APCC/WG/Inf. 17.1

(09.01.2008)

Item:

ENGLISH ONLY

APEC CLIMATE CENTER

PERFORMANCE OF MME SEASONAL PREDICTION AT APCC

(Submitted by APEC Climate Center)

Summary and Purpose of Document

This document introduces some outputs from the APCC's MME forecasts and its performance, and future plans

ACTION PROPOSED

For the perusal of the WG participants

References: APCC forecasts and other products (see http://www.apcc21.net)

1. Introduction

In the past 20 years, climate scientists have made tremendous advances in understanding and modeling the variability and predictability of the climate system since the dynamical predictability recognized (Charney and Shukla 1981; Shukla 1981, 1985; Miyakoda et al 1986) and boundary-forced predictability broadened the possibility of climate prediction (Charney and Shukla 1981; Shukla 1985; Bengtsson et al. 1993). Prediction of seasonal-to-interannual climate variations has become operational since the NCEP and ECMWF started to produce operational ensemble forecast using atmospheric general circulation models (AGCMs) (Tracton and Kalnay 1993; Palmer et al. 1993). A number of meteorological centers worldwide have implemented routine dynamical seasonal predictions using coupled atmosphere-ocean-land climate models, such as ECMWF, NCEP, and Bureau of Meteorology Research Centre (BMRC) (Palmer et al. 2004; Saha et al. 2006; Wang et al. 2002). It has been also recognized that multi-model ensemble (MME) seasonal prediction is superior to any individual models due to effective reduction in inherent model errors (Krishnamurti et al. 1999, 2000; Doblas-Reyes et al., 2000; Shukla et al. 2000; Palmer et al. 2000, 2004; Kharin et al. 2002; Barnston et al. 2003; Yun et al., 2003 and 2005). Now, the MME prediction has become operational at the European Center for Medium range Weather Forecasting (ECMWF) in Europe, APEC Climate Center (APCC) in Asia-Pacific region, and International Research Institute for Climate and Society (IRI) in USA.

2. The MME Set Up at APCC

The APEC Climate Center is a major APEC science activity that was established in November 2005 during the leaders meeting of the Asia-Pacific Economic Forum in Busan, Korea. It produces seasonal and monthly forecasts of climate conditions for all seasons around the globe. Till 2007, APCC was issuing operational seasonal forecasts four times a year. However, since January 2008, APCC has started issuing monthly rolling 3-month forecasts since January.

APCC climate forecasts are based on model simulations from 15 prominent climate forecasting centers (See Figure 2. 1) and institutes in the APEC region. These forecasts are collected and combined using state-of-the-art schemes to produce a statistically 'consensual' forecast. The APCC forecasts are based not just on the magnitude of the seasonal changes that are predicted, but also take into accounts their simulated probability.

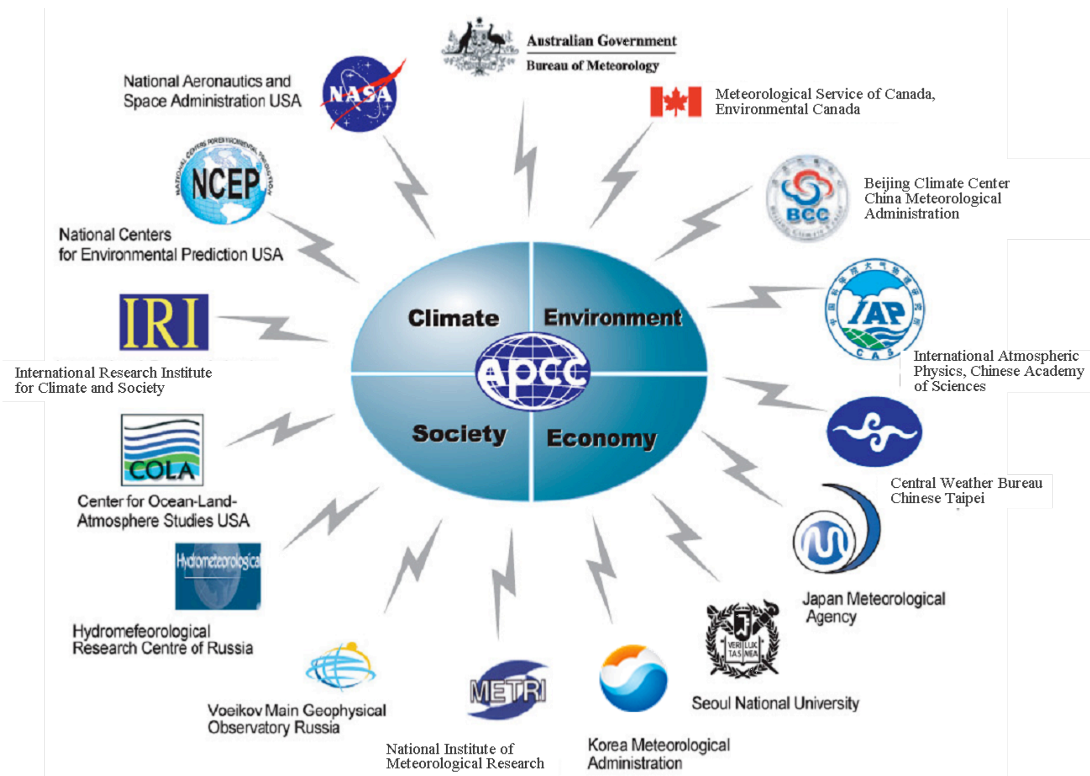


Figure 2. 1 Multi-Institutional cooperation

Original dynamical model data including forecasts and hindcasts are firstly collected from the model holders in APEC members. Then these data are subject to standardization of format. These data are stored in each file with only one variable, one ensemble member and one month. Next, quality check procedures are performed for the forecast data, and the data, which clear the quality control, are used for further MME procedure of hindcast, in conjunction with observed datasets to develop to calculate the relevant hindcast statistics/relationships, and also to generate the MME forecasts.

APCC produces seasonal forecasts of precipitation, T850, Z500, with relevant hindcasts, applying five methods:

1. Simple composite method (SCM)
2. Probabilistic forecast (GAUS)
3. Step-wise pattern projection (SPP)
4. Multiple regression based blend of model ensemble means (MRG)
5. Synthetic multi-model ensemble (SSE)

The time schedule for APCC operational procedure is generally made as table 2.1. During the first 10 days in the month before the forecasting season, all participating model data are collected. From the middle of the second week, these data are processed into basic data with the same format and then Quality Checks are conducted for these basic data. Then, from the middle of the second week to the middle of the third week, APCC MME forecasts are carried out. After that, two days are needed for APCC outlook. The outlook is published every month after prior consultation and discussions with the working group and SAC of APCC (see Appendix-I for the latest monthly 3-month forecast outlook from APCC).

Table 2. 1 Time schedule for APCC operational procedure

The day in the month before the season	**1~10**	**11~15**	**16~21**	**22~25**
Mission	Data collection	Standardization & quality check	MME production	Outlook & uplo to website

Table 2. 2 Participating Models

Member Economies	Acronym	Organization	Model Resolution
Australia	POAMA	Bureau of Meteorology Research Centre	T47L17
Canada	MSC	Meteorological Service of Canada	1.875° × 1.875° L50
China	BCC	Beijing Climate Center/CMA	T63L16
	IAP	*Institute of Atmospheric Physics*	*5°×4° L9*
Chinese Taipei	CWB	Central Weather Bureau	T42L18
Japan	JMA	Japan Meteorological Agency	T63L40
Korea	GDAPS	Korea Meteorological Administration	T106L21
	GCPS	Seoul National University	T63L21
	NIMR	National Institute for Meteorological Research	5°×° L17
Russia	MGO	Main Geophysical Observatory	T42L14
	HMC	Hydrometeorological Research Centre of Russia	1.125°×1.406° L28
USA	COLA	Center for Ocean-Land-Atmosphere Studies	T63L18
	IRI	International Research Institute for Climate Prediction	T42L18
	NCEP	NCEP Coupled Forecast System	T62L64
	NASA	National Aeronautics and Space Administration	2.5°×2° L34

Table 2. 3 Hindcast/Forecast Data Specifications

Acronym	Hindcast			Forecast
	Type	Period	Number of ensemble members	Number of ensemble members
POAMA	SMIP	1981-2008	28	28
MSC	SMIP	1979-2003	10	10
BCC	SMIP	1983-2008	8	8
IAP	*SMIP*	*1979-2004*	*7*	*8*
CWB	SMIP	1979-2004	10	10
JMA	SMIP	1983-2006	51	51
GDAPS	SMIP	1979-2003	20	20
GCPS	SMIP	1979-2008	12	12
NIMR	SMIP	1979-2004	10	10
MGO	SMIP	1979-2004	6	10
HMC	SMIP	1979-2003	10	10
COLA	AMIP	1981-2002	10	10
IRI	AMIP	1979-2005	24	24
NCEP	Coupled	1983-2008	15	15
NASA	Coupled	1993-2008	6	18

Table 2. 4 Hindcast/Forecast Variables

Model	Prec	T850	Z500	SLP	T2m	U850	V850	U200	V200	OLR	TS
POAMA	+	+	+	+	+	+	+	+	+	+	+
MSC	+	+	+	+	+	+	+	+	+	/	/
BCC	+	+	+	+	+	+	+	+	+	/	+
IAP	+	+	+	+	+	+	+	+	+	+	/
CWB	+	+	+	+	+	+	+	+	+	/	+
JMA	+	+	+	+	+	+	+	+	+	/	/
GDAPS	+	+	+	+	/	+	+	+	+	/	/
GCPS	+	+	+	+	/	+	+	+	+	+	+
NIMR	+	+	+	+	/	+	+	+	+	/	/
MGO	+	+	+	+	+	+	+	+	+	+	/
HMC	+	+	+	+	+	/	/	/	/	/	/
COLA	+	+	+	+	+	+	+	+	+	/	/
IRI	+	+	+	+	+	+	+	+	+	+	+
NCEP	+	+	+	+	+	+	+	+	+	+	+
NASA	+	+	+	+	+	+	+	+	+	+	+

3. OPERATIONAL MME VERIFICATION

The results of forecast verification against observation are shown here from 2008MAM to 2008SON, which are the seasons after last APCC Symposium. Pattern anomaly correlation coefficients (ACC) are used here to evaluate MME prediction performance in global, East Asia and Australia, as samples of the performance (performance for the other regions can be assessed from our webpage). The forecasts from four deterministic MME Schemes are evaluated.

In 2008MAM, MME schemes show very good forecast skills for both precipitation and temperature over global and in East Asia. In Australia, the MME schemes still show high forecast skills for precipitation, however, they show lower forecast skill for temperature.

In 2008JJA, MME forecasts depict quite good performance for temperature over East Asia and in Australia. It is remarkable that the forecast skills for temperature produced by MME schemes are better than those for precipitation.

In 2008SON, Skill score by SPM scheme for precipitation is higher than those by other schemes generally over all regions. In general, MME schemes have generated much more skilful forecasts for precipitation and temperature in 2008MAM.

In the following, we show ACC calculated between the model/MME and observation for some forecast as an example.

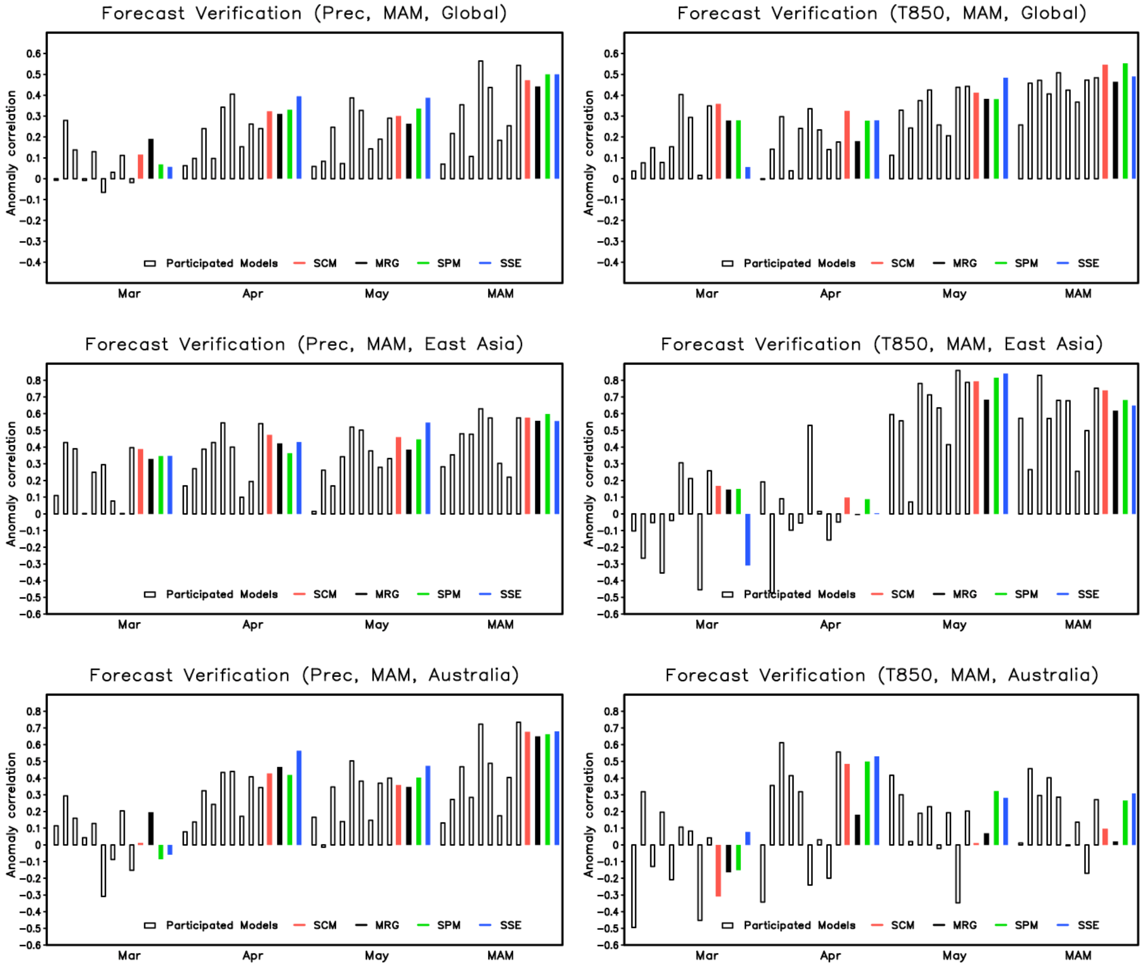
The ACC is pattern correlation between predicted and analyzed anomalies defined as,

$$ACC = \frac{\sum_{i=1}^{N} w_i (f_i - \bar{f})(o_i - \bar{o})}{\sqrt{\sum_{i=1}^{N} w_i (f_i - \bar{f})^2 \sum_{i=1}^{N} w_i (o_i - \bar{o})^2}},$$

