Multi-Model Ensemble Climate Prediction with CCSM and CFS

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Objectives

The four objectives of this study are all related to expanding multi-model seasonal prediction capabilities. First, we document the ENSO predictive capability of the NCAR CCSM3.0 and more recently CCSM3.5. This model is a natural candidate for inclusion in the U.S. operational multi-model prediction strategy (Higgins, personal communication 2006). Second, we document how CCSM3.0 (and CCSM3.5) can be combined with the current operational CFS to produce intraseasonal to interannual forecasts that are superior to either model alone. Third, we demonstrate how an ocean initial state using a particular ocean component (i.e., the Geophysical Fluid Dynamics Laboratory Modular Ocean Model; MOM) can be used in a coupled system that uses a different ocean component model (i.e., the Parallel Ocean Program; POP). This demonstration has the potential to simplify and broaden the multi-model prediction strategy, because institutions that do not have an independent ocean data assimilation system can more easily participate in prediction research. Fourth, we seek to show how an improved land initialization strategy impacts the forecast skill. Kirtman and Min (2009) describe in detail the results from the first three objectives in terms of SST predictions in the eastern Pacific. Paolino et al. present results showing impact of land surface initialization.

Results and Accomplishments

<u>ENSO Forecast Skill CCSM3.0 vs. CCSM3.5</u>

Figure 1 shows a specific example from forecasts initialized in January 1982. The plot shows Time–longitude equatorial Pacific SSTA cross sections for each CCSM3.0 and CCSM3.5. The first two columns correspond to the CCSM3.0 forecasts with (a) the observational estimate and (b) the ensemble mean. (c)–(h) Various CCSM3 forecast are denoted. Similarly, the last two columns [also labeled (a)–(h)] correspond to the CCSM3.5 forecast with (a) the observational estimate and (b) the ensemble mean. (c)–(h) The various CCSM3 forecasts are denoted. This particular case is an excellent example of how the improvement made to CCSM3.5 impact the systematic behavior of the forecasts. For example, typically CCSM3.0 predicts that the SSTA develops too early compared with observations and extend too far into the western Pacific. Both of these problems are significantly reduced with the CCSM3.5 forecasts.

Figure 2 shows the correlation coefficient for all retrospective forecasts initialized January 1982-1999 for CCSM3.0, CCSM3.5, CFS and the multi-model combination of all three models. For show lead time all three models indicate similar correlation with the observations, at longer leads the CCSM3.0 forecast are better correlated with the observations. More detailed statistical analysis indicates that multi-model forecast is statistically indistinguishable from the best model while which model is best model appears to be a function of lead time and initial month. Moreover, the multimodel forecast does appear to produce correlations that are significantly higher than the worst model, which again is a function of lead time and initial month. It is this fact that leads us to the conclusion that the multimodel improves the ‘‘overall’’ forecast skill and emphasizes how the multimodel ensemble can conceptually be thought of as smoothing out the vagaries in skill associated with individual model differences. Figures 3 and 4 show maps of anomaly correlation as a function of lead time.

Impact of Land Surface Initialization

The land surface initial conditions are initialized as follows: soil moisture and soil temperature are derived from the Second Global Soil Wetness Project (GSWP-2) daily data. GSWP-2 reports only soil wetness, so the initial soil moisture for a particular layer and column is considered to be either all liquid or all ice, depending on the corresponding soil temperature at that point. Profile data for different column types are restricted in the same manner as in the Common Land Model (CLM), which is the land surface component of the CCSM. We first compute the normalized anomalies of the GSWP-2 soil moisture from a 10-year climatology, and then combine those anomalies with the mean statistics from a 30-year CLM run, after a 100-year spin-up.

