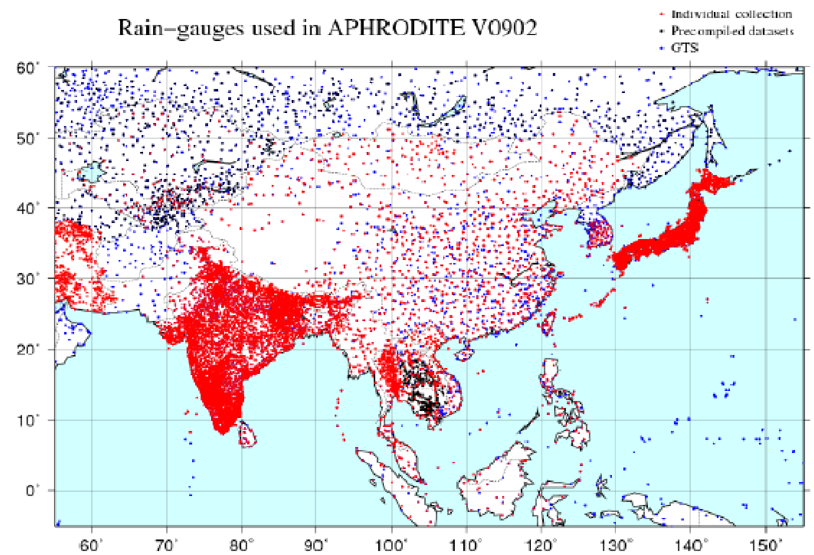

Fig. 3: Distribution of rainguage stations for monsoon Asia, collected data by the APHRODITE project (Yatagai et al., 2009).

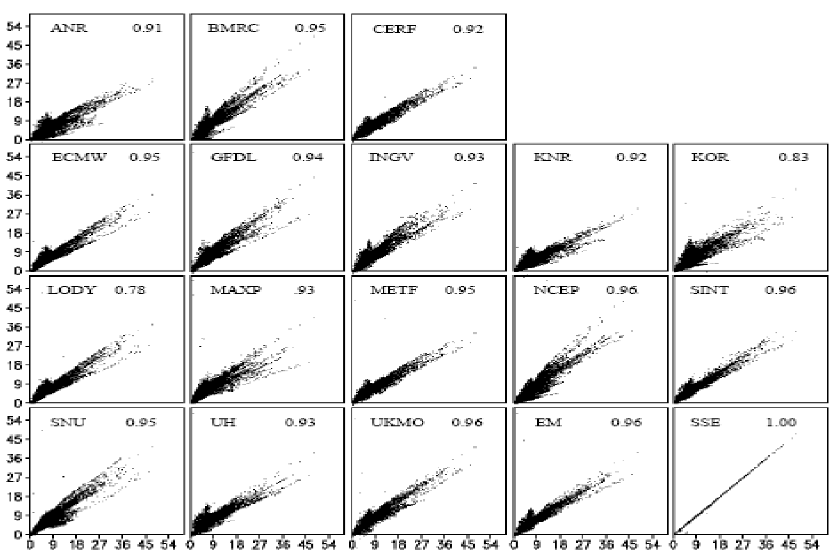

Fig. 4: Relation between forecasted and observed precipitation (mm/day, includes results from all grid points), over the monsoon Asia region, during JJA, for the precipitation climatology from 16 coupled models for the downscaled precipitation at the higher resolution of $0.25^{o}X0.25^{o}$.

