

Introduction to the KMA-Met Office Joint Seasonal Forecasting System and Evaluation of its Hindcast Ensemble Simulations

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1. Introduction

Dynamical seasonal forecasts using coupled models, *i.e.*, 1-tier approach, are now routinely made at many operational centers in the world. For example, among twelve Global Producing Centers (GPCs) that have contributed for providing their own real-time seasonal forecast to WMO Lead Center for Long-Range Forecast Multi Model Ensemble (LC-LRFMME), seven centers are using coupled models while only five centers are still based on two-tier approach. The rapid transition from two-tier to one-tier approach in seasonal forecast are mainly caused by recent progresses in development of coupled climate models and enlargement of understanding air-sea interactions obtained from international collaborative efforts such as TOCA program (Wang *et al.*, 2009). In this context, Korea Meteorological Administration (KMA), as the WMO LC-LRFMME jointly with NOAA and one of the GPCs, is also trying to replace its operational seasonal forecast model with a coupled model by the collaboration with U. K. Met Office.

Recently, the GloSea4 (Global Seasonal Forecasting System version 4) of the Met Office based the HadGEM3-AO was implemented and hindcast ensemble simulations for 14 years from 1996 to 2009 have been accomplished. The purpose of this article is to introduce the KMA-Met Office Joint Seasonal Forecasting system and to evaluate overall performance of its retrospective seasonal forecast particularly in terms of predictability and skill scores. Section 2 briefly describes the joint forecast system, the model, and design of hindcast simulations. Results of predictability and skill scores on sea surface temperature, precipitation and surface air temperature are shown in Section 3. Finally, Section 4 summarizes the results and further works for the operation of joint system.

2. GloSea4 and its Hindcast Simulations

2.1 GloSea4 and Joint Forecasting System

GloSea4 is the fourth version of the Met Office seasonal ensemble prediction system based on the latest version of HadGEM3 (Hewitt *et al.*, 2010). It consists of the UM (Met Office Unified Model) for atmosphere, NEMO (Nucleus for European Modeling of the Ocean) for ocean, CICE (Los Alamos sea ice model) for sea ice, and MOSES (Met Office Surface Exchange Scheme) for land surface components with OASIS flux coupler. The spatial resolution in the current configuration (GA 2.0) is N96L85 for atmosphere, which is approximately 135 km in the horizontal with 85 vertical levels, and tri-polar ORCA1L75 for ocean, in which the horizontal grid distance are 1 degree with 1/3 of a degree between 20°S and 20°N with 75 vertical levels from the sea surface to the bottom. Details of the GloSea4 description are given in Arribas *et al.* (2011).

One of the distinctive features of the GloSea4 compared to other typical seasonal forecasting system including the current LRF system at KMA, *i.e.*, Global Data Assimilation and Prediction System (GDAPS), is that both the hindcast and forecast suites are run simultaneously, which allows preventing quite a burden of resources for producing model climatology a prior to make seasonal forecast if any modification of the system and/or bug fix is necessary. Hindcast and forecast suites are initialized with the weekly-based time cycle so that they can update initial conditions nearly real-time, which is quite valuable to maintain consistency from short-to-long-range forecasts. Eventually, the major benefit of KMA-Met Office joint forecasting system is to reducing uncertainties of seasonal forecast by share ensemble members as many as possible from two centers for both the hindcast and forecast suites. The only differences will be the initial condition for atmosphere that

comes from each center's own 4DVAR system. At this moment, since the KMA does not have its own ocean and sea-ice data assimilation system, initial conditions for ocean and sea-ice will be obtained from the Met Office.

