Six month–lead downscaling prediction of winter to spring drought in South Korea based on a multimodel ensemble

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[1] The potential of using a dynamical-statistical method for long-lead drought prediction was investigated. In particular, the APEC Climate Center one-tier multimodel ensemble (MME) was downscaled for predicting the standardized precipitation evapotranspiration index (SPEI) over 60 stations in South Korea. SPEI depends on both precipitation and temperature, and can incorporate the effect of global warming on the balance between precipitation and evapotranspiration. It was found that the one-tier MME has difficulty in capturing the local temperature and rainfall variations over extratropical land areas, and has no skill in predicting SPEI during boreal winter and spring. On the other hand, temperature and precipitation predictions were substantially improved in the downscaled MME. In conjunction with variance inflation, downscaled MME can give reasonably skillful 6 month–lead forecasts of SPEI for the winter to spring period. Our results could lead to more reliable hydrological extreme predictions for policymakers and stakeholders in the water management sector, and for better mitigation and climate adaptations. **Citation:** Sohn, S.-J., J.-B. Ahn, and C.-Y. Tam (2013), Six month–lead downscaling prediction of winter to spring drought in South Korea based on a multimodel ensemble, *Geophys. Res. Lett.*, *40*, doi:10.1002/grl.50133.

1. Introduction

[2] Precipitation deficits have effects on several hydrological sectors such as the ground water, reservoir storage, soil moisture, snowpack, and streamflow [*McKee et al.*, 1993]. South Korea is susceptible to droughts, abnormal aridity, and dust storms in boreal spring. Droughts in the region are associated with anomalous large-scale atmospheric circulation in the northern hemisphere [*Kim et al.*, 2005]. Some major droughts in midlatitudes of the northern hemisphere can also be attributed to atmospheric teleconnections related to tropical sea surface temperature variability [*Hoerling and Kumar*, 2003; *Schubert et al.*, 2007]. Among the four seasons, boreal winter brings the smallest amount of rain to the region; rainfall accumulated in winter can be very important in determining the springtime drought condition. Capturing hydrological variations from winter to spring is therefore essential for properly predicting droughts in South Korea.

[3] There are a number of indicators, such as the Palmer drought severity index (PDSI) [*Palmer*, 1965] or the standardized precipitation index (SPI) [*McKee et al.*, 1993], that can be used to define hydrological extremes. Recently, a new multivariable standardized precipitation evapotranspiration index (SPEI) has been proposed to quantify drought severity [*Vicente-Serrano et al.*, 2010]. SPEI is able to incorporate the effect of hydrological balance between precipitation and potential evapotranspiration, the latter being sensitive to air temperature. The SPEI combines the sensitivity of PDSI to changes in evaporation demand with the simplicity of calculation and the multitemporal nature of SPI [*Vicente-Serrano et al.*, 2010] (see also section 2 and Supporting Information, section A1, for more details). Figure 1 gives the 6 month mean anomalous surface air temperature and precipitation in the December to May period from 1983/1984 to 2003/2004 averaged over South Korea. They are seen to be highly variable and fluctuate with comparable timescales. Also shown are the corresponding SPEI values covering the same period. A strong covariability between SPEI and precipitation can be seen; this means that drought is mostly attributed to the deficit of precipitation in the region. On the other hand, notice that the air temperature is positively correlated with rainfall (with a correlation coefficient of 0.56, exceeding the 99% significance level). During the peak of El Niño in boreal winter and the ensuing spring, the climate in East Asia tends to be warmer and wetter than normal [*Wang et al.*, 2000]. This implies that changes of precipitation can be in concert with those of temperature. More importantly, there is a robust warming trend in the temperature record (see Figure 1; exceeding the 99% significance level based on a two-tailed Student's t test). This will increase drought severity due to increased evapotranspiration. Overall, the above implies that hydrological extremes, as identified by the multivariable SPEI, might therefore be different from those based on the single-variable SPI. It thus seems imperative to consider both the effects of temperature and precipitation variability on extreme drought in order to properly define long-term hydrological variations over South Korea.