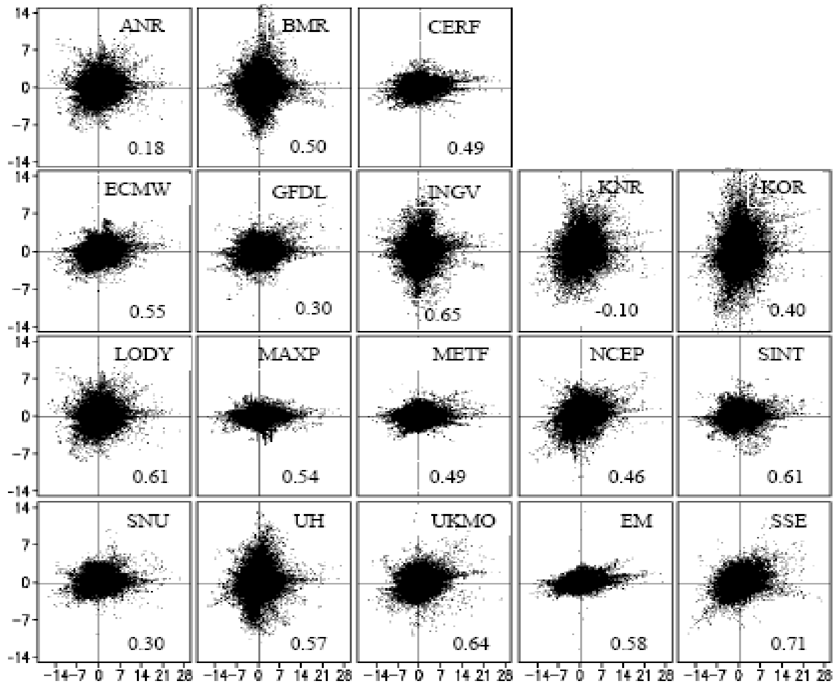

Fig. 5: Scatter plot for JJA Precipitation anomaly (mm/day), over the larger Monsoon Asia region for all the member models, ensemble mean EM and the superensemble SSE. The inset numbers at the bottom of each panel shows the value of the correlation between the predicted and the observed estimates of the rainfall anomalies.

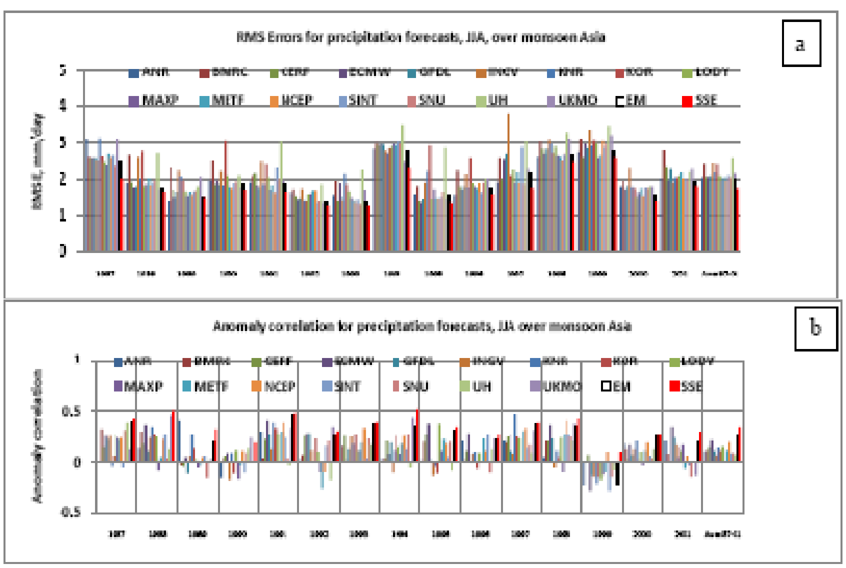

Fig 6: Showing along the ordinate the (a) RMS error (b) Anomaly correlations respectively, for the rainfall anomaly over the monsoon Asia region. The abscissa denotes the years. The yearly set of histograms carry forecasts for each of the 16 models, all separately identified by a different color. The last set of histograms show the 16 year averaged skills.