2.2 Hindcast Simulations

The ECMWF-interim reanalysis (ERA-interim) is used to initialize the atmosphere and land surface because there is no atmospheric reanalysis available for the HadGEM3-AO. In the case of land surface variables, an anomaly initialization approach, in which ERA-interim anomalies are calculated and then added to the HadGEM3 model climatology, is followed to avoid the inconsistency from the very different land surface model used in HadGEM3 and ERA-interim reanalysis. The ocean field is initialized in the same way as in the forecast suite, *i.e.*, the GloSea4 Ocean Data Assimilation scheme which consists of a parallel version of the Met Office optimal interpolation scheme used for short-range ocean forecasting, except for the fact that atmospheric fluxes to force the ODA scheme are obtained from the ERA-interim rather than from the operational NWP system. The hindcast period is 14 years from 1996 to 2009. Initial dates are 1st, 9th, 17th, and 25th of each month. In order to generate ensemble members by considering model uncertainties, 3 members per each initial date are generated using the stochastic kinetic energy backscatter scheme version 2 (SKEB2) (Shutts, 2005). Therefore, in total, number of 7-month-long integration of the GloSea4 system is 2,016.

3. Results

The observation dataset used for evaluation of the GloSea4 in this study are Hadley Center's sea surface temperature, CMAP precipitation, and ERA-interim reanalysis for the surface air temperature.

3.1 Sea Surface Temperature

Figure 1 shows the bias of seasonal mean SST from 1-month and 3-month lead forecasts. As forecast lead-time increases, in general, the SST bias also increases. In the results of 1-month lead forecasts, the

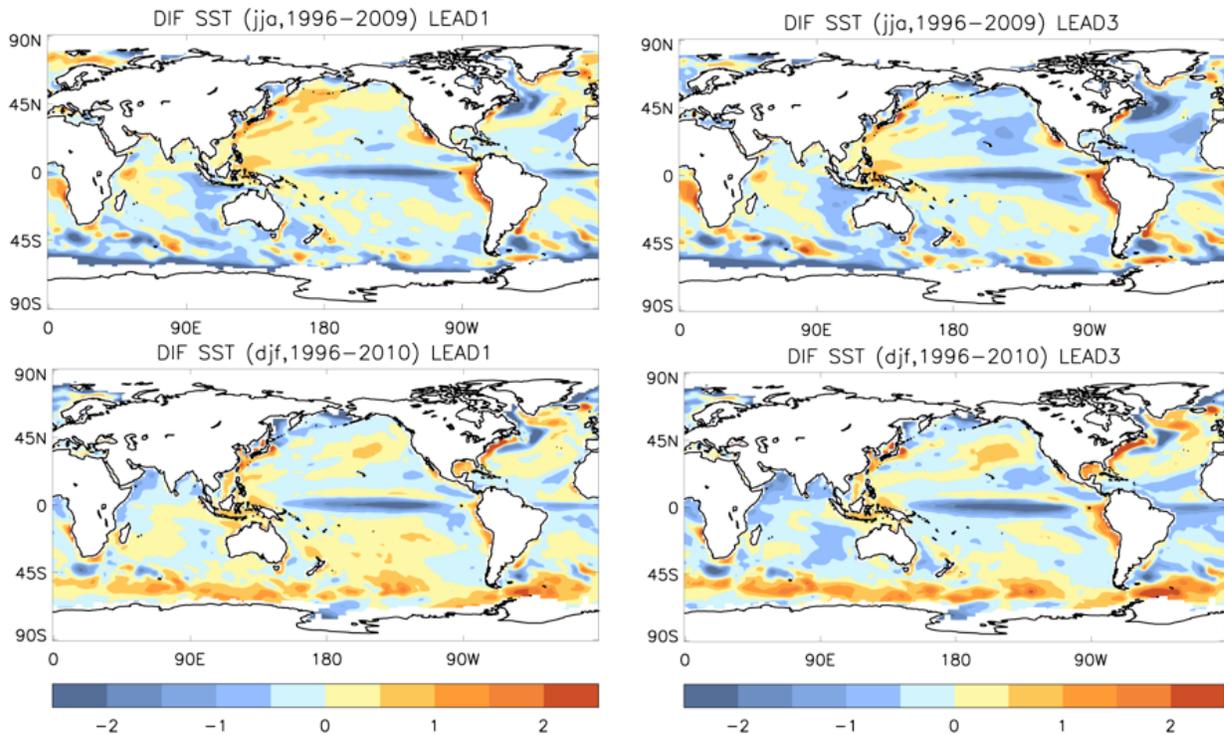


Fig. 1 Biases of seasonal mean SST for boreal summer (upper) and winter (lower) seasons. Left and right panels are obtained from the results one and three months' forecasting lead-time simulations.