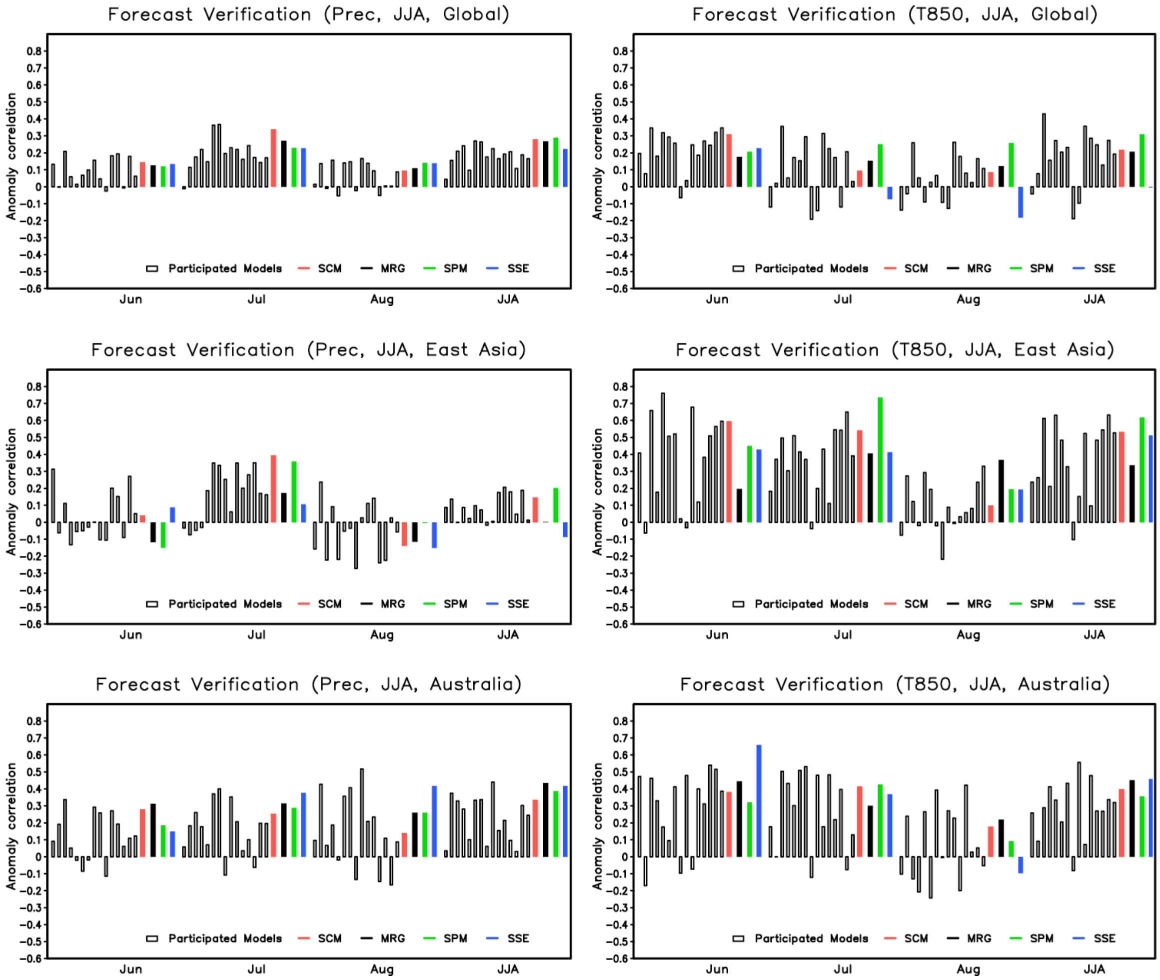
where over bar is time average.

ACC indicates spatial similarity between forecast and observation map. The score always ranges from -1.0 to 1.0. If the forecast is perfect, the score of ACC equals to 1.0. Results of ACC for forecast verification of 2008 are shown in the following figures.

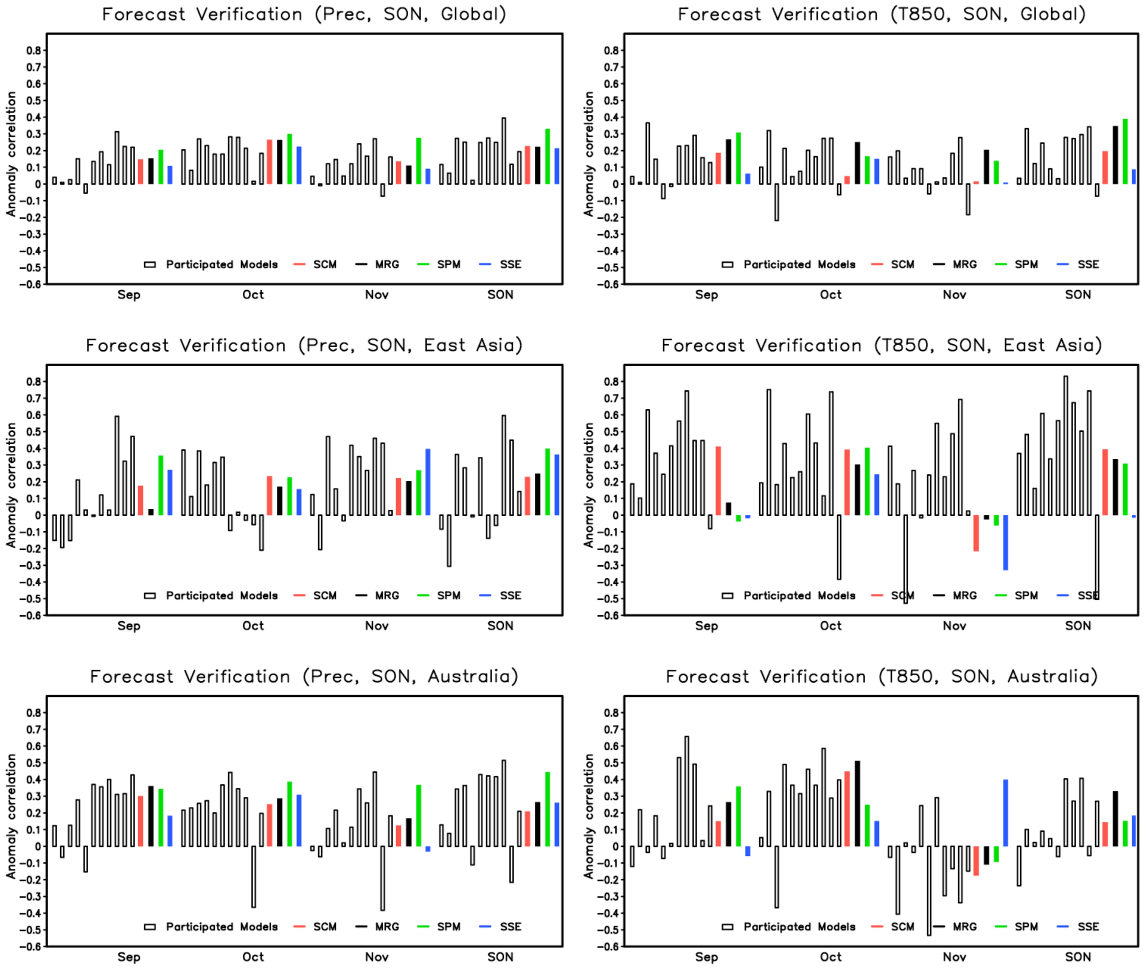
a. 2008 MAM


Forecast Verification (Prec, MAM, Global)
Forecast Verification (T850, MAM, Global)
Forecast Verification (Prec, MAM, East Asia)
Forecast Verification (T850, MAM, East Asia)
Forecast Verification (Prec, MAM, Australia)
Forecast Verification (T850, MAM, Australia)
Anomaly correlation
Participated Models
SCM
MRG
SPM
SSE
Mar
Apr
May
MAM

b. 2008 JJA


Forecast Verification (Prec, JJA, Global)
Forecast Verification (T850, JJA, Global)
Forecast Verification (Prec, JJA, East Asia)
Forecast Verification (T850, JJA, East Asia)
Forecast Verification (Prec, JJA, Australia)
Forecast Verification (T850, JJA, Australia)
Anomaly correlation
Participated Models
SCM
MRG
SPM
SSE
Jun
Jul
Aug
JJA

c. 2008 SON


Forecast Verification (Prec, SON, Global)
Forecast Verification (T850, SON, Global)
Forecast Verification (Prec, SON, East Asia)
Forecast Verification (T850, SON, East Asia)
Forecast Verification (Prec, SON, Australia)
Forecast Verification (T850, SON, Australia)
Anomaly correlation
Participated Models
SCM
MRG
SPM
SSE
Sep
Oct
Nov
SON

4. Experimental 1-tier MME prediction

4.1 Introduction

Some of the recent studies such as the APCC-supported CliPAS research results suggest reshaping the strategy for predicting summer rainfall in APCC operational system, and point to the necessity to establish one-tier MME forecast system. These studies suggest that the summer monsoon cannot be adequately predicted by prescribing forecasted SST (the so called two-tier approach). For example, the results from recent studies by CliPAS, a project funded by APCC, show that the one-tier models have better skill than two-tier models, particularly in monsoon prediction. In general, it is expected that the APCC operational MME prediction, which currently mainly consists of two-tier predictions can be improved through including more one-tier model predictions. APCC has initiated a 6-month coupled MME climate prediction to provide a longer lead forecast. APCC has also recently started development of a CCSM3-based in-house coupled climate prediction. A coupled SST-nudging initialization scheme has been developed and hindcast experiments are to be carried out. The 1-tier MME efforts have experimentally taken off as described below.

4.2 Implementation

Since February 2008, APCC has initiated experimental 6-month 1-tier MME prediction. The forecast data from 5 coupled models, namely, UH, SNU, SINTEX-F, POAMA and NCEP models are being used in this project. The first three model data is obtained through CliPAS (The pre-processing is carried out in-house for the three CliPAS models). The MME forecasts are generated 4-times a year, with the initial conditions of the first month of February, May, August and November. For 2008, the forecasts for MAMJJA, JJASON, SONDJF, and DJFMAM have been generated. As of now, we have generated forecasts based on two deterministic (simple composite and step-wise pattern projection method) and also the APCC probabilistic scheme. Our MME forecast results, for JJASON and DJFMAM, 2008 with the initial conditions of May and November, 2008 are shown in the below pages. The results include forecasts from a deterministic method (simple composite method) and a probabilistic (GAUS) method. Some hindcast verification statistics are also presented.

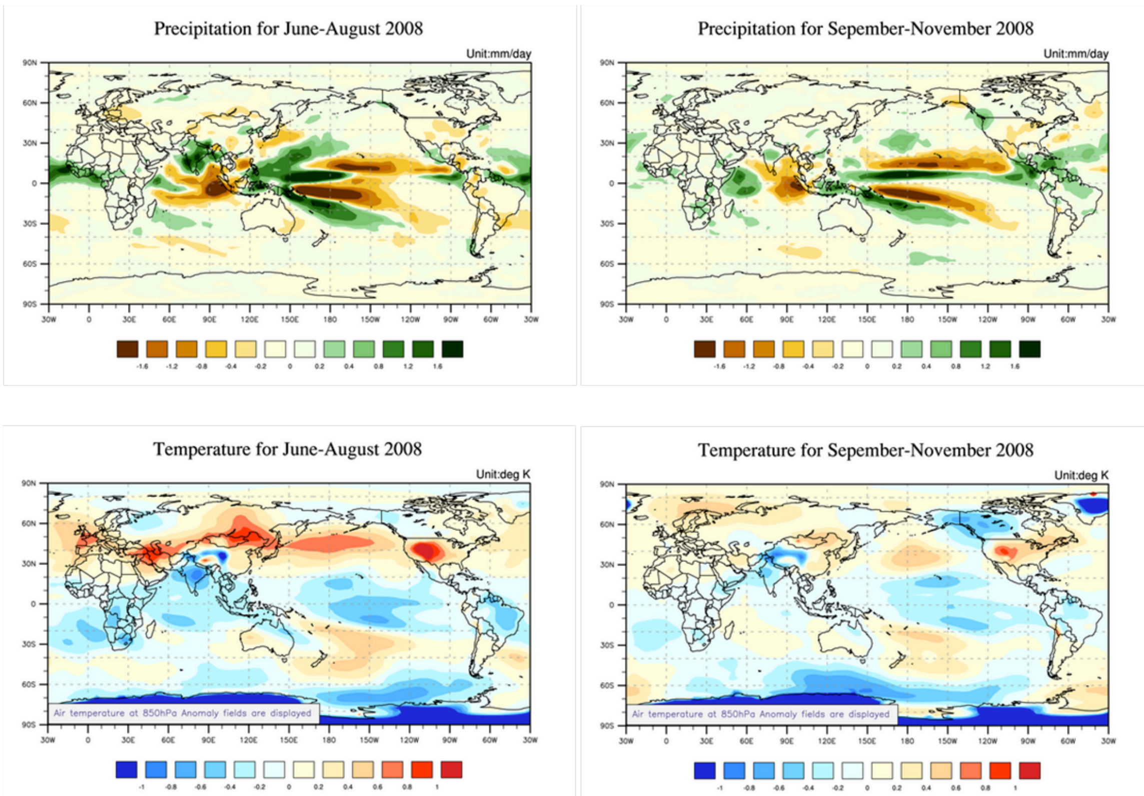


Figure 4.1 Precipitation and temperature forecast for JJASON 2008 over the globe using the SCM method.