The GSWP-2 soil data are reported for six layers, from top to bottom, with depths of 10, 20, 20, 20, 30, and 50 cm, for a total depth of 1.5 m. The CLM soil column consists of 10 layers, and is 3.4 meters deep, with the bottom two layers spanning 2.0 meters. The initial soil data are created by imposing the GSWP-2 anomaly for the layer containing the depth of the CLM layer on the CLM climatology. Where the CLM layer overlaps two GSWP-2 layers, weighted anomalies are used. The bottom CLM layer is set to model climatology, and layer nine is relaxed to climatology. Initial soil data south of 60°S are set equal to the model climatology.

Initial values for the CLM vegetation variables are taken from a seven-day CAM only spin-up forecast, using the same atmospheric initialization as used in the fully coupled forecast. Initial snow depth and snow temperature are taken from daily values of the ERA-40 reanalysis. We have used the same formulation as the CLM in assigning initial snow depth for up to five snow layers. Snow is assigned to each column type according to the proper CLM formulation. Snow water equivalent is computed using the CLM formulation, after computing snow density from a mean of the ERA-40 skin temperature and 2 meter temperature.

In comparison with a previous set of forecast experiments which had initialized only the observed ocean state, there is firm evidence that we produce a much better representation of the interannual variability of the soil surface. The seasonal forecast of soil moisture is far superior, due in part to the ability of the CCSM3.0 to persist large-scale anomalies present in the initial soil state. The superior land surface forecast leads to a superior seasonal forecast of surface temperature. There is little evidence of an improved forecast of precipitation over land; although there is a suggestion of an improvement in the forecast over ocean. The improvement in the 2m surface temperature is shown in Fig. 5 and described in more detail in Paolino et al. (2010).

Intraseaonal Reforecasts

The focus of this part of the project is to assess the skill of a multi-model ensemble for *intraseasonal* prediction. In this phase of the project, the NCEP/Climate Forecast System (CFS) re-forecast experiments are used together with re-forecast experiments performed by the CO-Is (B. Kirtman and D. Paolino) using the NCAR/Community Climate System Model version 3.5 (CCSM3.5). The skill of the individual model forecasts and a multi-model ensemble forecast, formed by combing the two models, is assessed for a commonly used index of the Madden-Julian Oscillation (MJO).

The CCSM3.5 intraseasonal re-forecast experiments were initialized from 21-30 April, and 22-31 October for the years 1981-1999 and run for 1-year. The CFS re-forecast experiments (Saha et al. 2005) were initialized on the 1-3, 9-13, 19-23, and last two days of each month for the years 1981-2005 and run for 9-months. The overlapping years and initial dates between the two sets of re-forecasts are used to assess the skill in forecasting the MJO index. There are nine overlapping initial dates (Apr 21, 22, 29, 30; Oct 22, 23, 30, 31) over 19 overlapping years (1981-1999).

The real-time multivariate MJO index (RMM) of Wheeler and Hendon (2004) is the metric for the MJO that has been adopted by the Clivar MJO Working Group and is being used for their multi-model ensemble prediction efforts (Gottshalck 2008). The RMM index is determined from a combined empirical orthogonal function (CEOF) analysis of equatorially averaged zonal winds (200 hPa and 850 hPa) and outgoing longwave radiation (OLR). The index consists of the first two principal component time series of the combined EOFs and are in quadrature, describing an oscillation (Figure 6, top panels). The model fields are projected onto the observed CEOFs to calculate the model forecasted RMM indices. It is noted that for RMM1 > 0 (RMM1 < 0), the convection associated with the MJO is in the Maritime Continent (Western Hemisphere) regions. For RMM2 > 0 (RMM2 < 0), the maximum in convection is located in the Indian Ocean (Western Pacific). This index has been calculated for the CFS and CCSM.