[4] To predict extreme hydrological droughts, it is necessary to have reliable forecasts of deficit or surplus of precipitation with a lead time of 6 months or beyond. However, predicting the summer mean precipitation over the Asian summer monsoon region, even with a 1 month lead, remains challenging for climate models [*Wang et al.*, 2007, 2008a, 2008b, 2009; *Kug et al.*, 2008; *Lee et al.*, 2010, 2011]. This study evaluates the potential of using one-tier multimodel ensemble (MME) products for long-lead drought predictions. *Kang et al.* [2009] used statistically downscaled global model outputs to derive regional climate information. Here, we developed a 6 month–lead prediction system for hydrological extremes over 60 stations in South Korea based on downscaled MME

All Supporting Information may be found in the online version of this article.

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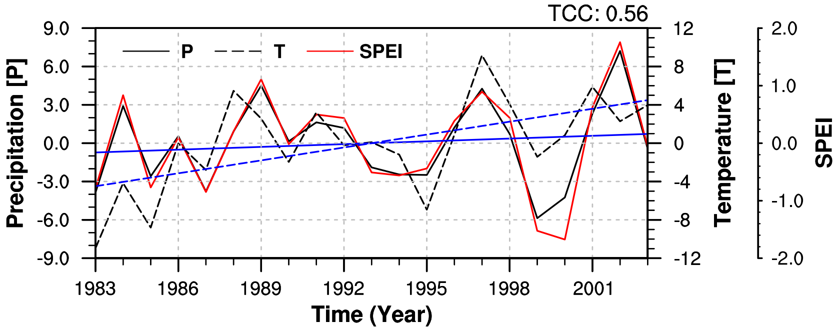

Figure 1. Time series of the observed December to May anomalous precipitation (black solid line), surface air temperature (black dashed line), and the standardized precipitation evapotranspiration index (SPEI) (red solid line) during the 1983/1984 to 2003/2004 period, averaged over 60 station locations in South Korea. The correlation between the former two time series exceeds the 99% significance level, and its value is given in the upper right. Solid and dashed straight lines (in blue) show the linear trend of the precipitation and temperature measurements, respectively.

(DMME) rainfall and temperature products. In the remaining sections of this report, the data sets and methodology being used will be described, and the performance of the 6 month–lead DMME prediction system in capturing hydrological extremes over South Korean will be presented, followed by concluding remarks.

2. Data sets and methodology

[5] The precipitation and surface air temperature data for calibrating and validating SPEI predictions were based on observations obtained from 60 stations in South Korea (see *Sohn et al.* [2012b]). For model data, historical retrospective forecasts from five different coupled models participating in the APEC Climate Center (APCC) one-tier MME 6 month prediction [*Sohn et al.*, 2012a] were considered. The APCC one-tier MME comprises the APCC seasonal prediction system based on the Community Climate System Model [*Jeong et al.*, 2008], Predictive Ocean Atmosphere Model for Australia from the Bureau of Meteorology Research Center [*Wang et al.*, 2008c], the National Centers for Environmental Prediction Coupled Forecast System [*Saha et al.*, 2006], and coupled general circulation models from Seoul National University [*Ham and Kang*, 2010] and Pusan National University [*Sun and Ahn*, 2011]. All historical predictions were initiated in November and targeted for December to May, with the common hindcast period of 1983/1984 to 2003/2004. A brief summary of the model experiments can be found in Table 1.

[6] In order to predict hydrological extremes more accurately, we proposed to use temperature and precipitation products from DMME. The regression-based coupled pattern projection method with optimal predictor selection was used for statistical downscaling [*Kang et al.*, 2009; *Sohn et al.*, 2012b]. The novelty of this approach is the use of model output statistics [*Wilks*, 1995] for predicting meteorological variables on the station scale. Previous downscaling studies using APCC MME products mainly focus on products from atmospheric general circulation models [*Kang et al.*, 2009]. On the other hand, our pool of predictors comprises both atmospheric variables (namely, sea level pressure, 2 m air temperature, 500 hPa geopotential height, 850 hPa temperature, and 850 and 200 hPa winds) and the oceanic variable of sea surface temperature. The latter is included because of the potential linkage between tropical sea surface temperature and hydrological variations in midlatitudes (see Introduction).