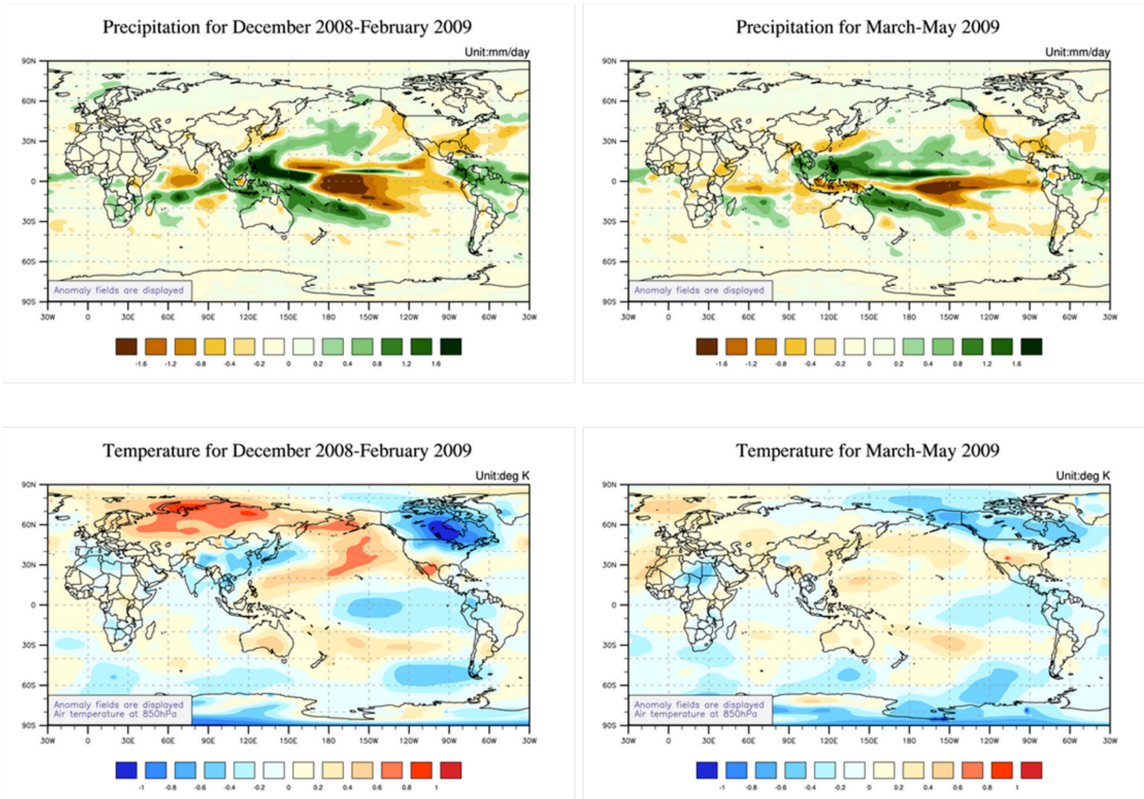


Figure 4.2 Same as Figure 4.1 but for DJF2008-MAM 2009.

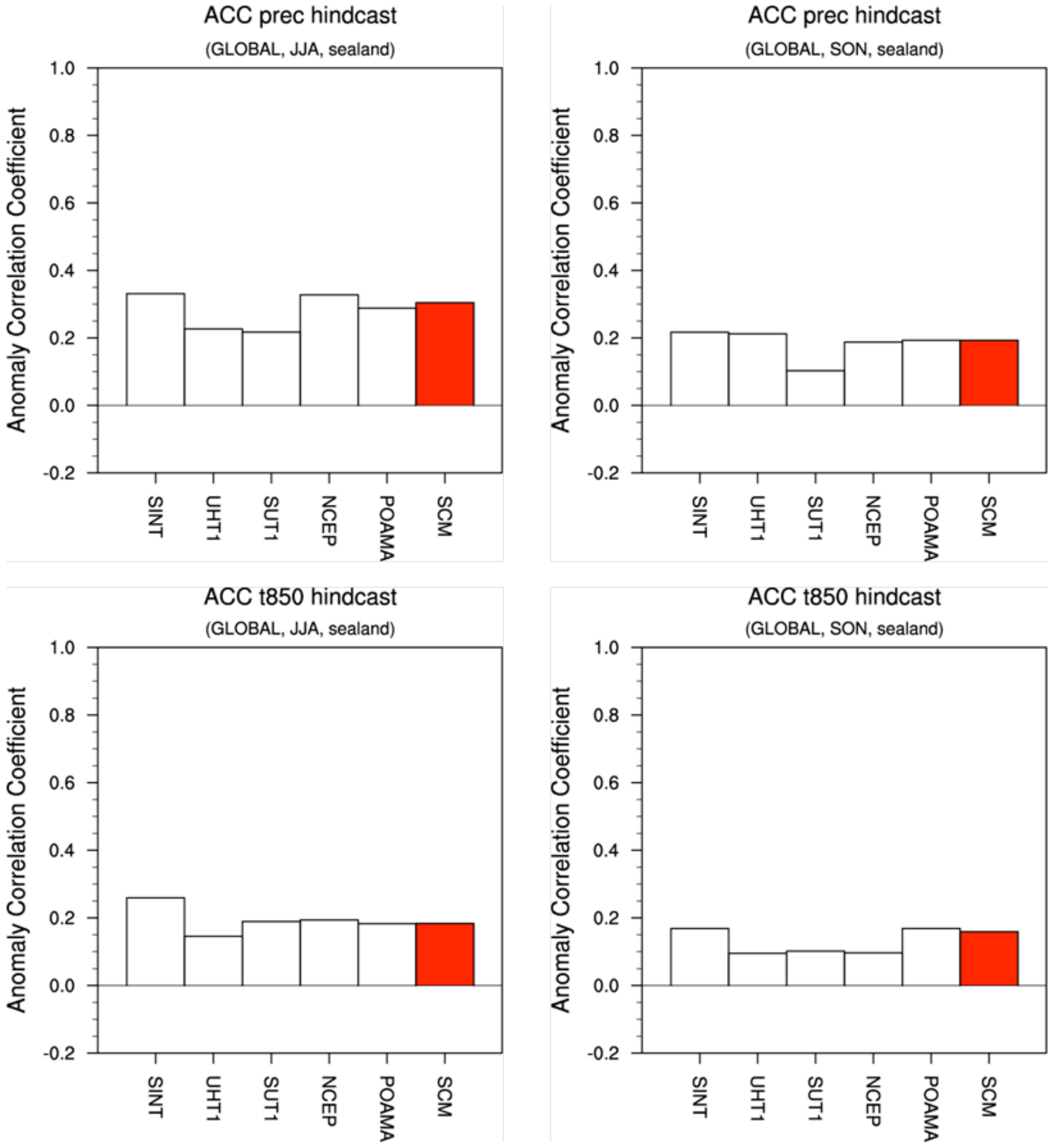


Figure 4.3 Precipitation and temperature hindcast verification for JJA and SON (averaged over the globe).

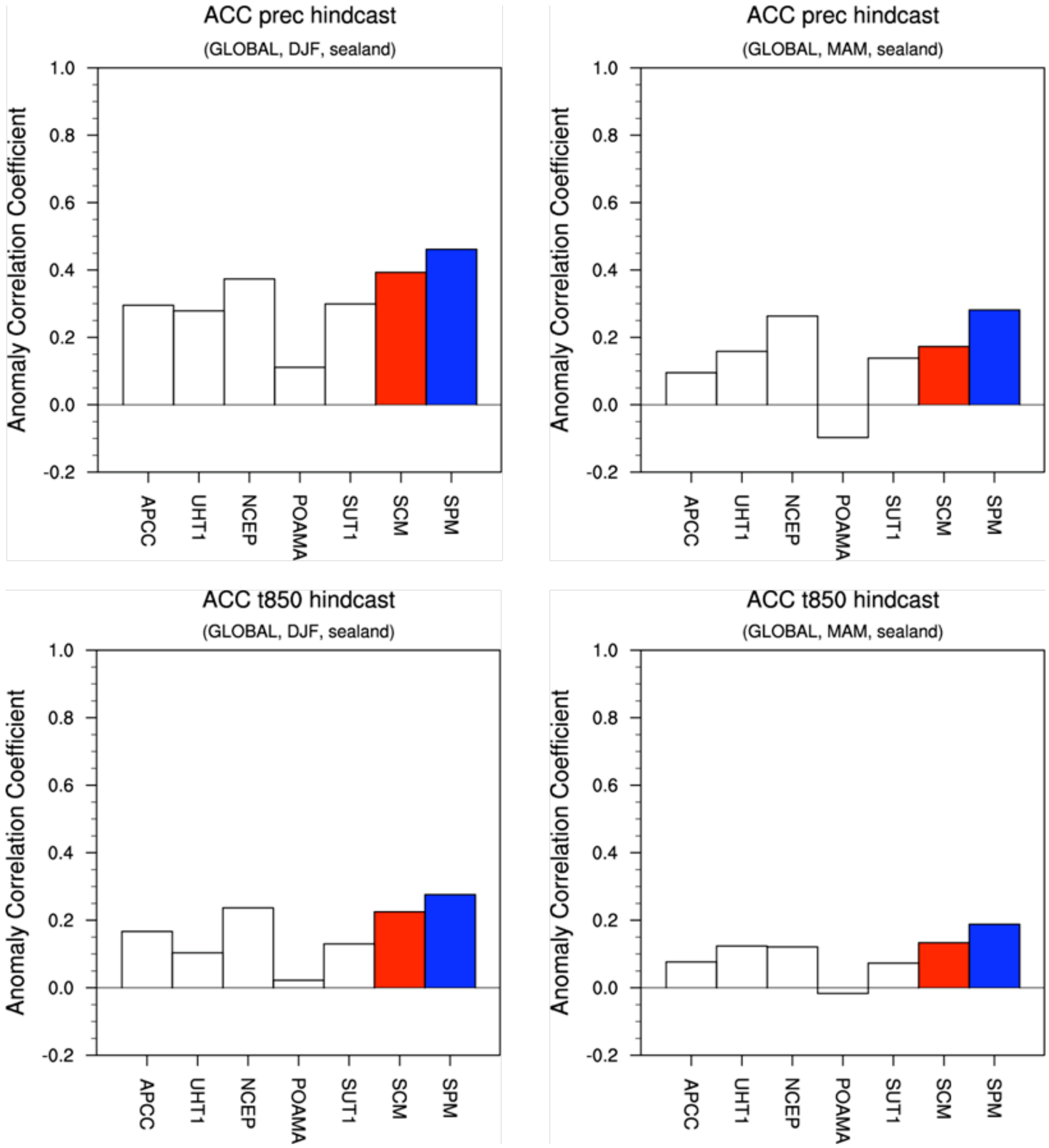


Figure 4.4 Same as Figure 4.3 but for DJF and MAM.

4. 3 In-house coupled model project

Based on encouragements from SAC to develop in-house capacities in coupled model, and also to increase the number of forecast samples, APCC has also experimentally initiated a project to operationalize the Community Climate System Model Version 3 (CCSM3) by developing a simple initialization scheme based on coupled SST nudging. In order to make the initial condition for nudged SST simulation, firstly the AGCM was integrated from 1971 to 1982 with observed SST forcing. And then, the OGCM carried out using the simulated AGCM fluxes for the same period. Using the final balanced conditions of the synchronous AGCM and OGCM simulation, to generate the initial data for hindcast and forecast, the coupled nudged SST simulation is implemented from Jan. 1982 to recent using OISST forcing. Finally, the hindcast simulation is generated from Nov. 1st for each year for DJFMAM forecast using the nudged initial condition without any forcing or flux correction. Four ensembles with the atmospheric initial condition for Nov. 1st, Nov. 3rd, Nov. 5th, and Nov. 7th and ocean I.C. for Nov. 1st were carried out. The preliminary result shows good for ENSO prediction and evolution up to 3 month. However, it is losing the predictability after 4 month. So, we plan to improvement of initialization scheme for hindcast and forecast.