strongest cold bias appears along the equatorial Pacific both for the boreal summer and winter seasons. The spatial pattern of SST bias seems to be somewhat systematic, particularly in the southern Hemisphere, which shows overall cold bias in JJA but warm bias in DJF season. Despite the general increase in the amplitude of SST bias according to the forecast leading time, its spatial structure is fairly similar and persistent to each other. On the contrary to the skill scores (*e.g.*, bias or anomaly correlation) that indicate the performance of the model against the observation, signal-to-noise ratio is a measure of predictability that implies that how much the each ensemble member spreads compared to ensemble mean variance. The results of signal-to-noise ratio show also persistent spatial patterns with decreasing values according to the forecast leading months (not shown). As expected, predictability in boreal winter season is higher than in summer season regardless to the forecast leading time.

Anomaly correlations of the NINO3.4 SST anomalies for the four different initial months are shown in Figure 2. Each month has 12 ensemble members with time-lagged initial dates and SKEB2 physics. Overall, skill scores for NINO3.4 index are higher in cold season than in warm season. The skill score drops rapidly from April to July from the simulations initialized on February and November, which is associated limitation of predictability of SST during the spring time, called “spring barrier”. The spring barrier issue is one of the common problematic features in coupled GCM, and suspected to be associated with failure of surface wind stress over the equatorial Pacific. It is interesting to note skill score for the JJA forecast is relatively lower than other seasons in the beginning of the forecast, however; the score remains with persistent and relatively higher values for the longer forecast lead-time. The red lines in Figure 2 denote the score calculated from the ensemble mean, and black solid, dashed and dotted lines are average, maximum and minimum values from each individual

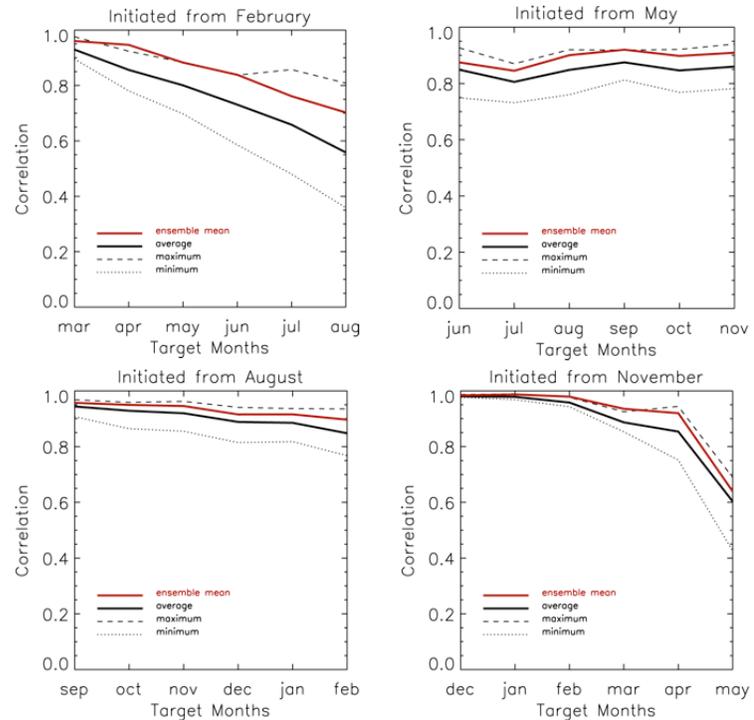


Fig. 2 Correlation skill for the SST anomaly averaged over the NINO3.4 area from the simulations initialized in February, May, August, and November.