The skill of RMM1 and RMM2 are compared for the individual models and a multi-model ensemble combination of the two. The multi-model ensemble is produced by averaging the RMM values of the two individual models. The average anomaly correlation skill for all of the overlapping cases as a function of lead-time is shown in Figure 6 (left panels) for RMM1 (top) and RMM2 (bottom). The skill of the individual models (CFS in red; CCSM in blue) is shown with the skill of the 2-member multi-model ensemble (black). Clearly, one of the models has significantly better skill than the other. The CFS anomaly correlations fall below 0.5 around day-14 for RMM1 and around day-10 for RMM2, while the CCSM skill is above 0.5 up to about day-25 for RMM1 and day-20 for RMM2. The relatively poor skill by the CFS is likely due to a well-known issue related to the initialization of the CFS re-forecasts (A. Vintzileos, personal communication). It is noted that the two-member MME has similar skill to the CCSM and appears to have slightly better skill at longer lead-times for RMM1.

The skill comparisons described above are not completely fair comparisons since the skill of the individual models is shown for only a single ensemble member, while the MME is shown for two ensemble members. Therefore, all possible combinations of 2-member lagged average ensembles are generated for the overlapping cases. For example, ensembles are made by averaging the individual model forecasts initialized on Apr 21 and 22 for the same verifying calendar dates. For the multi-model ensemble, a lagged ensemble is produced for the case of Apr 21 from the CCSM and Apr 22 from the CFS and also Apr 21 from the CFS and Apr 22 from the CCSM. This is done for all possible combinations of 2-member lagged ensembles from the two models. The average anomaly correlation skill of these ensemble forecasts is shown in Figure 6 (right panels) for RMM1 (top) and RMM2 (bottom). Not surprisingly, the 2-member lagged average ensemble for each of the individual models has better skill than the single-member versions shown in the left panels. With this more realistic comparison, the skill of the multi-model ensemble is generally less skillful than the CCSM with the exception of lead-times greater than 22-days for RMM1. The key point to derive from these results is that the multi-model ensemble is able to provide skillful forecasts despite the fact that one of the models has exceptionally poor skill. Although the less skillful model could have been identified a priori in these cases, this may not always be true.

*Highlight*s

- Intraseasonal skill in CFS and CCSM
- Improvements in land surface temperatures associated with land initialization
- Multi-model forecast skill

Publications

Kirtman, B. P., and D. Min, 2009: Multi-model ensemble ENSO prediction with CCSM and CFS. *Mon. Wea. Rev*., DOI: 10.1175/2009MWR2672.1.

Paolino, P. A., J. L. Kinter, B. P. Kirtman, D. Min and D. Straus, 2010: Impact of land surface initialization on seasonal forecasts with CCSM. (to be submitted).

Future Work
1. Forecast experiments with CCSM4.0 and CFSRR initial conditions.
2. Assess multi-model skill of larger sample of CCSM runs.
3. Assess multi-model skill of intraseaonal temperature and precipitation anomalies associated with the MJO (by projecting onto the RMM index) and 2 and 3-week forecasts of weekly anomalies. This will provide skill assessment in two ways: (a) in terms of the RMM index and (b) in terms of operational forecasts on these timescales (ie weekly forecasts) which must consider a larger set of interactions and phenomenon than just the MJO.