5. Statistical Downscaling

The current Global Circulation Models (GCM) have become the main tool of climate studies and climate prediction/projection on a wide range of time scales from months to decades and hundreds of year. State-of-the-art models are able to quite successfully reproduce large scale atmospheric processes, particularly response of large scale circulation to changes in external forcings such as concentration of radiatively active gases, large scale surface properties, etc. The MME, in general exhibits better performance than most of the component models in any given 3-month period, and predicts the large scale features quite reasonably (However, the models and the MME are not adequate to forecast local rainfall owing to the limitations in capturing the complex spatio-temporal dynamical interactions and physical processes as well as due to the still relatively coarse resolution. To provide accurate information for regional applications, climate prediction products have to be downscaled. Since last two years, APCC has developed in-house expertise (see (Kang et al, 2008 and other references therein). It has successfully developed and implemented a regression-based statistical downscaling technique for Korea. It is based on multi-predictor optimal selection and coupled pattern projection method (Kang et al, 2008). Since Feb. 2008, the predictions of precipitation and temperature based on the downscaling scheme have been operationally provided for 60 Korean stations for every month (As an example, Figure 6. 1).

Experimental probabilistic interpretation of multi-model downscaled forecasts was carried out for one season. APCC plans to continuously make efforts on probabilistic downscaling based on accounting for combined uncertainty associated with regression and model spread. Moreover, development of a temporal downscaling method based on weather generator is initiated for fine-scale temporal information (e.g., wet/day days, rainfall amount, etc.).

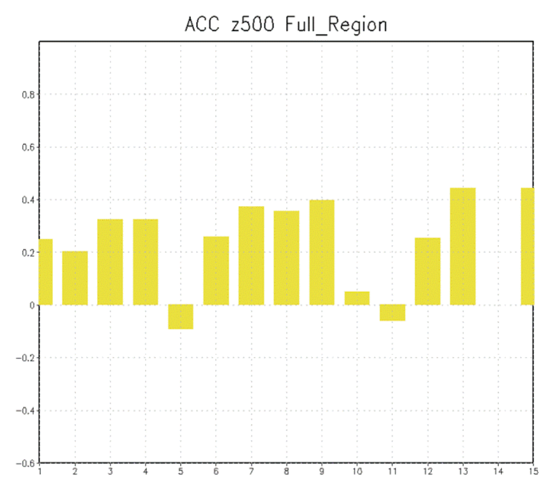


Figure 5. 1 Forecast ACC (between MME hindcasts and observed values) for globally averaged geopotential height anomalies (500 hPa) for SON 2008.

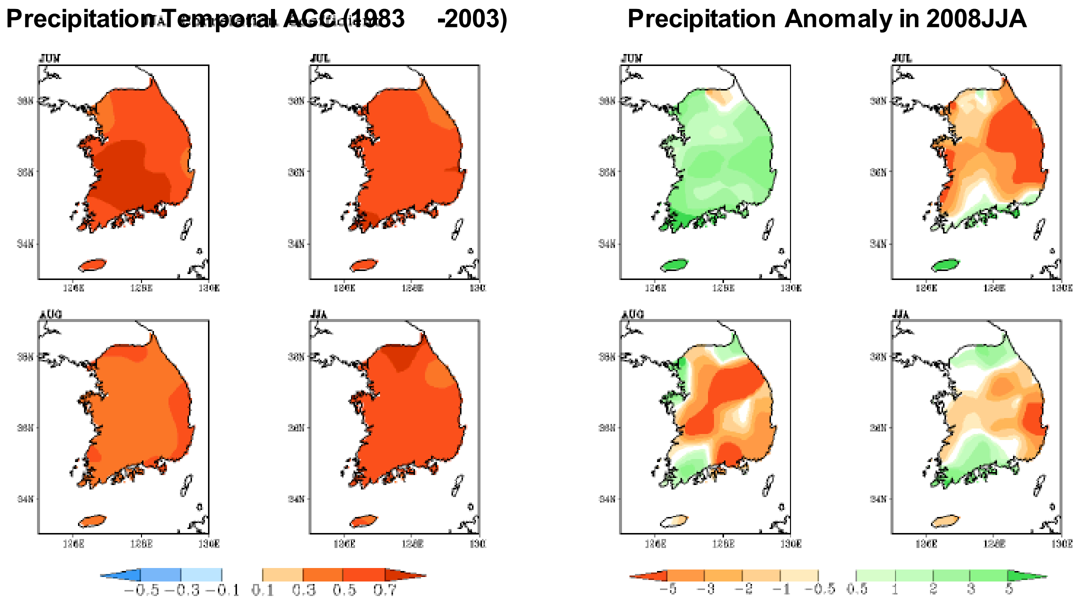


Figure 5. 2 Hindcast ACC of downscaled forecast precipitation (left panels) and temperature (right panels) for June, July, August, and JJA with corresponding observed station data.

6. Concluding Remarks

From the skill scores presented for the monthly 3-month rolling operational forecasts, it is seen that in some forecasts, such as 2008MAM, the forecast skills of the MME are higher than the individual models. In some other months, some of the individual models skills are better than those of the MME. However, it can be seen that the individual models do not perform consistently at the same skill, and the MME skills are invariably better than most of the individual models. Having said that, the skills of the MME are modest in many forecasts, and also the skills mostly come from the tropical regions. This indicates that we need to improve the MME skills. Recent research provides a clue that selection of a combination of a set of models is crucial for improving the skills, and APCC is planning to carry out some test in this direction. We are also exploring the potential use of using non-linear techniques such as Artificial Neural Network.

Also, to improve the forecast leads as well the skill, an Experimental 6-month 1-tier MME prediction has been initiated at APCC by using the 3-Clipas provided and two operational coupled predictions during last year. So far, the forecasts for MAMJJA 2008, JJASON2008, SONDJF2008, and DJFMAM2009 along with the relevant hindcast procedure have been completed with initial conditions of February 2008, May 2008, August 2008, and November 2008. The most important challenge is the limited number of the available coupled forecast as well as the limited number of ensembles, which seem to limit the skills of the first three months to the levels of the current operational prediction.. Another practical concern for this project is that the three CliPAS models provide the forecasts in a research mode, and can not always provide the data by the required deadline (15th of the month in which the forecasts are processed) to meet the for operational procedure requirement. Efforts will be carried out to procure more 1-tier forecast datasets, with more number of ensembles. The ongoing in-house development of an operational version CCSM3, expected to be operational by the end of 2009, is being carried out with an objective to support the 6-month 1-tier MME prediction. Forecasts are planned 4 times with a lead of 1-7 months from 2009, with forecast and hindcast verifications. We look forward to include more 1-tier model predictions as and when they are available. Including all those efforts, we are planning 12-month forecast using 1-tier MME prediction by the end of 2010.

Other developmental work involves the development of a probabilistic forecast verification system. Another important product being developed at APCC is an MME-based drought prediction system, in which the well-known standardized precipitation index (SPI; McKee et al. 1993) will be predicted and provided every month with due verification. As a complement to this service, APCC has also started an online drought monitoring product recently, which is provided from the monitoring WebPages of APCC ((http://www.apcc21.net/climate/climate03_11.php). The details can be seen from Appendix-II.

The APCC/CliPas research indicates that that the MME relies on good models. So the improvement of models is essential and remains a long-term goal of APCC international project. Significant improvement of climate models requires long-term and devoted efforts, and thus, must rely on of the efforts of individual climate institutions. To meet this goal, APCC is also starting to provide a feedback mechanism on systematic model errors to model providers.

References

Barnston, A. G., S. J. Mason, L. Goddard, D. G. Dewitt, and S. E. Zebiak, 2003: Multimodel ensembling in seasonal climate forecasting at IRI. *Bull. Amer. Meteor. Soc.*, **84**, 1783-1796.

Bengtsson, L., U. Schlese, E. Roeckner, M. Latif, T. P. Barnett, and N. E. Graham, 1993: A two-tiered approach to long-range climate forecasting. *Science,* **261**, 1027-1029.

Chang, Y., Schubert, S. D. and Suarez, M. J. 2000. Boreal winter predictions with the GEOS-2 GCM: the role of boundary forcing and initial conditions. Q. J. R. Meteorol. Soc. 126, 2293–2321.

Charney and J. Shukla, 1981: Predictability of monsoons. Paper presented at the Monsoon Symposium in New Delhi, India, 1977, and published in the book *Monsoon Dynamics*, Eds., Sir James Lighthill and R. P. Pearce, Cambridge University Press, pp. 99-110.

Doblas-Reyes, F. J., M. Deque, and J.-P. Piedelievre, 2000: Multi-model spread and probabilistic seasonal forecasts in PROVOST. *Q. J. R. Meteorol. Soc*. **126**, 2069-2088.

Kang, H., C.-K. Park, N. H. Saji, and Ashok Karumuri, 2008: Statistical downscaling of precipitation in Korea using multi-model output variables as predictors. Mon. Wea. Rev. (accepted).

Kharin. V. V., and F. W. Zwiers, 2001: Skill as a function of time scale in ensembles of seasonal hindcasts. Climate Dyn., 17, 127-141.

Kharin, V. V. and Zwiers, F. W. 2002. Notes and correspondence: Climate predictions with multi-model ensembles. J. Climate 15, 793–799.

Kharin, V. V., and F. W. Zwiers, 2003: Improved seasonal probability forecasts. *J. Climate.,* **16**, 1684–1701.

Krishnamurti, T. N., C. M. Kishtawal, Z. Zhang, T. E. LaRow, D. R. Bachiochi, and co-authors, 1999: Improved weather and seasonal climate forecasts from multi-model superensemble. *Science* **285**, 1548-1550.

Krishnamurti, T. N., Kishtawal, C. M., Zhang, Z., LaRow, T. E., Bachiochi, D. R. and co-authors. 2000a. Improving tropical precipitation forecasts from a multi-analysis superensemble. J. Climate 13, 4217–4227.

Krishnamurti, T. N., C. M. Kishtawal, D. W. Shin, C. E. Williford, 2000b: Multi-model superensemble forecasts for weather and seasonal climate. *J Climate* **13**, 4196-4216.

Krishnamurti, T. N. and Sanjay, J. 2003. A new approach to the cumulus parametrization issue. Tellus 55A, 275–300.

Leith, C. E., 1973: The standard error of time-average estimates of climatic means. J. Appl. Meteor., 12, 1066-1068.

Madden, R. A., 1976: Estimates of the natural variability of time-averaged sea-level pressure. Mon. Wea. Rev., 104, 942-952.

Miyakoda, K., J. Sirutis, and J. Ploshay, 1986: One month forecast experiments-without boundary forcings. *Mon. Wea. Rev*., 114, 2363-2401.

Palmer, T. N., F. Molteni, R. Mureau, R. Buizza, P. Chapelet, and J. Tribbia, 1993 : Ensemble prediction. In EXMWF 1992 Seminar : Validation of Models over Europe, ECMWF.

Palmer, T. N., C. Brankovic, and D. S. Richardson, 2000: A probability and decision-model analysis of PROBOST seasonal multi-model ensemble integrations. *Q. J. R. Meteorol. Soc.* **126**, 2013-2034.

Palmer, T. N., A. Alessandri, U. Andersen, P. Cantelaube, M. Davey, and co-authors, 2004: Development of a European multi-model ensemble system for seasonal to interannual prediction (DEMETER). *Bull. Amer. Meteor. Soc.*, **85**, 853-872.

Pavan, V. and Doblas-Reyes, J. 2000. Multi-model seasonal hindcasts over the Euro-Atlantic: skill scores and dynamic features. Climatic Dyn. 16, 611–625.

Peng, P., Kumar, A., Van den Dool, A. H. and Barnston, A. G. 2002. An analysis of multi-model ensemble predictions for seasonal climate anomalies. J. Geophys. Res. 107, 4710

Press, W. H., S. A. Teukolsky, W. T. Vettering, and B. P. Flannery, 1992: Numerical Recipes in Fortran. 2d ed. Cambridge University Press, 963 pp.

Saha, S., S. Nadiga, C. Thiaw, J. Wang, and Coauthors, 2006: The NCEP climate forecast system. *J. Climate*, 1**9**, 3483-3517.

Shukla, J., 1981: Dynamical predictability of monthly means. *J. Atmos. Sci*., **38,** 2547-2572

Shukla, J., 1985: Predictability. *Large-Scale Dynamical Processes in the Atmosphere*, B. J. Hoskins and R. P. Pearch, Eds., Academic Press, 87-122.

Stanski, H. R., L. J. Wilson, and W. R. burrows, 1989: Survey of common verification methods in meteorology. WMO World Weather Watch Tech. Rep. 8, WMO TD 538, 114p.

Stephenson, D. B. and Doblas-Reyes, F. J. 2000. Statistical methods for interpreting Monte Carlo ensemble forecasts. Tellus 52A, 300–322.

Tracton, M. S., and E. Kalnay, 1993: Operational ensemble prediction at the National Meteorological Center: Practical aspects. *Wea. Forecasting*, **8**, 379-398.

Wang, B., J.-Y. Lee, J. Shukla, I.-S. Kang, E. K. Jin, C.-K. Park, and coauthors, 2007: Multi-model ensemble dyamic seasonal prediction of APCC/CliPAS, *will be submitted to J. Climate*.

Wang, Guomin, R. Kleeman, N. Smith, and F. Tseitkin, 2002: The BMRC coupled general circulation model ENSO forecast system. Mon. Wea. Rev. 130, 975-991.

