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Improvement of Grand Multi-model Ensemble Prediction Skills for the Coupled Models of APCC/ENSEMBLES Using a Climate Filter

Doo Young Lee[1, 2], Joong-Bae Ahn[2], Karumuri Ashok[3], and Andrea Alessandri[4]

[1]*APEC Climate Center, Busan, Republic of Korea*

[2]*Department of Atmospheric Sciences, Pusan National University, Busan, Republic of Korea*

[3] *Centre for Climate Change Research, Indian Institute of Tropical Meteorology, Pune, India*

[4]*Italian National Agency for New Technologies,*
Energy and Sustainable Economic Development (ENEA), Roma, Italy

1. Introduction

In this work, we apply the concept of the climate filter (Lee *et al.* 2011) for potential improvement of a grand MME, derived from a combination of APEC Climate Center (APCC) MME seasonal prediction system (Lee *et al.* 2009) and ENSEMBLES (Weisheimer *et al.* 2009; Alessandri *et al.* 2011) in order to explore whether the methodology can improve the skills of the grand MME, constituent MMEs, and individual models.

2. Data and methodology

2.1 Data

- Target seasons and Periods

The boreal winter (December through February, DJF) hindcast outputs for the period of 1983-2005

- Model data set

Seven coupled models involved in the operational 6-month MME seasonal prediction system of the APCC and five coupled models from the European Commission FP7 project called ENSEMBLES for seasonal to annual predictions – totaling twelve coupled model hindcast sets – are used in this study.

- Observed data set

The atmospheric variables (NCEP-DOE R2, Kanamitsu *et al.* 2002), precipitation (CMAP, Xie and Arkin 1997) and sea surface temperature (OISST V.2, Reynolds *et al.* 2002) from 1983 to 2005 are also used as observations.

2.2 Statistical methods

For MME prediction, we adopt a simple composite method (Peng *et al.*, 2002; Lee *et al.* 2009, 2011), known as simple arithmetic mean of bias corrected predictions, with equal weights to predictions from individual models.

The standard *t*-test (Wilks 1995) is employed to compute the statistical significance of the correlations. The degrees of freedom for the temporal correlation is estimated as N-2, where N is 23, the number of winter seasons during the study period. To find the significance levels for spatial pattern correlations, we use the effective spatial degree of freedom (ESDOF) (Wang and Shen 1999).

Finally, to calculate seasonal anomalies of each model parameter as well as those from observations for each year, we follow the standard leave-one-out cross validation method (Jolliffe and Stephenson 2003). We also use the cross validation method in each target year while applying the climate filter for all hindcast periods.

Correspondence to: Doo Young Lee, APEC Climate Center and Department of Atmospheric Sciences, Pusan National University, Busan, Republic of Korea; E-mail: dylee@apcc21.net.

3. Results

3.1 Climate Filter

At the temporal correlation pattern of Figure 1, high correlations with magnitudes of more than 0.4, significant at 95% confidence level from a *t*-test, are generally located along 10°S-10°N. Especially, there is a strong association of the local rainfall in the central and western tropical Pacific with the zonal circulation.