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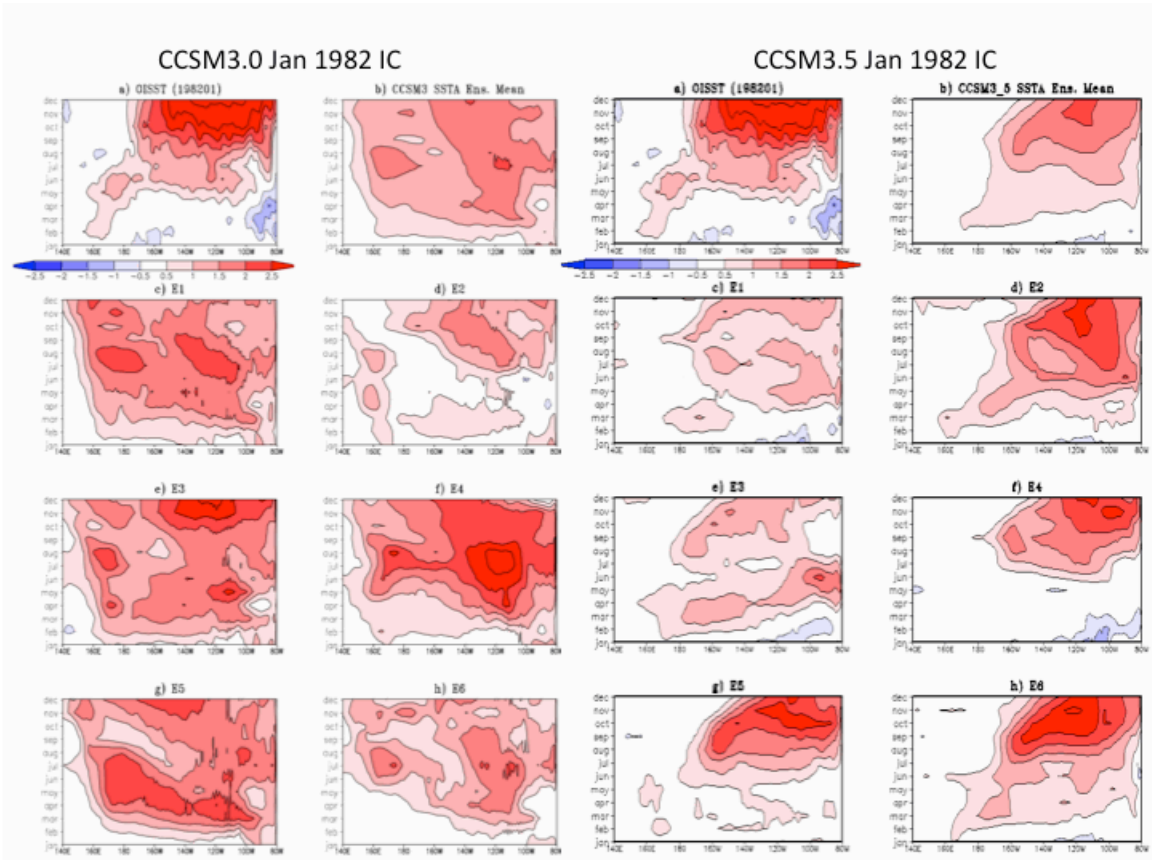

Figure 1: The plot shows Time–longitude equatorial Pacific SSTA cross sections for each CCSM3.0 and CCSM3.5. The first two columns correspond to the CCSM3.0 forecasts with (a) the observational estimate and (b) the ensemble mean. (c)–(h) Various CCSM3 forecast are denoted. Similarly, the last two columns [also labeled (a)–(h)] correspond to the CCSM3.5 forecast with (a) the observational estimate and (b) the ensemble mean. (c)–(h) The various CCSM3 forecasts are denoted. In this case the forecast were initialized in January 1982.