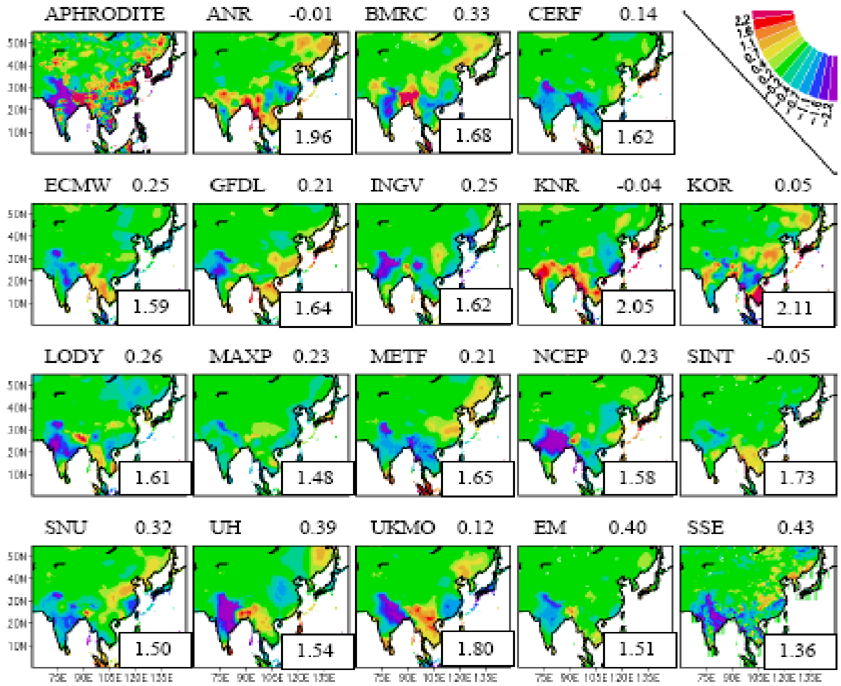

Fig. 7: JJA precipitation anomaly for 1987. First panel shows the observed rainfall anomalies, last two panels show the results for the ensemble mean and superensemble, the other panels show the results for each of the member models.

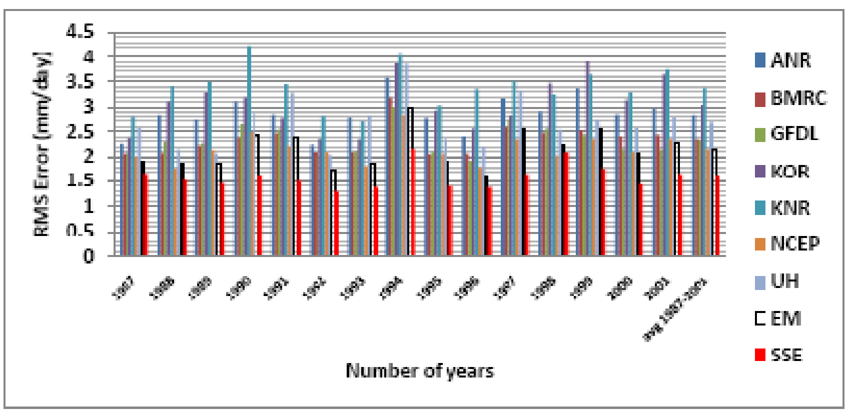

Fig 8: The vertical bars shows RMS error (along ordinate) for single model ensemble mean as compared to the overall ensemble mean (clear bar) and superensemble (red bar) shown in at far right for each year . Also shown in the far right side is the overall average for 15 years. These results pertain to the larger monsoon domain. The least RMS error are seen for the superensemble in the far right of each sets of bar.

Table 1: Details of sixteen global coupled models used in this study.

Name (Institute)	Atmospheric component			Oceanic component			Ens. member
	Model	Resolution	Initial Condition	Model	Resolution	Initial Condition	
AOR (FSU)	FSUGSM with Arakawa-Schubert convection and new radiation (band model)	T63L14	ECMWF with physical initialization	HOPE global	5^o longitude, 0.5^o-5^o latitude, 17 levels	Coupled assimilation relaxed to observed SST	10
KNR (FSU)	FSUGSM with Kuo convection and new radiation (emissivity-absorptivity model)	T63L14	ECMWF with physical initialization	HOPE global	5^o longitude, 0.5^o-5^o latitude, 17 levels	Coupled assimilation relaxed to observed SST	10
KOR (FSU)	FSUGSM with Kuo convection and old radiation (emissivity-absorptivity model)	T63L14	ECMWF with physical initialization	HOPE global	5^o longitude, 0.5^o-5^o latitude, 17 levels	Coupled assimilation relaxed to observed SST	10
CFS (NCEP)	GFS	T62L64	CFS SST forecast	MOM3	1^ox$1/3^o$, 40 levels	Ocean data assimilation	15
POAMA 1.5 (Australia)	Bureau of Meteorology Research Center (BMRC) Atmospheric Model (BAM3)	R47L17	From latest atmosphere and ocean conditions from Global Atmospheric Sampling Program	Australian Community Ocean Model 2 (ACOM2)	-2^ox0.5^o-1.5^o, 31 levels	From ocean assimilation that was based on optimum interpolation (OI) technique.	10
CERFACS (France)	ARPEGE	T63L31	ECMWF 40-yrs Re-analysis (ERA-40)	OPA 8.2	2^ox2^o, 31 levels	Forced by ERA-40	9
ECMWF (Europe)	IFS	T95L40	ERA-40	HOPE-E	1.4^ox0.3^o-1.4^o, 29 levels	Forced by ERA-40	9