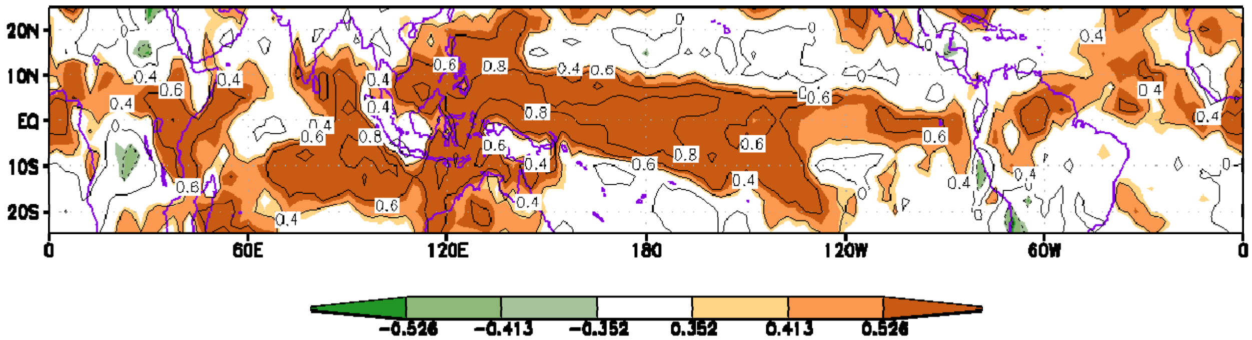

Fig. 1 Temporal correlation patterns between the observed Walker circulation and precipitation for the boreal winter (DJF) during the period of 1983-2005. Shading indicates statistically significant correlation coefficients at the 90% (0.352), 95% (0.413) and 99% (0.526) confidence levels from a Student's two-tailed t-test.

From the relationship in Figure 2, it can be discerned that the strong relationship between the observed Walker circulation with Niño 3.4 (-0.9, significant at 99% confidence level from a *t*-test) is well reproduced by hindcasts of all model Walker circulations. We utilize the coefficient of variation (*i.e.*, the squared correlation coefficient) between the Walker circulation and the Niño 3.4 index as a weight for the Walker circulation field to compute the ENSO-associated Walker circulation. Based on these points, we believe that it is an important measure of model fidelity to predict the tropical rainfall from model simulations of ENSO-associated Walker circulation in the tropical Pacific and also minimum requirement for any model with necessary fidelity.

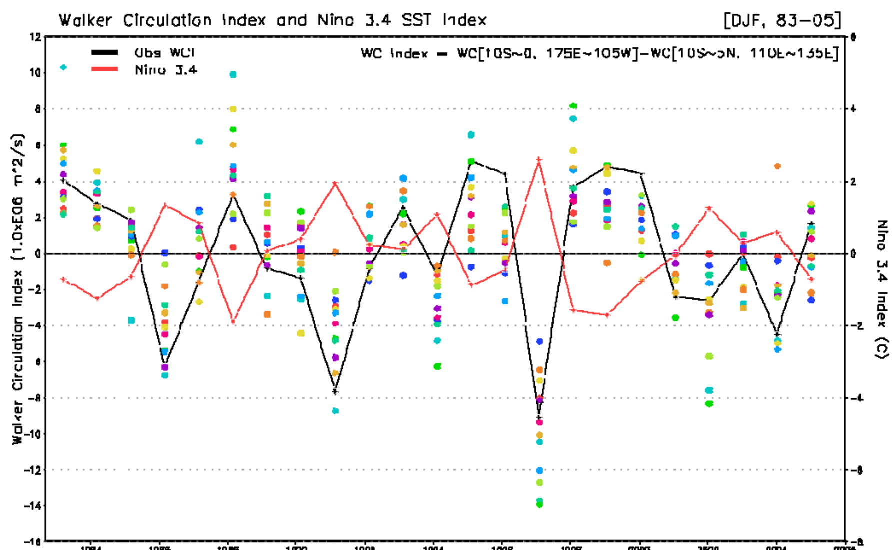

Fig. 2 Time series of SST anomalies from Niño 3.4 (solid red line), and Walker circulation index of observation (solid black line) and individual models (colored circles), which is defined by difference of Walker circulation between the tropical eastern Pacific (10°S-0°, 175°E-105°W) and the tropical western Pacific (10°S-5°N, 110°E-135°E) from 1983 to 2005.

3.2 Evaluation of the hindcast relationship in the tropical Pacific

Specifically, we use two empirical criteria to grade the individual model skills.

(i) The slope of the regression line fitted between the observed and simulated pattern correlations of tropical rainfall and ENSO-associated Walker circulation should be larger than 0.5 and less than 1.5.

(ii) Statistically significant temporal correlation between these observed and simulated pattern correlations is more than 0.5 (significant at ~99% confidence level from a Student's two-tailed *t*-test).