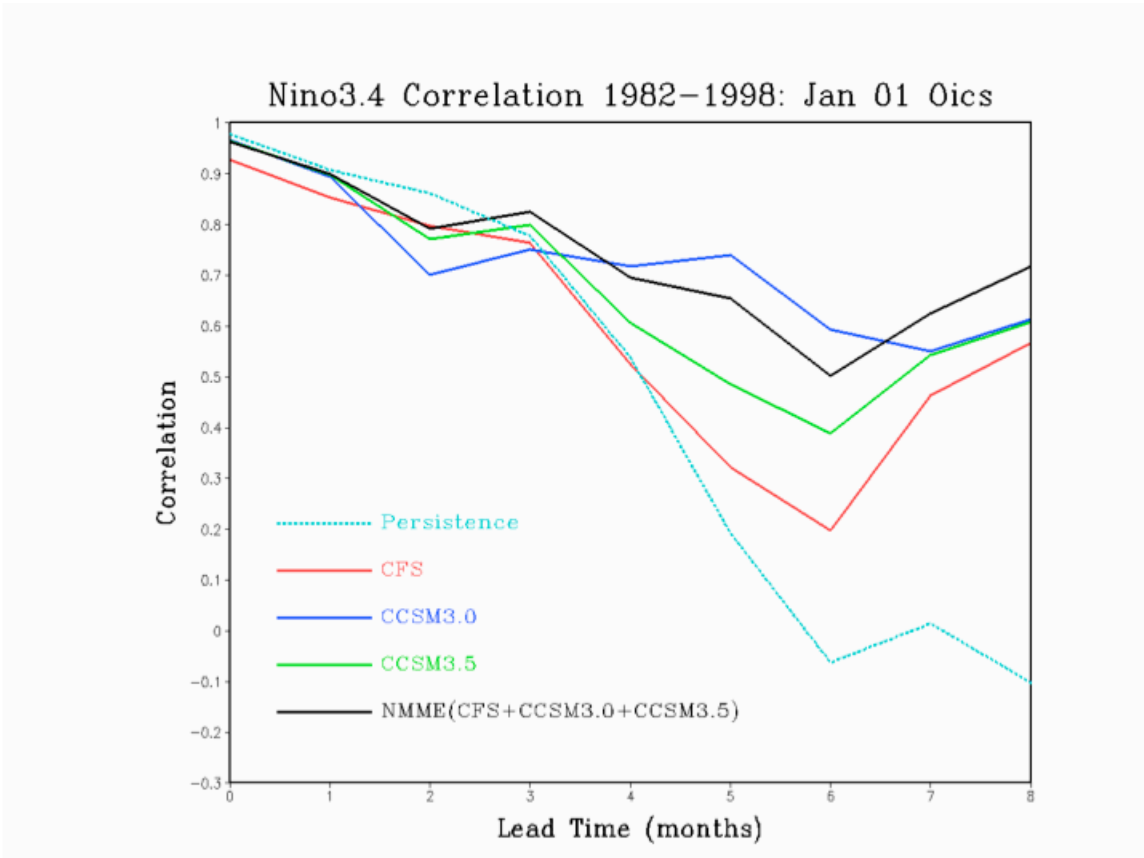

Figure 2: Nino3.4 (top) correlation coefficient for ensemble mean forecasts initialized in January.

