A SNU/CES Dynamical Seasonal Prediction System

In-Sik Kang, June-Yi Lee, and Myong-In Lee
Climate and Environment System Research Center, Seoul National University, Seoul, Korea

1. Introduction

Many parts of the world, particularly the Asian-Pacific region, have experienced serious natural disasters associated with unusual climate events, resulted in loss of life, destruction of shelters and food reserves, disruption of food production, and health risks. Moreover, the agricultural, industrial, and economic productivities are heavily dependent on the variability of the weather and climate in this region. Recent climate fluctuations, particularly related to recent history breaking El-Nino have demonstrated to many decision makers in weather-sensitive industries that climate variabilility has significant economic impacts. As a consequence, there have been increasing interests on the weather and climate forecasts and continuing efforts in developing long-range seasonal prediction system as well as those in short-range weather forecasts.

Regarding to the seasonal prediction, as the regional climate system is apparently subjective to the global climate variability, recent activities in operational weather centers and universities rely on the predictions based on the global atmospheric general circulation models (AGCMs). With all its progression and successes, however, current models still have many predictability limitations, mostly due to the coarse horizontal resolution, and hence the uncertainties in the sub-grid scale parameterizations. In addition, uncertainties in the sea surface temperature forecast that is regarded as a most important in the interannual variability of the climate contaminate the forecast skill significantly.

Based on the years of effort, we integrate the individual prediction system developed respectively into a unified prediction system. As will be discussed later, it contains the improved ENSO (El-Nino and Southern Oscillation) and global sea surface temperature (SST) prediction system that is more accurate than the SST persistency method. Also, dynamical prediction outputs are transformed to the regional forecast with the help of statistical downscaling technique, which alleviates the inaccuracy of the dynamical model by relating model outputs to the observation data statistically. The system finally combines the dynamical model prediction with the statistical prediction, giving a more improved seasonal prediction skill score.

This study describes the structure of the dynamical seasonal prediction system developed at Climate Environment System Research Center (CES) in Seoul National University and shows the prediction skill of the system.

2. Seasonal Prediction System

A 6-month lead seasonal prediction system established is made by utilizing the dynamical and statistical methods. Figure 1 shows the schematic diagram of the prediction system. The dynamical prediction system consists of SNU/AGCM (Seoul National University/ Atmospheric General Circulation Model; Kim et al. 1998; Lee et al. 2001) with a horizontal spectral truncation at T63 and 20 vertical levels, the global SST prediction system, and a statistical downscaling scheme. The global SST prediction system consists of the intermediate coupled ocean atmosphere model over the tropical Pacific between 20S and 20N (Kang and Kug 2000) and the statistical SST prediction system over the globe other than the tropical Pacific region. The statistical model utilizes the coupled pattern projection method, by identifying the SST patterns related to each grid point SST with some lead time. The local SST is then predicted by projecting the SST patterns identified to the SST fields of the lead times. The monthly mean SSTs over the globe are predicted for 7 months from the starting month, which is one month before the forecast target season. The initial condition is taken from the National Centers for Environmental Prediction/the National Center for Atmospheric Research (NCEP/NCAR) reanalysis data. It includes not only the atmospheric variables but land surface variables, such as soil moisture, snow depth and soil temperature those are supposed to be pretty important for the season variability of the atmosphere.

The dynamical prediction utilizes 10 member ensemble integrations of the SNU/AGCM driven by the forecasted sea surface temperature forcing as a boundary condition. In general, the dynamical model shows a poor predictability skill for the seasonal forecast. To overcome this problem, a statistical inversion or downscaling process is applied to the dynamical model outputs. The downscaling method is developed based on the pattern projection method by relating the observed station data (temperature and precipitation) to the model predicted circulation statistics.

To identify the model patterns associated with local climate, we need a long historical hindcast prediction data. In other words, 20 year prediction hindcast for 1979-1998 has been performed to develop the statistical downscaling method. The procedure of the 20 year hindcast adapted is the same as that of CLIVAR/Seasonal Model Intercomparison Project (SMIP2) The SMIP2 uses the observed SST instead of the predicted SST. Therefore, the SMIP2 does not provide the actual predictability but the potential predictability of the present system.