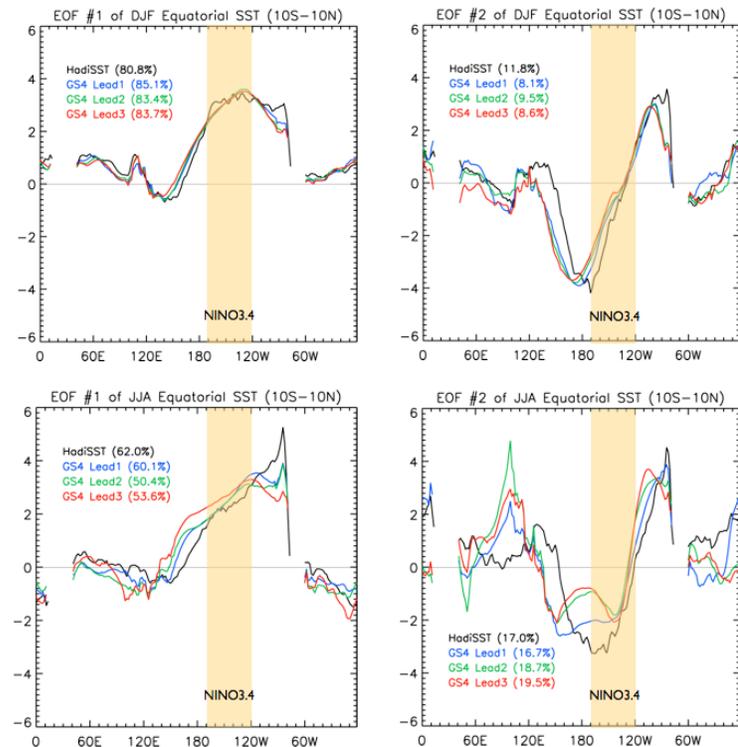


Fig. 3 The first (left panel) and second (right panel) leading EOF modes for the SSTA averaged over 10S-10N. Black, blue, green, and red lines indicate observation, GS4 results with one, two, and three month lead time, respectively.

ensemble members. It is clearly recognized that scores from the ensemble mean are quite close to the maximum scores of individual member, or in some cases, it is superior to maximum of individual ensemble members.

In order to investigate SST variability, EOF analysis was conducted for the SST anomaly against the latitudinal mean between $10^{\circ}\text{S}\sim 10^{\circ}\text{N}$ (Fig. 3). During the boreal summer (JJA), the observed leading mode represents a peak SSTA in the Nino 3 region rather than 3.4 region (lower left in Fig. 3). Meanwhile, that of boreal winter (DJF) is apparent in somewhat wide areas including both the Nino3.4 and Nino 3 areas. Those patterns of leading mode of SSTA along the equator are captured pretty well by the GloSea4. In JJA, the variability of SST over central Pacific tends to be overestimated by the GloSea4, which are getting stronger to the longer forecast lead-time. From the second leading mode during DJF season, the area of strong variability extends westward in results from the GS4 compared to the observation.

3.2 Precipitation and Surface Air Temperature

Since the hindcast period of the GloSea4 is somewhat short (only 14 years), the corresponding correlation value with 0.05 and 0.01 significance levels are somewhat higher which are about 0.45 and 0.61, respectively. As like in other coupled seasonal forecasting system, significant anomaly correlation scores for the surface air temperature and precipitation are concentrated mainly over tropical regional about between $20^{\circ}\text{S}\sim 20^{\circ}\text{N}$ (Fig. 4). It is clear that anomaly correlation scores are decreasing rapidly in accordance with the forecast leading month. East Asia region, in which the skill scores are quite low as in other extra-tropical areas, meaningful scores with 0.05 significance levels are limited only spring and autumn seasons surface air temperature in cases of less than three months' forecast leading time (not shown). Nevertheless, in terms of practical sense of seasonal forecast, it is promising to note that biases of surface air temperature and precipitation over East Asia are quite systematic and persistent as a function of forecast leading months.