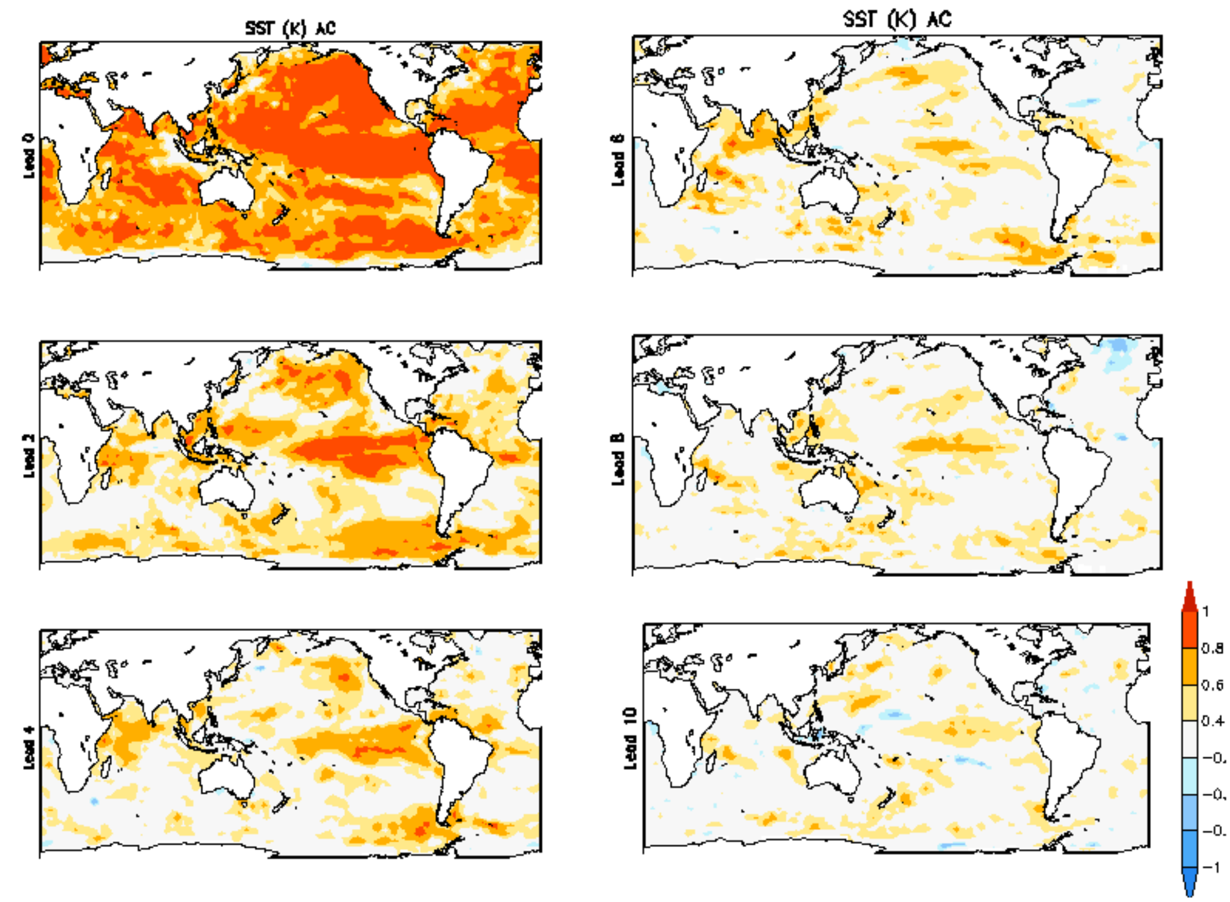

Figure 3: CCSM3.5 SST anomaly correlation as a function of lead-time.