It is not insufficient for 20-year hindcast data to apply conventional training-forecast method in statistical downscaling. Thus, 1-year-out cross validation scheme is adapted. In this method, training period is for the rest of year (19 years) except forecast target year and 20-year regional forecasts are produced.

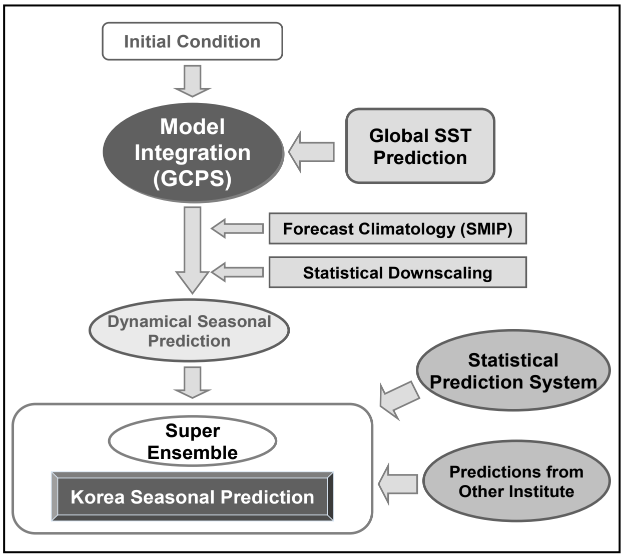

Figure 1. Schematic diagram of seasonal prediction system.

Figure 2 illustrates the potential predictability skill for the monthly rainfall in summertime before and after applying the statistical downscaling. For calculating predictability score, temporal correlations are obtained between actual observations and prediction outputs in each grid box for the 20 years hindcasts (1979-1998). In Fig 2a, it is mentioned that without the downscaling there are some predictability signal only in the tropical region and other oceanic region but no predictability skill in the extratropics. However, Fig. 2b shows pretty improved predictability with above 0.4~0.5 correlations over most of the entire regions. It implies the importance of statistical downscaling which seems to eliminate the systematic biases in the prediction system.

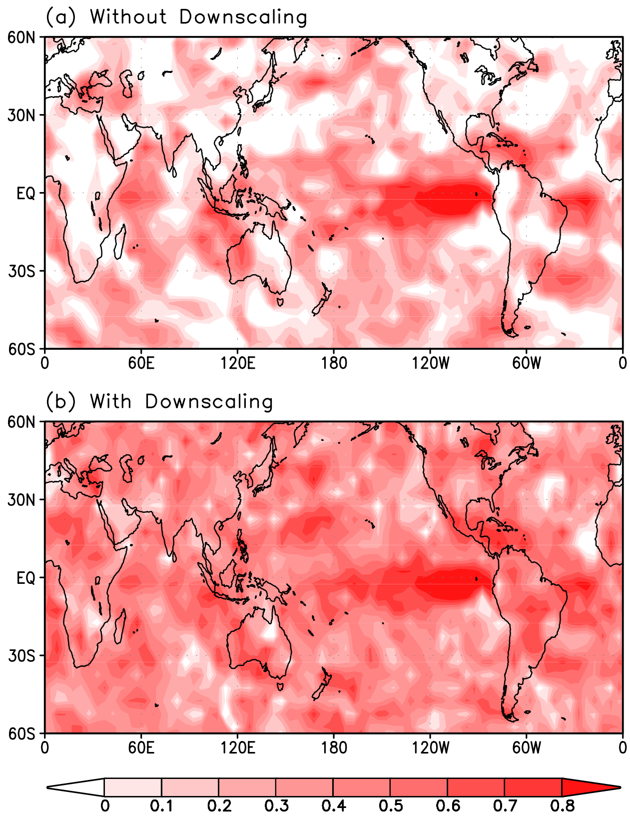

Figure 2. Predictability maps for the monthly precipitation in summertime (a) without statistical downscaling and (b) with statistical downscaling. Darker shaded areas indicate the regions showing higher predictability. For the predictability score, Correlations are calculated between the forecasted and the observed for the 20 years (1979-1998) in each grid box.