Yun, W.-T., L. Stefanova, and T. N. Krishnamurti, 2003: Improvement of the superensemble technique for seasonal forecasts. *J. Climate* **16**, 3834-3840.

Yun, W.-T., L. Stefanova, A. K. Mitra, T. S. V. V. Kumar, W. Dewar, and T. N. Krishnamurti, 2005: A multi-model superensemble algorithm for seasonal climate prediction using DEMETER forecasts. *Tellus* **57A**, 280-289.

Zwiers, F. W., 1996: Interannual variability and predictability in an ensemble of AMIP climate simulations conducted with the CCC GCM2. Climate Dyn., 12, 825-848.

APPENDIX – I

The APEC CLIMATE CENTER

Climate Outlook for January-March 2009

BUSAN, 24 December, 2008 - Synthesis of the latest computer model forecasts at the APEC Climate Center (APCC), located in Busan, Korea, indicates colder than normal conditions in northwest North America during January-March 2009. On the other hand, warmer-than-normal conditions may prevail in Eastern East Asia as well as in Northern Europe. South America is expected to receive less-than-normal rainfall, except in the equatorial regions.

Current Climate Conditions

During the period from October through the second week of December, anomalously warm or near-normal temperatures persisted in most land regions around the globe except in the following few: northwest Africa, the Alaska, eastern USA and Mexico, Chile and several small pockets in South America, western Australia, the Middle East and several pockets in Asia; since December, most of Canada also is experiencing cooler than normal anomalies. In southern hemisphere, Australia and New Zealand received near-normal to slightly surplus rainfall; the signals in Australia actually shifted from dry in October to wet since November. Most of the nations in South America received near-normal to below normal rainfall. In general, near-normal to below normal rainfall was also observed in the northern hemisphere land regions. While the predictions were successful in capturing anomalous temperature (rainfall) signals in the East Asia, Australia, the Eastern Pacific, southern portions of South America (Central Canada, southern USA), the temperature (rainfall) anomalies in Central Asia, Canada (Indonesia, the western tropical Africa) could not be predicted correctly. The weak tripolar sea surface temperature conditions in the tropical Pacific since March 2008 resemble a so called La Niña Modoki condition. In the recent four weeks, the cold anomalies in the central tropical Pacific have slightly strengthened further; also, low level easterly wind anomalies are seen in the tropical western Pacific since November.

Forecast

The APCC forecast for January-March 2009 indicates continuing near normal conditions in the tropical Pacific. A horse-shoe shaped anomalies of temperature as well as rainfall, centered in the tropical western Pacific, are expected, extending from the Northwest Pacific through the Philippines, Indochina, most of Indonesia and Malaysia, Papua New Guinea and adjoining Polynesian islands; the Indonesian region adjoining the Indian Ocean may, on the other hand, receive less than normal rainfall. The northeast Australian continent may receive slightly more than normal rainfall.

The western tropical South America may experience moderately colder and wetter-than-normal signals, while to its east, dry and warm conditions are predicted. Further north, the southern North America is expected to receive less than normal rainfall with warmer-than-normal conditions. Colder than normal conditions in the northwest North America may be experienced.

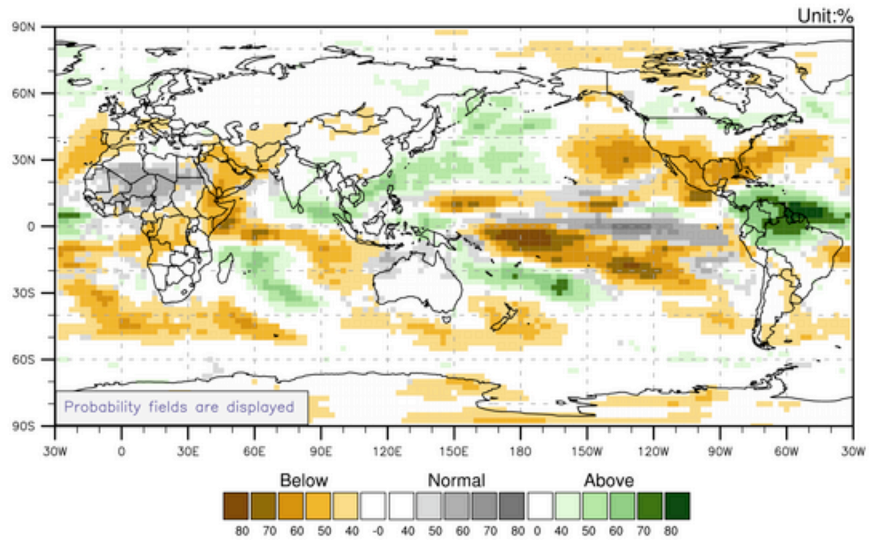
East Asia, including southeastern China region, Korean peninsula and Japanese archipelago, may experience slightly warmer than normal conditions, with the predicted signal extending west through Russia and Northern Europe. Near normal rainfall signals are likely in Korean peninsula, while near normal to slightly surplus (deficit) signals can be expected in Japanese archipelago (southeast Chinese region). The Middle East and adjoining northeast African region, along with central parts of the Africa, are likely to experience continuing warm and slightly drier-than-normal conditions.

Indian region may experience above normal temperatures, with slightly more than normal rainfall in its southernmost region.

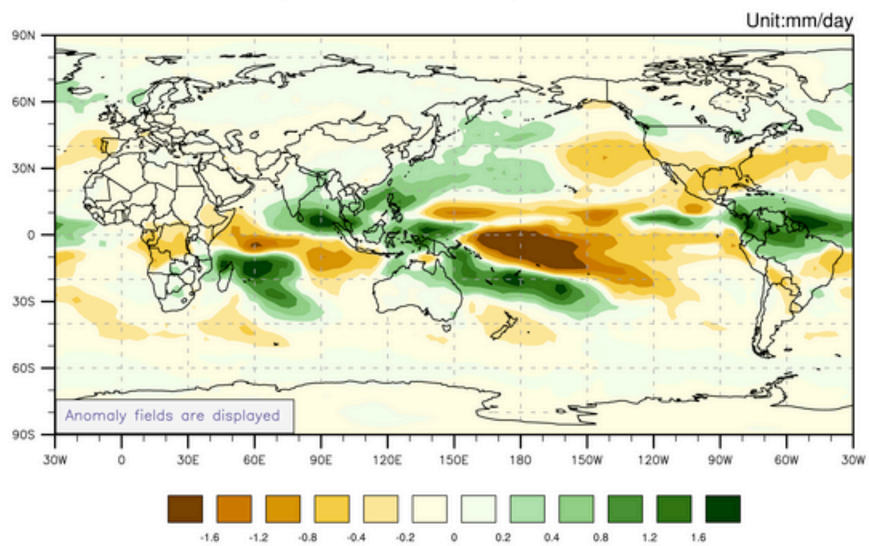
In view of the evolving signals, tropical Pacific needs to be watched for any possible further developments.

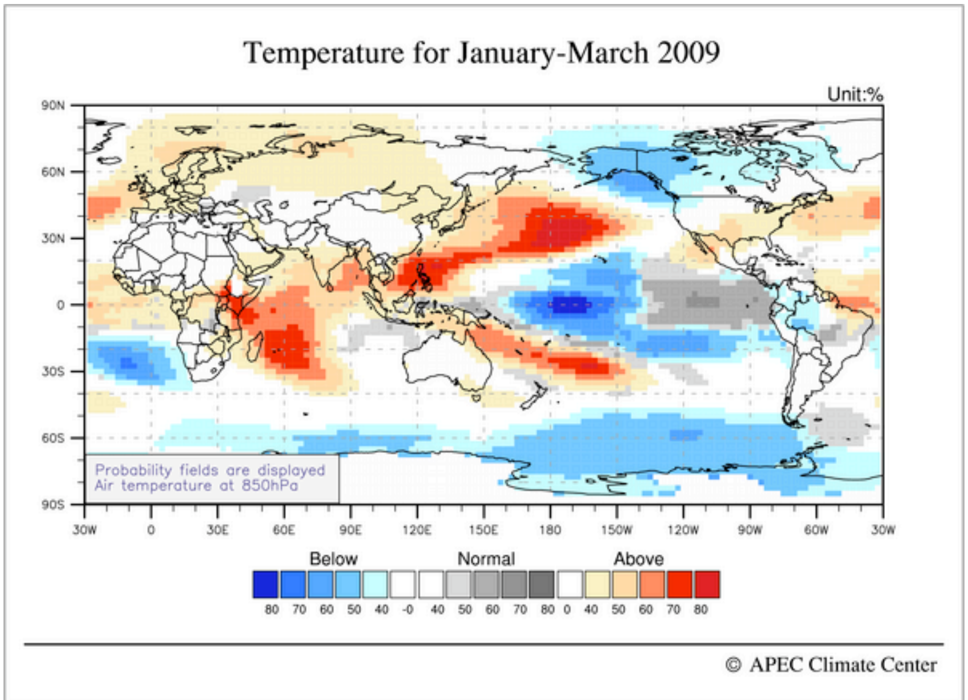
The APEC Climate Center is a major APEC science activity that was established in November 2005 during the leaders meeting of the Asia-Pacific Economic Forum in Busan, Korea. It produces seasonal and monthly forecasts of climate conditions for all seasons around the globe. APCC collects seasonal forecasts from 15 institutes in the APEC region: National Aeronautics and Space Administration USA, National Centers for Environmental Prediction USA, International Research Institute for Climate and Society USA, Center for Ocean-Land-Atmosphere Studies USA, Hydrometeorological Research Center of Russia, Voeikov Main Geophysical Observatory of Russia, National Institute of Meteorological Research Korea, Korea Meteorological Administration, Seoul National University, Japan Meteorological Agency, Central Weather Bureau Chinese Taipei, Institute of Atmospheric Physics China, Beijing Climate Center, Meteorological Service of Canada and the Australian Bureau of Meteorology.
APCC climate forecasts are based on model simulations from 15 prominent climate forecasting centers and institutes in the APEC region. These forecasts are collected and combined using state-of-the-art schemes to produce a statistically 'consensual' forecast. The APCC forecasts are based not just on the magnitude of the seasonal changes that are predicted, but also take into accounts their simulated probability.
Further details and verification for the forecasts on a long term basis are available at http://www.apcc21.net*. The forecast verification is based on a retrospective forecast period of all the models for the period 1983-2003.*