Four out of 12 models, namely, model 2, 5, 8 and 9 (Figures 3b, 3e, 3h and 3i) successfully represent the realistic rainfall relationship with the local ENSO-associated Walker circulation in the tropical Pacific (100°E~60°W, 10°S~10°N) for the boreal winter season.

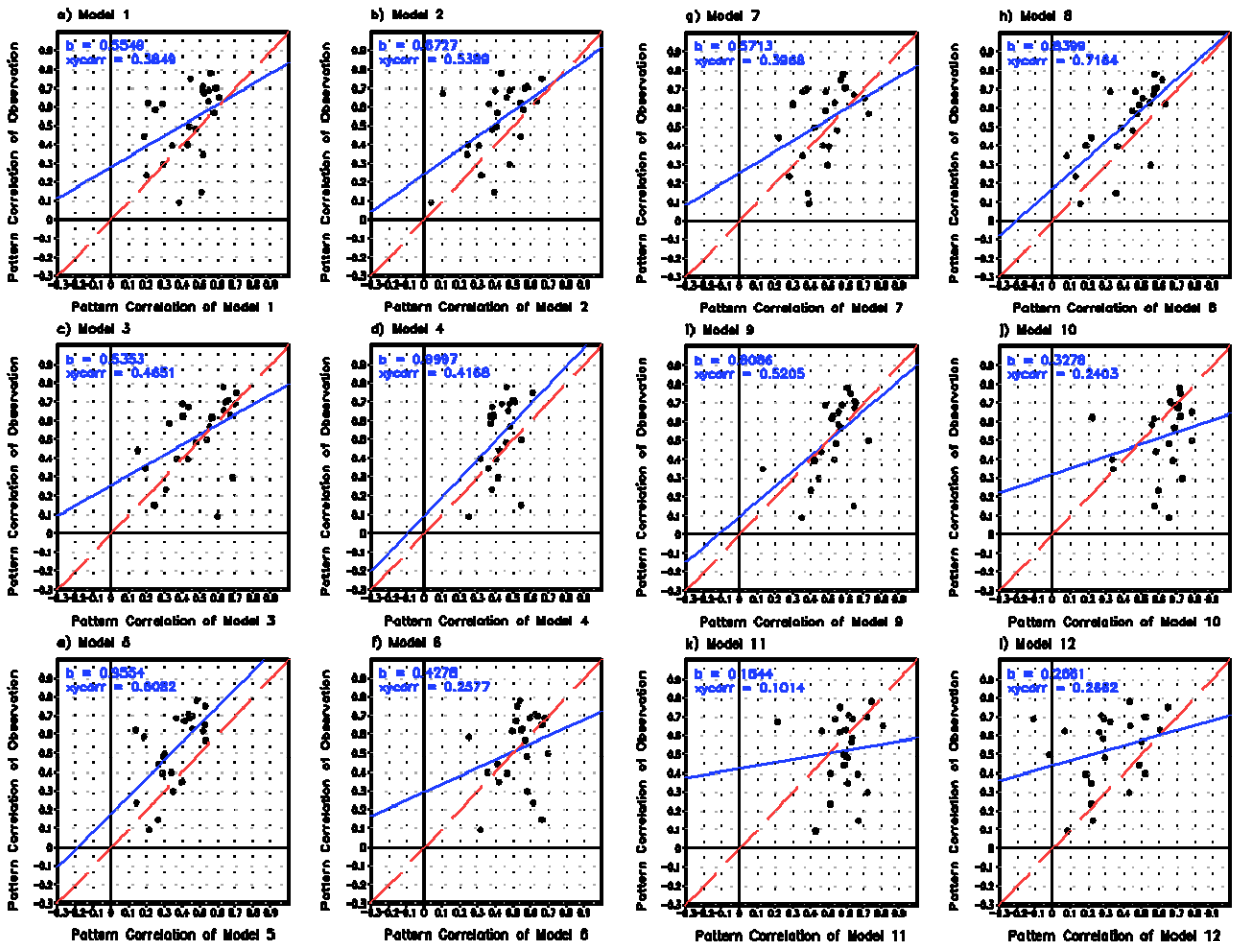

Fig. 3 Scatter diagrams depicting spatial pattern correlation between the ENSO-associated walker circulation and precipitation from observation (Y-axis) over the tropical Pacific region, for 23 boreal winters, plotted against those from the individual models (X-axis). The slope 'b' from the fitted regression line is provided in the upper left. The 'xycorr' represents the temporal correlations of each model with observation.