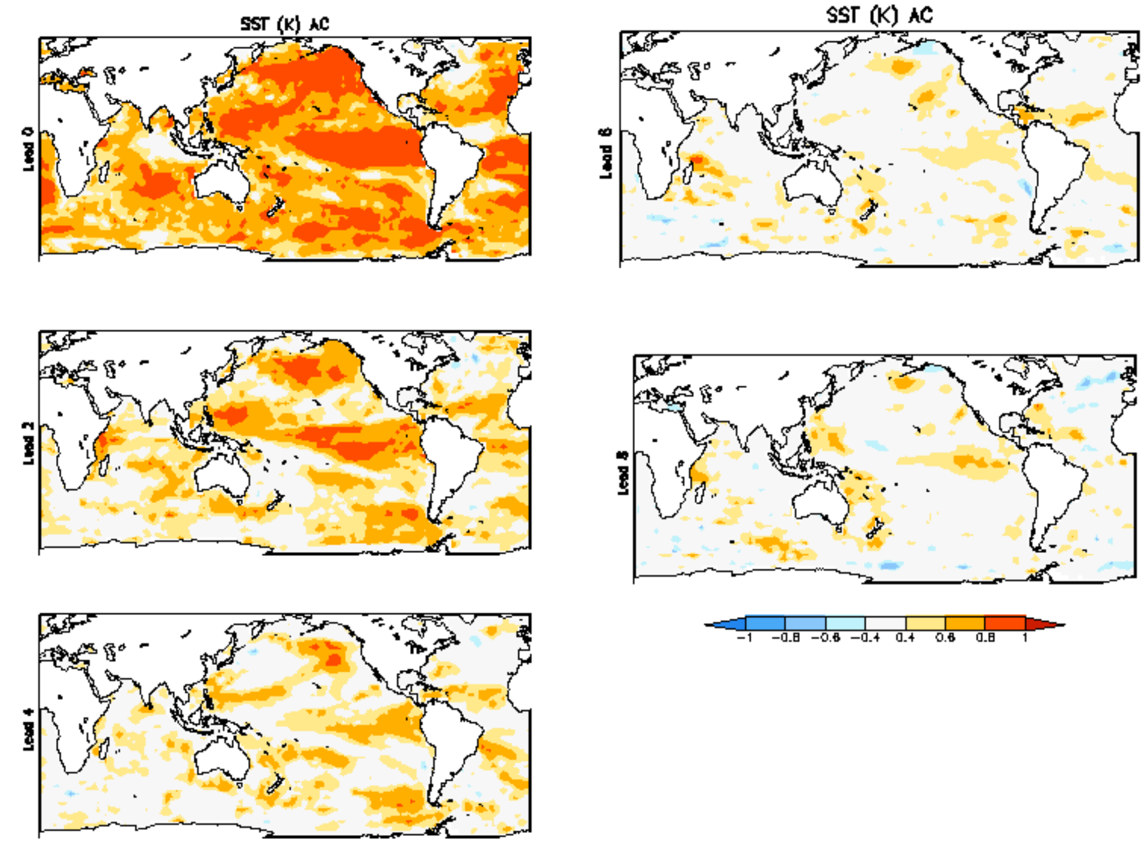

Figure 4: CFS SST anomaly correlation as a function of lead-time.