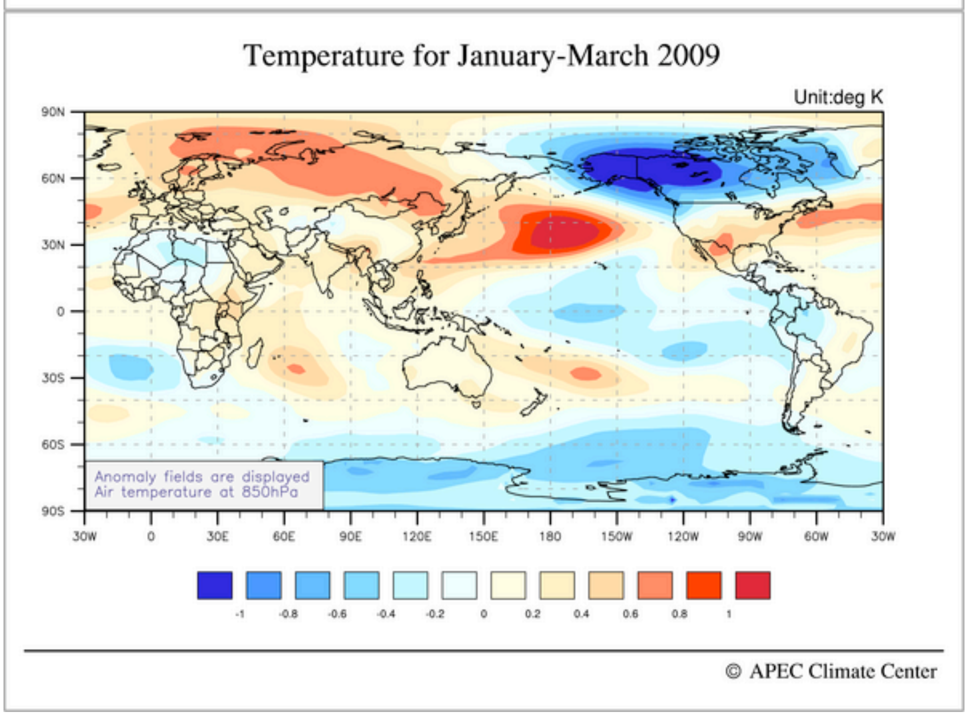
Precipitation for January-March 2009



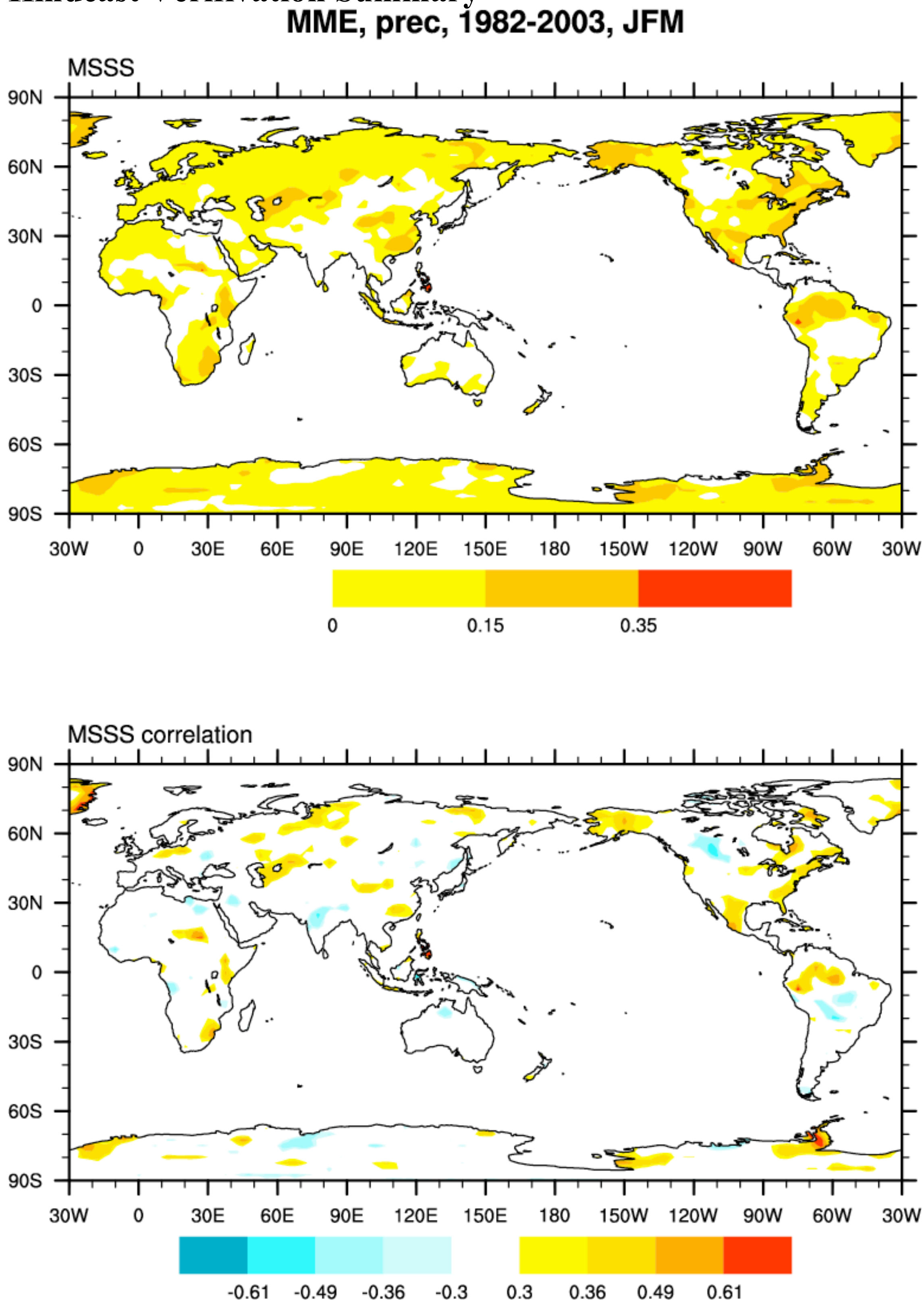
Precipitation for January-March 2009



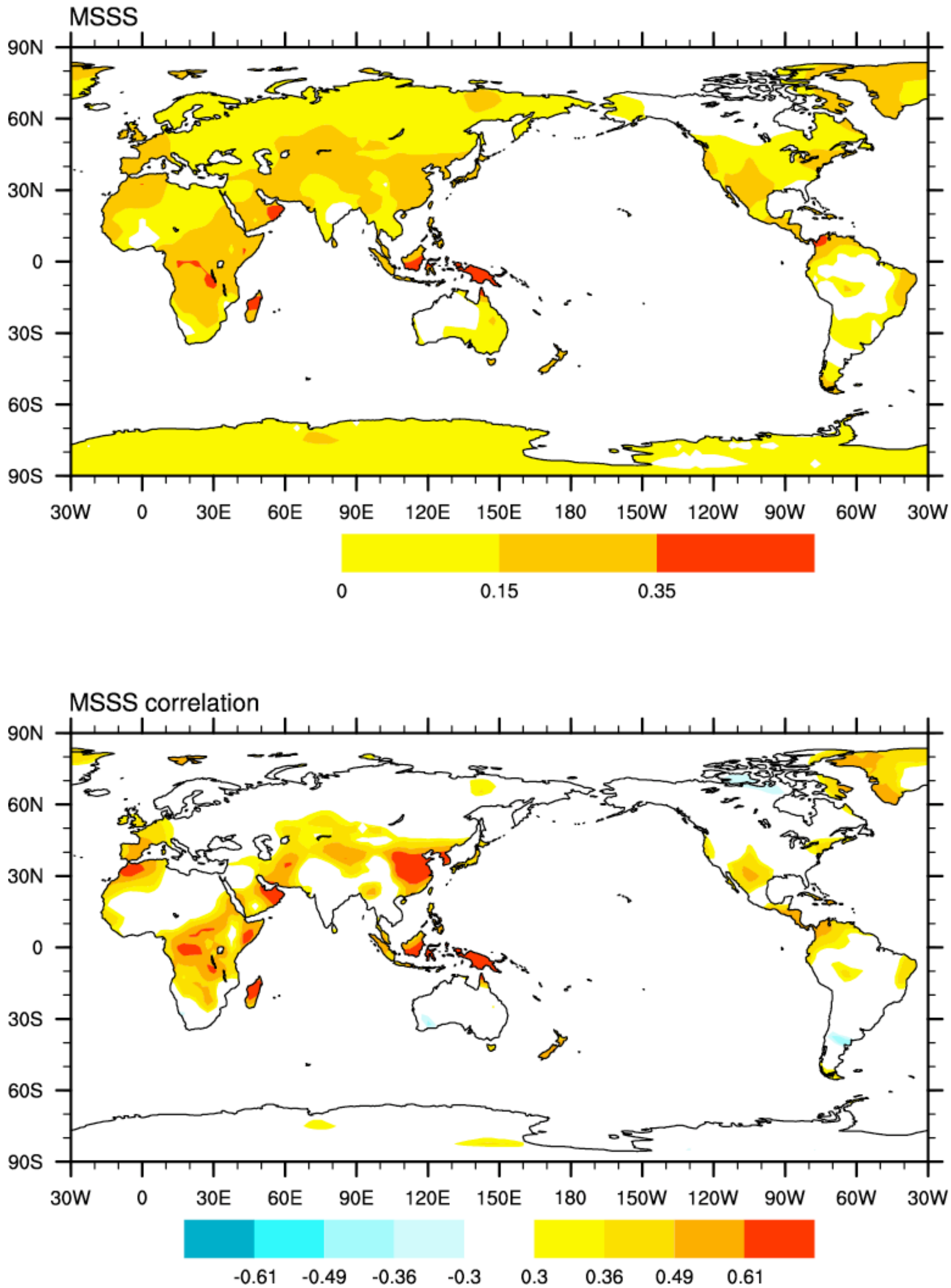

Temperature for January-March 2009
Unit:%
90N
60N
30N
0
30S
60S
90S
30W 0 30E 60E 90E 120E 150E 180 150W 120W 90W 60W 30W
Probability fields are displayed
Air temperature at 850hPa
Below
Normal
Above
80 70 60 50 40 -0 40 50 60 70 80 0 40 50 60 70 80
© APEC Climate Center

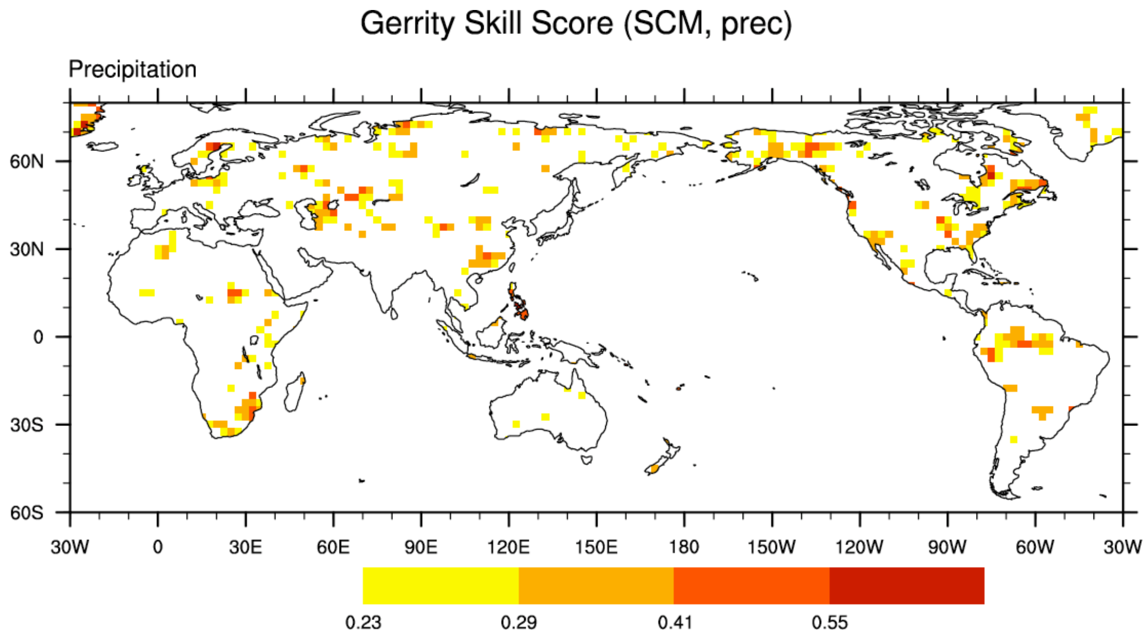

Temperature for January-March 2009
Unit:deg K
90N
60N
30N
0
30S
60S
90S
30W 0 30E 60E 90E 120E 150E 180 150W 120W 90W 60W 30W
Anomaly fields are displayed
Air temperature at 850hPa
-1 -0.8 -0.6 -0.4 -0.2 0 0.2 0.4 0.6 0.8 1
© APEC Climate Center