4. Summary and Further Works

In this study, overall skill of the GloSea4 system, which will be operated as an operational seasonal forecasting system at KMA and joint system between KMA and Met Office, have been examined. The skill scores obtained from hindcast ensemble simulations seem to be comparable against with other coupled climate models. However, it should be carefully investigated within intercomparison framework to find out strength and weakness of the GloSea4. Robust evaluation of hindcast ensemble runs including the Asian monsoon, sub-seasonal variability such as MJO and their impacts over Asia should be further investigated. In addition, horizontal resolution both for the atmosphere and ocean will be increased a prior to the operation up to N216 (~ 60 km) and quarter degrees (in extra-tropical region), respectively.

Acknowledgements. This study was supported by the Grant NIMR-2011-B-2. The authors are grateful for the Met Office colleagues, Drs. A. Arribas and C. MacLachlan for their providing successful implementation of the GloSea4 to the KMA.

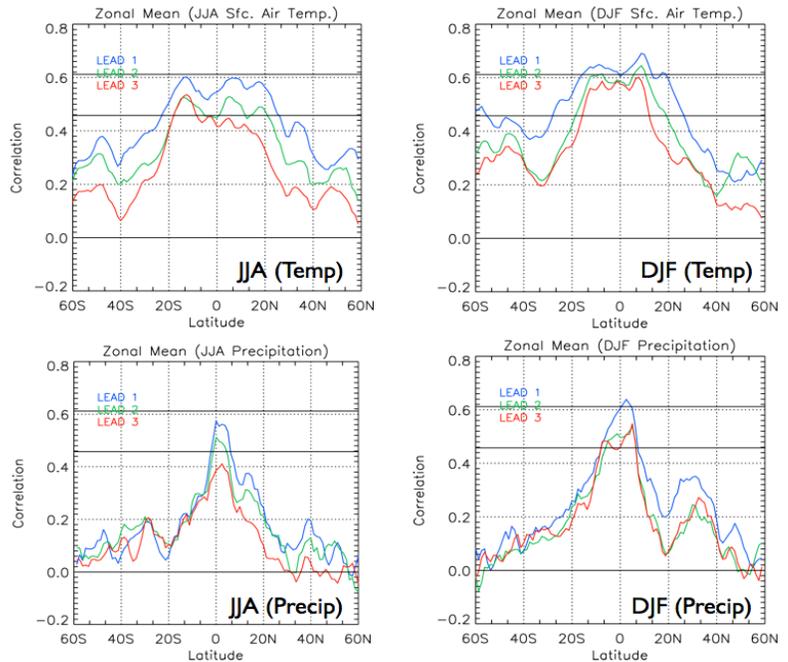


Fig. 4 Anomaly correlation of surface air temperature (upper) and precipitation (lower) for JJA (left panel) and DJF (right panel). Blue, green, and red lines indicate one, two and three months' forecast leads.

References

- Arribas, A., M. Glover, A. Maidens, K. Peterson, M. Gordon, C. MacLachlan, R. Graham, D. Fereday, J. Camp, A. A. Scaife, P. Xavier, P. McLean, A. Colman, and S. Cusack, 2011, The GloSea4 Ensemble Prediction system for seasonal forecasting, *Mon. Wea. Rev.*, **139**, 1891-1910.
- Hewitt, H. T., D. Copesey, I. D. Culverwell, C. M. Harris, R. S. R. Hill, A. B. Keen, A. J. McLaren, and E. C. Hunke, 2010, Design and implementation of the infrastructure of HadGEM3: The next generation Met Office climate modeling system. *Geosci. Model Dev. Discuss.*, **3**, 1861-1937.
- Shutts, G., 2005: A kinetic energy backscatter algorithm for use in ensemble prediction systems. *Quart. J. Roy. Meteor. Soc.*, **131**, 3079-3102.
- Wang, B. and co-authors, 2009: Advance and prospectus of seasonal prediction: Assessment of the APCC/CliPAS 14-model ensemble retrospective seasonal prediction (1980-2004), *Clim. Dyn.*, **33**, 93-117.