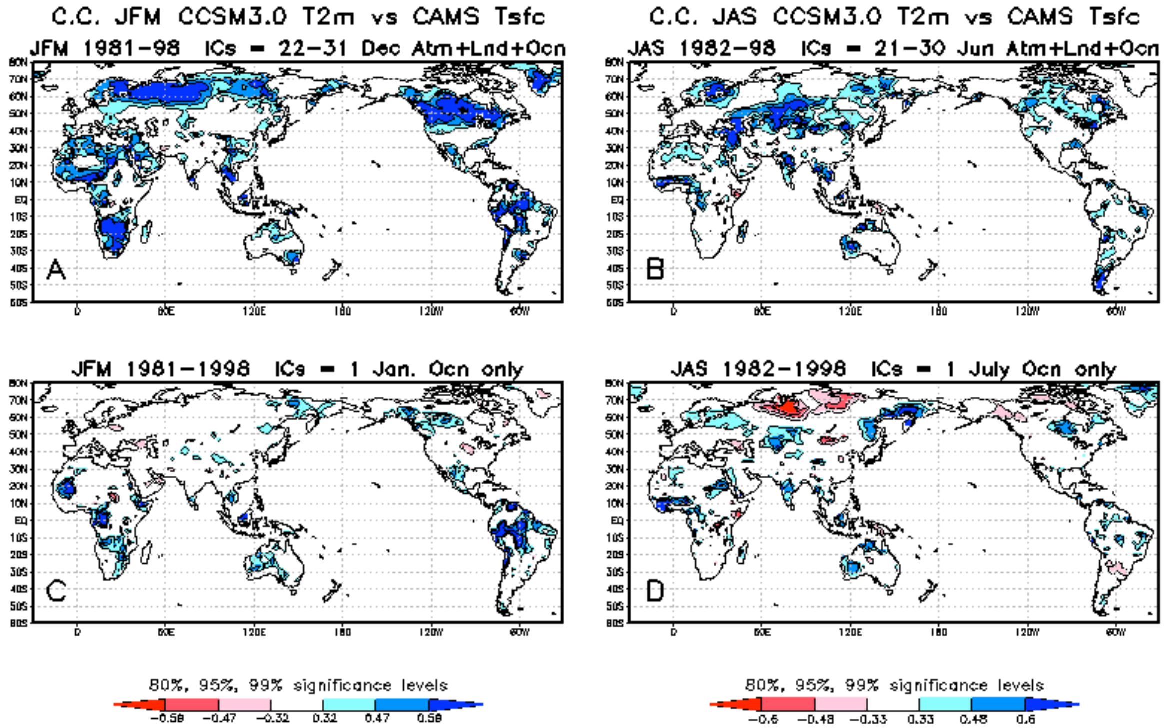

Figure 5: A) Correlation 2-meter temperature for CCSM3.0 *Full* forecast versus CAMS observed surface temperature for JFM 1981-1998. B) As in A), but for JAS 1982-1998. C) Correlation 2-meter temperature for CCSM3.0 *Ocean-only* forecast versus CAMS observed surface temperature for JFM 1981-1998. D) As in C), but for JAS 1982-1998. 80, 95 and 99% significance levels are shaded.

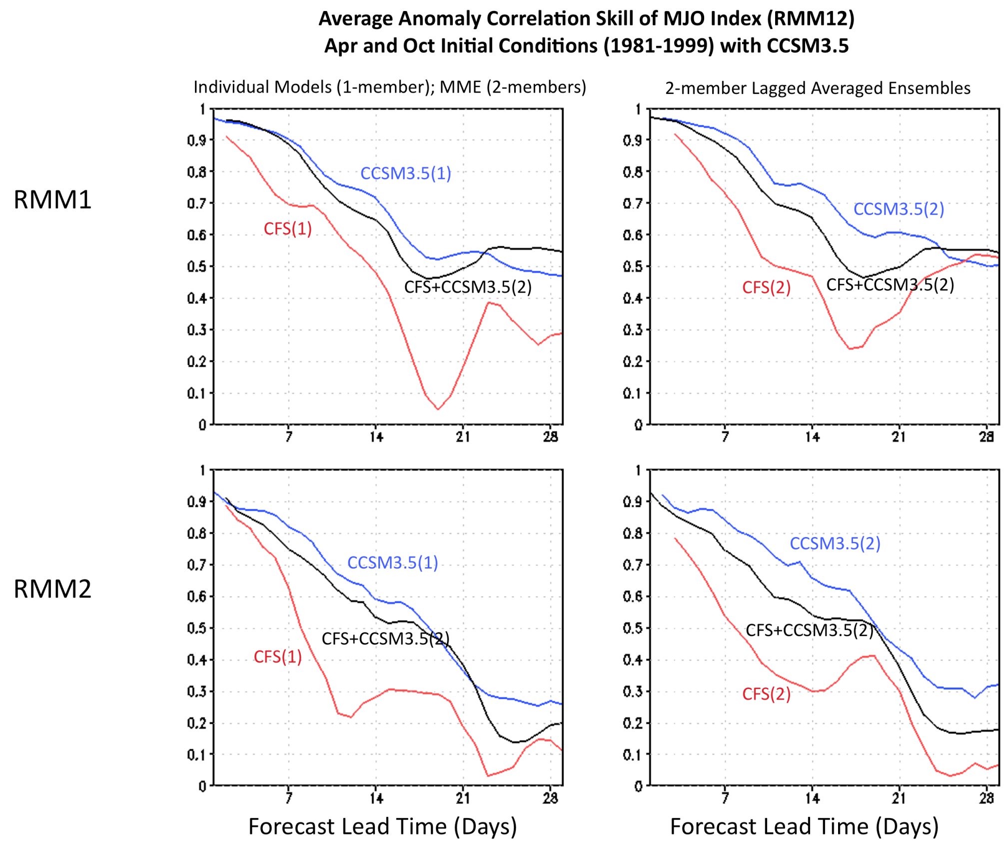

Figure 6 Average anomaly correlation skill of the RMM index (RMM1 top panels; RMM2 bottom panels) as a function of lead time for a set of re-forecast experiments with April and October initial conditions for the years 1981-1999 from the CFS (red), CCSM (blue), and a multi-model ensemble of the CFS+CCSM (black). Left panels show theskill of the individual models with a single ensemble member and the two-member MME. Right panels show the skill of two-member lagged average ensembles for the individual models and the MME.