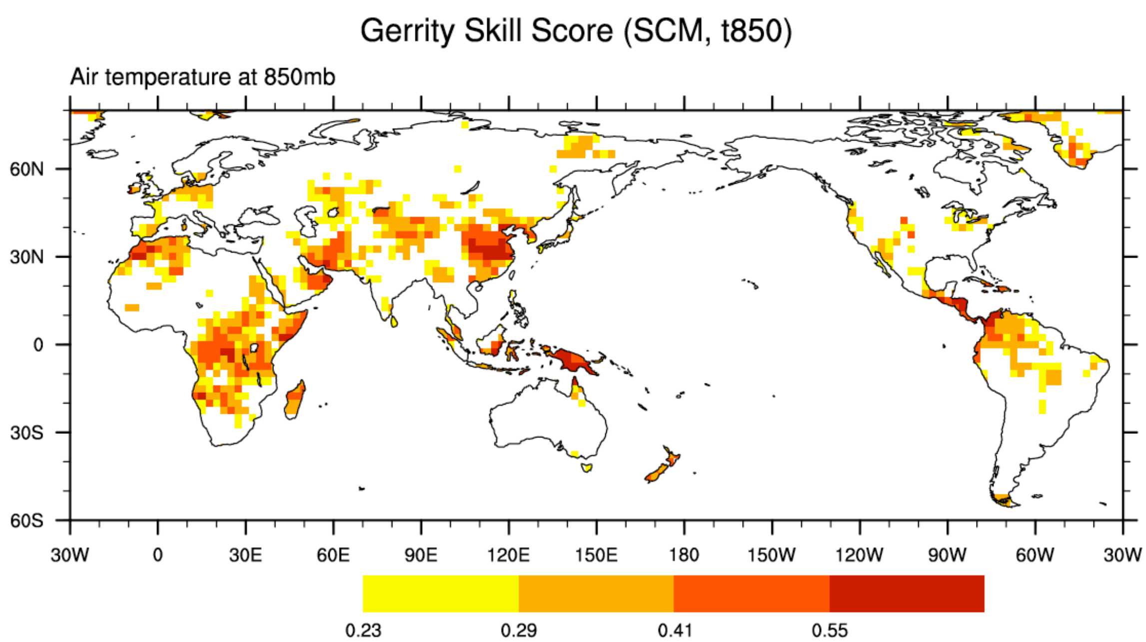
Hindcast Verifivation Summary

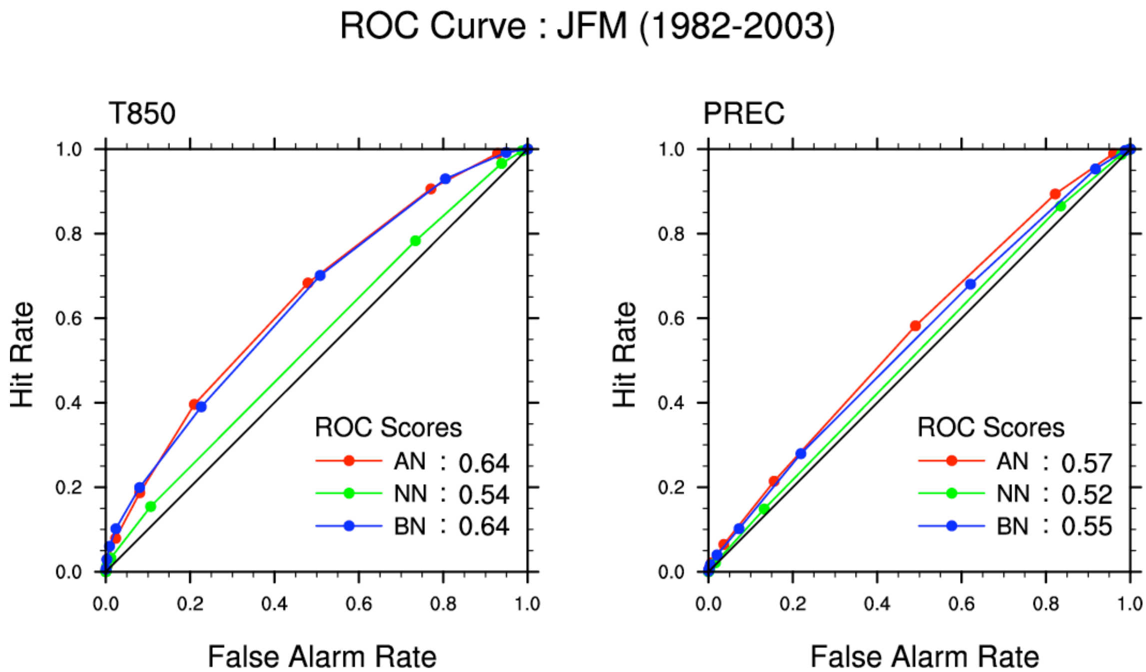


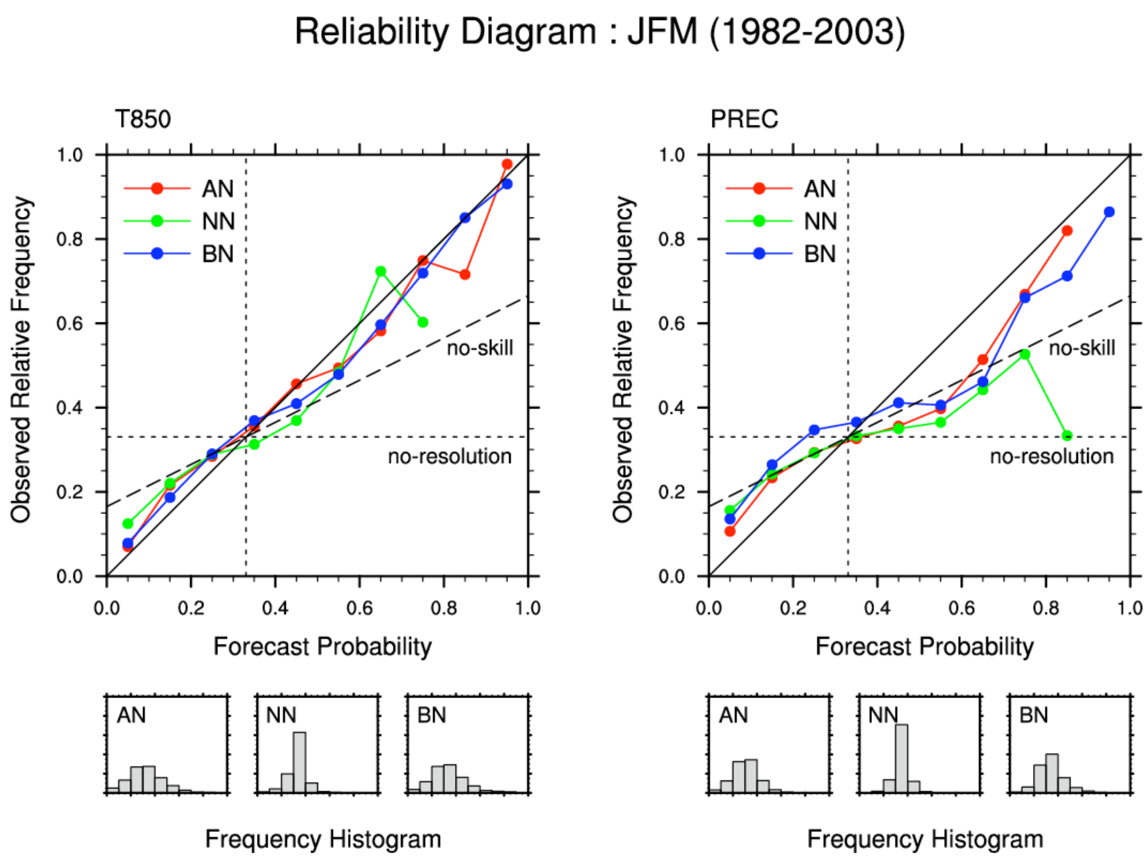
MME, t850, 1982-2003, JFM




Gerrity Skill Score (SCM, prec)
Precipitation
60N
30N
0
30S
60S
30W
0
30E
60E
90E
120E
150E
180
150W
120W
90W
60W
30W
0.23
0.29
0.41
0.55


Gerrity Skill Score (SCM, t850)
Air temperature at 850mb
60N
30N
0
30S
60S
30W
0
30E
60E
90E
120E
150E
180
150W
120W
90W
60W
30W
0.23
0.29
0.41
0.55


ROC Curve : JFM (1982-2003)
T850
PREC
Hit Rate
False Alarm Rate
ROC Scores
AN : 0.64
NN : 0.54
BN : 0.64
AN : 0.57
NN : 0.52
BN : 0.55


Reliability Diagram : JFM (1982-2003)
T850
PREC
Observed Relative Frequency
Forecast Probability
AN
NN
BN
no-skill
no-resolution
Frequency Histogram

APPENDIX-II

Drought Monitoring and Prediction

The impacts of drought are associated with the costs and losses in areas of economic, social, or environmental areas directly or indirectly. Drought monitoring is essential to develop a good prediction system, mitigate losses caused by drought and to set up preparedness strategies. Starting from 2008, global drought was monitored experimentally, and the product be provided to the public in 2009. Also experimental drought prediction based on MME is provided.

The APCC Global Drought Monitoring (http://www.apcc21.net/climate/climate03_11.php) is based on the Standardized Precipitation Index (SPI; McKee et al. 1993) maps for the last 1-month, 3-month, 6-month and 12-month periods using monthly precipitation at 2.5°x2.5° resolution. SPI between -1.0 to -1.49 indicates moderate drought, -1.5 to -2.0 severe drought, and less than -2.0 extreme drought conditions. The SPI is estimated by transforming the observed rainfall distribution for the recent 30 yrs, usually fitted to a Gamma distribution, into a standardized normal distribution on an equal probability basis. For global drought prediction, we use normalized MME forecast anomaly with global precipitation climatology (CAMS_OPI).

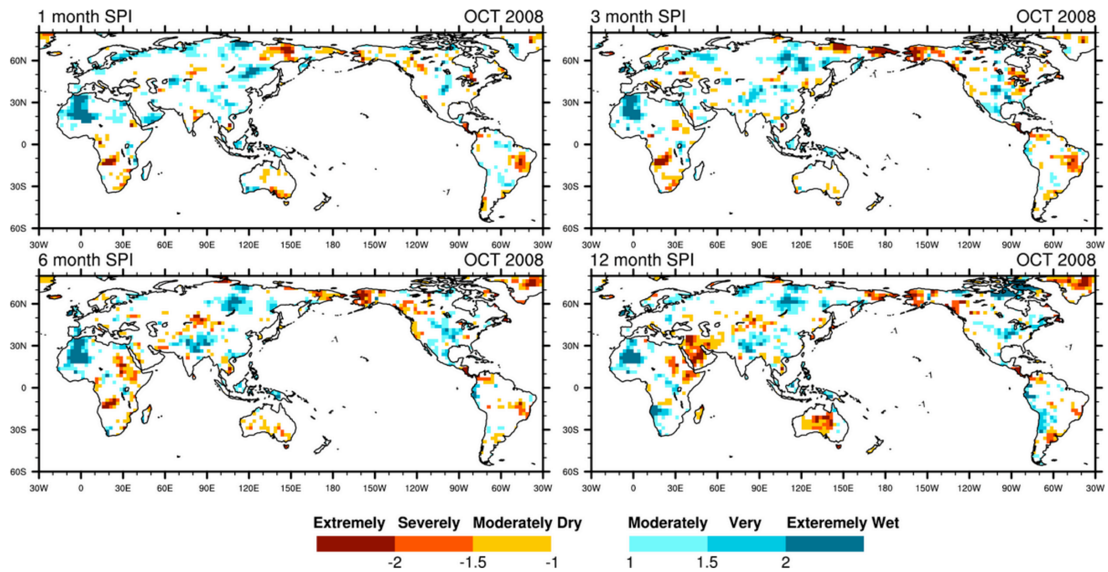


Figure. A. 1 Standardized Precipitation Index maps for the last 1-month, 3-month, 6-month and 12-month periods on October 2008.

APPENDIX III. Multi-Model Ensemble Methodologies

3.1 Simple Composite Method (SCM)

Multi-model ensemble (MME) technology has been considered as one of efficient solution to improve the weather and climate forecasts. The basic idea of MME is to avoid model inherent error by using a number of independent and skilful models in the hope of a better coverage of the whole possible climate phase spaces. SCM is a deterministic forecast scheme as a simple arithmetic mean of predictions based on individual member models. In SCM, there is an assumption that each model is relatively independent and to some extent, it has the capability to forecast the regional climate well, therefore we can expect a well model forecast by simple composite of each model prediction from different models. This scheme keeps the model dynamics due to the simple spatial filtering for each variable at each grid point. In addition, this simple scheme contains the common advantage and limitation of the model predictions, therefore, it could be a good benchmark used to evaluate other MME schemes.

SCM forecast constructed with bias-corrected data is given by

$$S_t = \overline{O} + \frac{1}{N}\sum_{i=1}^{N}(F_{i,t} - \overline{F_i}) \qquad (3.1.1)$$

where, $F_{i,t}$ is the i^{th} model forecast at time t, $\overline{F_i}$ and $\overline{O}$ is the climatology of the i^{th} forecast and observation, respectively, and N is the number of forecast models involved. Therefore, the SCM results are generated by the combination of bias-corrected model forecast anomalies. Skill improvements result from the bias removal and from the reduction of the climate noise by ensemble averaging. In this scheme, the ensemble mean assigns the same weight of *1/N* to each of the *N* member models in anywhere regardless of their relative performance.

3.2 Stepwise Pattern Projection Method (SPM)

The new MME method (MME-SPPM) is based on the statistical downscaling method, which is named the stepwise pattern projection model (SPPM). The SPPM technique is an improved version of the current APCC MME method, CPPM. The major differences between the two techniques lie in the procedure for pre-predictor selection and the optimal choice of posterior prediction. It is shown that MME-SPPM offers better skill over the regions in which the average of individual model skill is poor.

The SPPM procedure consists of three steps: pre-predictor selection, pattern projection, and optimal choice of prediction. In the first step, qualified predictors are selected based on cross-validated correlation for the training period. The predictor field is reconstructed by using the selected 100 predictors at different grids which are best correlated with the predictand. In the second step, the covariance pattern is constructed between observed and reconstructed predicted pattern and then prediction is obtained by projecting predicted pattern on the covariance pattern using the following equation:

$$X_P(t) = \sigma_Y \sum_i \frac{COV(i) \bullet X(i,t)}{\sigma_X^2(i)} \qquad (3.2.1)$$

where is the new predicted predictand at time t, is the observed standard deviation of predictand, is the covariance pattern between observed predictand and reconstructed predictor field, is the predictor at grid i and time t, and is the variance of the predictor at grid i. In the final step, we determine whether or not the selected predictand is predictable at each grid point using double cross-validation with a given threshold correlation skill, say 0.3. The threshold value of correlation skill is subjectively chosen here. Thus, the rigorous test will be needed to determine the value for optimal prediction. If the prediction skill of double cross validation with the selected predictor pattern does fall below the threshold value, we consider the predictand is not predictable and then give up that predictor and prediction at that grid point. To make a final MME prediction, we apply a simple multi-model composite using available prediction after applying SPPM to individual models. We performed sensitivity study in order to determine optimal parameters of SPPM package based on independent forecast experiment. We also developed the method to produce improved multi-model probabilistic forecast after applying SPPM to each model.

3.3 Multiple Regression (MRG)

The conventional multi-model superensemble forecast (Krishnamurti et al., 2000b) constructed with bias-corrected data is given by

$$S_t = \overline{O} + \sum_{i=1}^{n} a_i (F_{i,t} - \overline{F}_i) \qquad (3.3.1)$$

Where, $F_{i,t}$ is the i^{th} model forecast for time t, $\overline{F}_i$ is the appropriate monthly mean of the i^{th} forecast over the training period, $\overline{O}$ is the observed monthly mean over the training period, a_i are regression coefficients obtained by a minimization procedure during the training period, and n is the number of forecast models involved. The multi-model superensemble forecast in equation (3.3.1) is not directly influenced by the systematic errors of forecast models involved because the anomalies term $(F_{i,t} - \overline{F}_i)$ in the equation accounts for each model's own seasonal climatology.

At each grid point for each model of the multi-model superensemble the respective weights are generated using pointwise multiple regression technique based on the training period.

For obtaining the weights, the covariance matrix is built with the seasonal cycle-removed anomaly (F'),

$$C_{i,j} = \sum_{t=0}^{Train} F'_{i,t} F'_{j,t} \,, \qquad (3.3.2)$$

Where Train denote the training period, and i and j the ith and jth forecast models, respectively.