3.3 Sensitivity of the fidelity of various MME

We implement three separate MME hindcast experiments, which are, for convenience, named as the M12 (essentially a grand MME involving hindcasts from all the 12 models), the A4 (means a filtered grand MME involving hindcasts from the four performing models), and the B8 (uses the rest of the model hindcasts). Figure 4 indicates the time averages of the spatial pattern correlations between the observed and the simulated rainfall and temperature at 850 hPa from all the three MME experiments for six arbitrary regions. In the global and tropical regions, slightly better performances of the M12 are essentially due to the relatively better performances of the B8 predictions in these regions. Meanwhile, in the four extratropical regions, the gap between the MME prediction skills of the A4 and those of the B8 is significantly different.

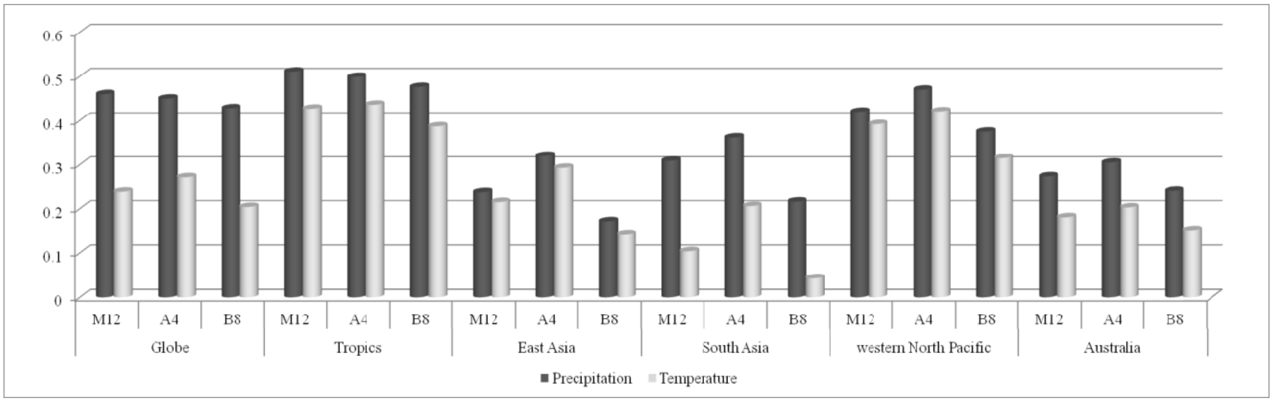

Fig. 4 Time average of pattern correlations between the observed and simulated precipitations and those for the temperature at 850 hPa from M12, A4, and B8 over the six regions of the Global region (0°-360°E, 90°S-90°N), Tropics (0°-360°E, 20°S-20°N), East Asia (90°E-150°E, 20°N-50°N), South Asia (60°E-120°E, 10°N-40°N), western North Pacific (120°E-160°E, 10°N-40°N), and Australia (110°E-180°E, 50°S-10°S).

4. Summary and conclusion

In order to grade the individual model hindcast performances of two different MME systems, we utilize a climate filter concept using evaluation of the relative capabilities of each model. We explore the possible use of this climate filter method to filter models with better fidelity, and finally introduce an optimized MME suite with enhanced seasonal prediction skills. We find that the MME prediction skills from four better performing models are indeed significantly higher as compared to those from the rest of the non-performing models, and those from the all-inclusive 12 model grand MME. This research indicates that the MME is better skilled if models that can reproduce realistic observed feature are used.

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