FRCGC (SINTEX-F)	ECHAM-4	T106L19	NCEP/DOE Reanalysis-2	OPA 8.2	2^o(lon)x2^o cos(lat), 31 levels	SST nudging scheme	9
GFDL	AM2.1	2.5^ox2^o, 34 levels	NCEP/DOE Reanalysis-2	OM3.1 (MOM4)	1^ox$1/3^o$, 50 levels	Ocean data assimilation	10
INGV (Italy)	ECHAM-4	T42L19	Coupled AMIP type	OPA 8.1	2^ox0.5^o-1.5^o, 31 levels	Forced by ERA-40	9
LODYC (France)	IFS	T95L40	ERA-40	OPA 8.2	2^ox2^o, 31 levels	Forced by ERA-40	9
MPI (Germany)	ECHAM-5	T42L19	Coupled run relaxed to observed SST	MPI Open Model Interface (MPI-OMI)	2.5^ox0.5^o-2.5^o, 23 levels	Coupled run relaxed to observed SST	9
MetFr (France)	ARPEGE	T63L31	ERA-40	OPA 8.0	182x152 GP, 31 levels	Forced by ERA-40	9
SNU (Seoul National University)	SNU	T42L21	NCEP/DOE Reanalysis-2	MOM2.2	1^ox$1/3^o$, 32 levels	SST nudging scheme	6
UH (University of Hawaii)	ECHAM4	T31L19	NCEP/DOE Reanalysis-2	UH Ocean	2^ox1^o, 2 levels	Thermocline-Depth nudging	10
UKMO (United Kingdom)	HadAM3	2.5^ox3.75^o, 19 levels	ERA-40	GloSea OGCM Third Hadley Center Coupled Ocean-Atmosphere GCM (HadCM3) based		Forced by ERA-40	9

Table 2: Table presents the acronyms for models name and their affiliation with the institute/university.

Acronyms for Model's Name	
ANR	FSU Coupled model with Arakawa-Schubert convection and New Radiation (band model)
BMRC	Bureau of Meteorology Research Center, Australia (also POAMA1)
CERF	European Center for Research and Advanced Training in Scientific Computation, France (CERFACS)
ECMW	The European Center for Medium range Weather Forecasting, UK
GFDL	Geophysical Fluid Dynamical Lab, USA
INGV	Istituto Nazionale de Geofisica e Vulcanologia, Italy
LODY	Laboratoire d'Océanographie Dynamique et de Climatologie, France
KNR	FSU Coupled model with Kuo convection and New Radiation (band model)
KOR	FSU Coupled model with Kuo convection and Old Radiation (emissivity-absorptivity model)
MAXP	Max-Planck Institut für Meteorologie, Germany
METF	Centre National de Recherches Météorologiques, Météo-France, France
NCEP	National Center for Environmental Prediction, USA
SINT	Scale INTeraction Experiment-FRCGC
SNU	Seoul National University, South Korea
UH	University of Hawaii, USA
UKMO	The Met Office, UK
Other Acronyms used in this study	
CRes	Coarse Resolution
DJF	December-January-February
DScl	Downscaled
EM	Ensemble Mean
JJA	June-July-August
MAM	March-April-May
OBS	Observation
SON	September-October-November
SSE	Synthetic Superensemble