The goal of regression is to express a set of data as a linear function of input data. For this, we construct a set of linear algebraic equations,

$C \cdot x = \tilde{o}'$, (3.3.3)

Where $\tilde{o}_j' = \sum_{t=0}^{Train} O_t' F_{j,t}'$ is a (n x 1) vector containing the covariances of the observations with the individual models for which we want to find a linear regression formula, and o' is seasonal mean-removed observation anomaly, C is the (n x n) covariance matrix, and x is an (n x 1) vector of regression coefficients (the unknowns). In the convectional superensemble approach, the regression coefficients are obtained using Gauss-Jordan elimination with pivoting. The covariance matrix C and o' are rearranged into a diagonal matrix C' and o'' , and the solution vector is obtained as

$$x^T = \left(\frac{\tilde{o}_1''}{C_{11}'}, \ldots, \frac{\tilde{o}_n''}{C_{nn}'} \right), \qquad (3.3.4)$$

where, the superscript T denotes the transpose.

The Gauss-Jordan elimination method for obtaining the regression coefficients between different model forecasts is not numerically robust. Problems arise if a zero pivot element is encountered on the diagonal, because the solution procedure involves division by the diagonal elements. Note that if there are fewer equations than unknowns, the regression equation defines an underdetermined system such that there are more regression coefficients than the number of $\{o_j'\}$. In such a situation, there is no unique solution and the covariance matrix is said to be singular. In general, use of the Gauss-Jordan elimination method for solving the regression problem is not recommendable since singularity problem like the above are occasionally encountered. In practice, when a singularity is detected, the superensemble forecast is replaced by an ensemble forecast.
SVD is applied to the computation of the regression coefficients for a set of different model forecasts. The SVD of the covariance matrix C is its decomposition into a product of three different matrices. The covariance matrix C can be rewritten as a sum of outer products of columns of a matrix U and rows of a transposed matrix V^T, represented as

$$C_{i,j} = \left(UWV^T\right)_{i,j} = \sum_{k=1}^{n} w_k U_{ik} V_{jk} , \qquad (3.3.5)$$

Here U and V are (n x n) matrices that obey the orthogonality relations and W is an (n x n) diagonal matrix, which contains rank k real positive singular values(w_k) arranged in decreasing magnitude. Because the covariance matrix C is a square symmetric matrix, $C^T = VWU^T = UWT^T = C$. This proves that the left and right singular vector U and V are equal. Therefore, the method used can also be called principal component analysis(PCA). The decomposition can be used to obtain the regression coefficients:

$$x = V \cdot \left[diag\left(\frac{1}{w_j} \right) \right] \cdot (U^T \cdot \tilde{Q}') \tag{3.3.6}$$

The pointwise regression model using the SVD method removes the singular matrix problem that cannot be entirely solved with the Gauss–Jordan elimination method.

Moreover, solving Eq. (3.3.6) with zeroing of the small singular values gives better regression coefficients than the SVD solution where the small values w_j are left as nonzero. If the small w_j values are retained as nonzero, it usually makes the residual | C · x 2 $\tilde{o}$ | larger (Press et al. 1992). This means that if we have a situation where most of the w_j singular values of a matrix C are small, then C will be better approximated by only a few large w_j singular values in the sum of Eq. (3.3.5).

3.4 Synthetic Super Ensemble (SSE)

Despite the continuous improvement of both dynamical and empirical models, the predictive skill of extended forecasts remains quite low. Multi-model ensemble predictions rely on statistical relationships established from an analysis of past observations (Chang et al., 2000). This means that the multi-model ensemble prediction depends strongly on the past performance of individual member models.

In the context of seasonal climate forecasts, many studies (Krishnamurti et al., 1999, 2000a,b, 2001, 2003; Doblas-Reyes et al., 2000; Pavan and Doblas-Reyes 2000;

Stephenson and Doblas-Reyes 2000; Kharin and Zwiers 2002; Peng et al., 2002; Stefanova and Krishnamurti, 2002; Yun et al., 2003; Palmer et al., 2004) have discussed various multi-model approaches for forecasting of anomalies, such as the ensemble mean, the unbiased ensemble mean and the superensemble forecast. These are defined as follows:

$$E_b = \frac{1}{N}\sum_{i=1}^{N}(F_i - \overline{O})$$

$$E_c = \frac{1}{N}\sum_{i=1}^{N}(F_i - \overline{F_i}) \qquad (3.4.1)$$

$$S = \sum_{i=1}^{N} a_i (F_i - \overline{F_i})$$

Here, E_b is the ensemble mean, E_c is the unbiased ensemble mean, S is the superensemble, F_i is the *i*th model forecast out of *N* models, $\overline{F_i}$ is the monthly or seasonal mean of the *i*th forecast over the training period, $\overline{O}$ is the observed monthly or seasonal mean over the training period, and a_i is the regression coefficient of the *i*th model. The difference between these approaches comes from the mean bias and the weights. Both the unbiased ensemble mean and the superensemble contain no mean bias because the seasonal climatologies of the models have been considered. The difference between the unbiased ensemble and the superensemble comes from the differential weighting of the models in the latter case. A major aspect of the superensemble forecast is the training of the forecast data set. The superensemble prediction skill during the forecast phase could be improved when the input multi-model predictions are statistically corrected to reduce the model errors.

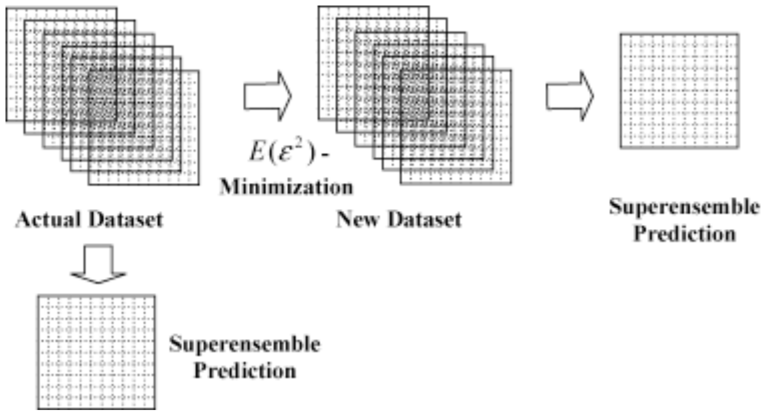


Fig. 3.4.1 Schematic chart for the proposed superensemble prediction system. The new data set is generated from the original data set by minimizing the residual error variance $E(\varepsilon^2)$ for each model

Figure 3.4.1 is a schematic chart illustrating the proposed algorithm. The new data set is generated from the original data set by finding a consistent spatial pattern between the observed analysis and each model. This procedure is a linear regression problem in EOF space. The newly generated set of EOF-filtered data is then used as an input multi-model data set for ensemble/superensemble forecast. The computational procedure for generating the new data set is described below.

The observation data (O) and the multi-model forecast data set (F_i) can be written as linear combinations of EOFs, which describe the spatial and temporal variability:

$$O(x,t) = \sum_n \widetilde{O}_n(t)\phi_n(x) \qquad (3.4.2)$$

$$F_i(x,T) = \sum_n \widetilde{F}_{i,n}(T)\varphi_{i,n}(x) \qquad (3.4.3)$$

Here, $\widetilde{O}_n(t)$, $\widetilde{F}_{i,n}(t)$ and $\phi_n(x)$, $\varphi_{i,n}(x)$ are the principal component (PC) time series and the corresponding EOFs of the nth mode for the observation and model forecast, respectively. Index *I* indicates a particular member model. The PCs in eqs. (3.4.2) and (3.4.3) represent the time evolution of spatial patterns during the training period (*t*) and the whole forecast time period (*t*). We can now estimate a consistent pattern between the observation and the forecast data, which evolves according to the PC time series of the training observations. The regression relationship between the observation PC time series and the number of PC time series of individual model forecast data can be written as

$$\widetilde{O}(t) = \sum_{n} \alpha_{i,n} \widetilde{F}_{i,n}(t) + \varepsilon_{i,n}(t) . \qquad (3.4.4)$$

With eq. (3.4.4) we can express the observation time series as a linear combination of the predictor time series. To obtain the regression coefficients $\alpha_{i,n}$ the regression is performed in the EOF domain. The regression coefficients $\alpha_{i,n}$ are found such that the residual error is minimized. The covariance matrix is constructed with the PC time series of each model. For obtaining the regression coefficients $\alpha_{i,n}$, the covariance matrix is built with the seasonal cycle-removed anomaly. Once the regression coefficients $\alpha_{i,n}$ are found, the PC time series of new data set is written as

$$\widetilde{F}_{i}^{reg}(T) = \sum_{n} \alpha_{i,n} \widetilde{F}_{i,n}(T) \qquad (3.4.5)$$

The new data set is now generated by reconstruction with corresponding EOFs and PCs:

$$\widetilde{F}_{i}^{syn}(x,T) = \sum_{n} \widetilde{F}_{i,n}^{reg}(T) \phi_{n}(x) . \qquad (3.4.6)$$

This EOF-filtered data set generated from the DEMETER coupled multi-model is used as an input data set for both multi-model ensemble and superensemble prediction systems that produce deterministic forecasts. What is unique about the new data set is that it minimizes the variance of the residual error between the observations and each of the member models. The residual error variance is minimized using a least-squares error approach.

3. 5 Probabilistic Multi-Model Ensemble (PMME)

Probabilistic forecast are categorized as below-, near-, and above-normal based on predictions obtained from each member model. Each member model predictions are available with different number of ensemble members. Three equiprobable categories are classified by using normal (Gaussian) fitting method. The three categories for each member model are defined from climatological chance of occurrence for each category is 33.3% for the hindcast period. For each category, the forecast probability is obtained by counting the number of individual members that prediction a seasonal mean in that category, and combining on the basis of full probability formula with the weight according to square root of ensemble size for each model. The more detail methodology is as following.

Gaussian approximation is underlain by the assumption that the variable is theoretically normally distributed, $T \sim N(\mu, \sigma)$ and all deviations from the Normal distribution are occasional due to the small sample size. This approach is not new, it is rather traditional and has been used in numerous studies in the past (Leith, 1973; Madden, 1976; Zwiers, 1996; Kharin and Zwiers, 2001; Kharin and Zwiers, 2003, and many others).

We use hindcast data for estimation of the tercile boundaries (x_b and x_a) and forecast data for estimation of the probabilities associated with each of the tercile. Within this approach, we assume that probability distribution functions of both hindcast and forecast are Gaussian PDFs.

We approximate probability distribution of the hindcast data with the normal one with parameters μ and σ estimated based on the hindcast sample (ensemble). The two boundaries to determine three equiprobable categories are defined as $x_b = \mu - 0.43\sigma$ and $x_a = \mu + 0.43\sigma$. Forecast data probability distribution is also approximated with normal one with parameters μ and σ estimated based on the forecast sample (ensemble). Probabilities of the terciles are estimated as,

$$P_x(B) = \Pr ob[x \le x_b] = \int_{-\infty}^{x_b} f(x)dx \qquad (3.5.1)$$

$$P_x(N) = \Pr ob[x_a < x \le x_b] = \int_{-\infty}^{x_a} f(x)dx - P_x(B) \qquad (3.5.2)$$

$$P_x(A) = \Pr ob[x_a < x] = 1 - P_x(B) - P_x(N) \qquad (3.5.3)$$

where $f(x)$ is Gaussian probability distribution function:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp(-\frac{(x-\mu)^2}{2\sigma^2}) \qquad (3.5.4)$$

and μ and σ are the mean and standard deviation of the forecast data (ensemble).

Figure 3. 2 illustrates the probabilities of observing X in one of the three equiprobable categories condition. The lower and upper threshold are defined by 33.3% and 66.7% cumulative quantiles, respectively, of a probability density function (PDF) fitting to climatological PDF.

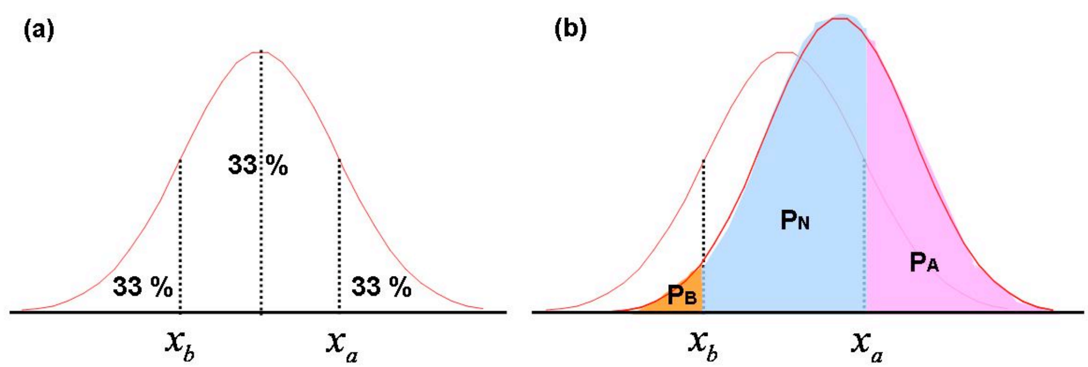


Figure 3.5.1 (a). Definition of the tercile borderlines using the climatological PDF. (b). Forecast probabilities of below-normal (P_B), near-normal (P_N), and above-normal (P_A).

For each grid point, in order to merge three category probabilistic forecasts (above-normal, near-normal, and below-normal) the chi-square (χ^2) test is applied. We estimate statistic

$$\chi^{2}* = \sum_{i=1}^{3} (O_i - E_i)^2 / E_i \ , \qquad (3.5.5)$$

where O is observed frequency and E is expected frequency equal to one third of ensemble size. Under the Null hypothesis (uniform probability distribution – forecast is uncertain) this statistic has χ^2 probability distribution. We set significance level at 0.05 and treat forecast certain and associated with maximal probability out of three categories if Null hypothesis is rejected.