The seasonal forecasts can be presented by either a deterministic or a probabilistic way. Probabilistic forecast can be more useful to get the forecast uncertainty as well as the mean expected value by showing a probability distribution of expected values, and, in addition, it can be further utilized in the economic value assessments. Figure 3 and Fig. 4 are one set of examples for the deterministic and probabilistic forecasts applied to the Korean mean January temperature in 2002, respectively. In the

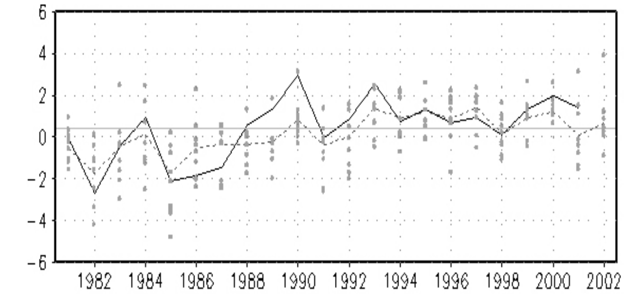

Figure 3. Two-month lead statistical prediction for the January surface temperature anomaly of Korea for 1981-2002 periods. Solid line indicates the observation and dotted ensemble mean prediction. Dots indicate the individual realizations.

January temperature in 2002, respectively. In the probabilistic forecasts, posterior probability can be obtained by Bayes' theorem (Katz and Murphy 1997), and expressed as

$$p_{x,f} = \frac{p_{f,x} p_x}{p_f} \tag{1}$$

where $P_{f,x}$ represents the probability distribution of observed climatolgy, P_x does that of the forecasted climatology, and P_f for the probability distribution of actual forecast for a specific year. Posterior probability ($P_{x,f}$) indicates the adjusted probability distribution by using historical hindcast performances of the system.

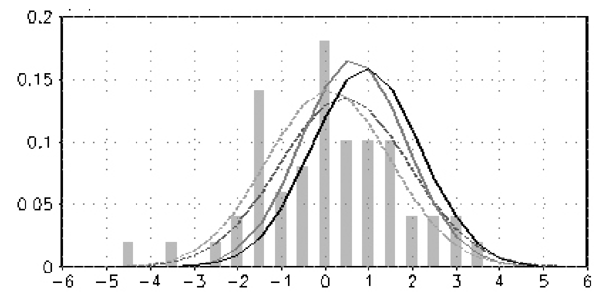

Figure 4. Probabilistic forecast for the Koran surface temperature in January 2002. Bar graph indicates the climatological distribution (1951-2000) and dotted light line indicates the normalized distribution derived from climatolgoical distribution ($P_{f,x}$). Dotted dark line indicates prior probability of the forecast system (P_x) obtained from 20 year predictions, and solid light for 2002 forecast (P_f). Posterior probability ($P_{x,f}$) is represented in solid dark line.

3. Conclusions

In this study, the newly developed 6-month lead seasonal prediction system was introduced. The seasonal prediction system has been developed by combing several systems individually developed for past several years at the SNU/CES: ENSO and global SST prediction systems, dynamical AGCM prediction system, statistical downscaling method, the statistical prediction systems, and super-ensemble technique. Not only dynamic ensemble predictions with massive supercomputing resources, but various statistical techniques and procedures are essential components to produce a reasonable predictability skill. The present prediction system produces not only the deterministic forecast but also the probability forecast.

Acknowledgements

This work was supported by the Korea Meteorological Administration and the Climate Environment System Research Center at SNU. The supercomputer time was supported by the 4th Supercomputing Application Support Program of Korea Institute of Science and Technology Information (KISTI).

References

Kang, I.-S., and J.-S. Kug, 2000: An El-Nino prediction system using an intermediate ocean and a statistical atmosphere, Geophys. Res. Lett.,27,1167-1170.

Katz, R.W., and A. H. Murphy, 1997: *Economic value of weather and climate forecasts*, Cambridge University Press, UK.

Kim, J.-K.,I.-S. Kang, and C.-H. Ho, 1998: East Asian summer monsoon simulated by the Seoul National University GCM, Intl. Conference on Monsoon and Hydrologic Cycle, Korea.

Lee, M.-I.,I.-S. Kang, J.-K. Kim, and B. E. Mapes, 2001: Influences of cloud-radiation interaction on simulating tropical intreaseasonal oscillation with an atmospheric general circulation model, J. Geophys. Res., 106, D13, pp 14,219-14,233.

Zebiak,S.E., and M.A.Cane, 1987: A model El Nino-Southern Oscillation, Mon.Wea.Rev.,115, 2262-2278.