[7] These nine model variables are used for downscaling and the predictor is the one with the best downscaling prediction skill. In this coupled pattern projection method for downscaling, the linkage between observed station data and each of the nine potential predictors was first revealed based on correlation analysis. The pattern projection method selects the optimal window for each station by performing global scanning of different variables. It was found that, for the same predictand, the most signal-bearing predictor can be different from one station to another (figures not shown). This is consistent with the notion that different factors are responsible for the interannual climate variations at different station locations, owing to the influence of local terrain [*Kang et al.*, 2009]. Using a single predictor therefore might not be adequate for specifying climate variations for all stations. Also, to avoid overestimation of skill scores, the above downscaling procedure was carried out based on a "leave-one-out" cross-validation framework [*Kang et al.*, 2009; *Sohn et al.*, 2012b]. Finally, cross-validated correlation coefficients were computed in order to assess the skill based on each individual predictor, and the best predictor as well as the associated transfer function was adopted for statistical downscaling. By repeating this for all years, a full

Table 1. Description of Models Used in This Study

Institute	Model	AGCM	Resolution	OGCM	Resolution	Ensemble Member
APCC	CCSM3	CAM3	T85 L26	POP1.3	gxlv3 L40	5
BMRC	POAMA	BAM3	T47 L17	ACOM2	0.5–1.5° lat × 2°lon L25	10
NCEP	CFS	GFS	T62 L64	MOM3	1/3° lat × 5/8° lon L27	15
PNU	PNU	CCM3	T42 L18	MOM3	0.7–2.8° lat × 2.8125° lon L29	5
SNU	SNU	SNU	T42 L21	MOM2.2	1/3° lat × 1° lon L32	6

Note: AGCM, Atmospheric General Circulation Model; OGCM, Oceanic General Circulation Model; CCSM, Community Climate System Model; POAMA, Predictive Ocean Atmosphere Model for Australia; NCEP, National Centers for Environmental Prediction; CFS, Coupled Forecast System; BMRC, Bureau of Meteorology Research Center; SNU, Seoul National University; PNU, Pusan National University.

set of downscaled predictions can be obtained. The final forecast of DMME is then the simple average of downscaled forecasts of the five models using their respective optimal predictors. Furthermore, appropriate inflation was applied to correct the small variance of MME and regression-based downscaled outputs [*Sohn et al*., 2012b]. The method simply rescales the variance of predicted rainfall and temperature to that based on their respective climate records.

[8] SPI identifies the standardized precipitation surplus or deficit within a period of time. It is found by first fitting the long-term precipitation record to a Gamma distribution, which is further transformed into a standardized normal distribution. The SPI value is then the "z-score" of the anomalous precipitation accumulated within a particular period [*McKee et al*., 1993]. The newly proposed SPEI, which is mathematically similar to SPI, makes use of both precipitation and temperature records [*Vicente-Serrano et al*., 2010]. It involves computing the accumulated deficit or surplus of climate water balance, which is the difference between precipitation and potential evapotranspiration, and the adjustment to a log-logistic probability distribution. Following *Vicente-Serrano et al*. [2010], potential evapotranspiration is calculated empirically from air temperature (*Thornthwaite* [1948]; see also section A1 for Supporting Information). Although the commonly used PDSI is also based on soil water balance, it assumes autoregressive characteristics with a fixed temporal scale of between 9 and 12 months. Thus, PDSI might not be suitable for monitoring shorter-term drought events [*Guttman*, 1998]. Here, we used the inflated DMME temperature and rainfall products for station-scale SPEI predictions over South Korea. Because the ultimate goal is to predict 6 month SPEI, we only consider 6 months of accumulated precipitation and temperature during December to May as inputs for SPEI calculations. The accumulation is based on monthly MME (or DMME) forecasts within the boreal winter to spring period. Temporal correlation [*Barnston*, 1994] as well as the linear error in probability score [*Potts et al*., 1996], which measures the error in the probability space rather than in the real measurement space, were used to assess the skill of extreme predictions.

3. Six month–lead DMME prediction for hydrological extremes in South Korea

[9] Figure 2 compares temporal correlation coefficient (TCC) between the observed and raw MME monthly mean rainfall and temperature, and that for DMME, at each station location from December to May. The values of TCCs averaged over the 60 stations, as well as the "distance" between the raw and DMME skill scores (defined as the square root of the sum of squares of averaged TCCs) are given in the same figure. It is clear that the overall skill of DMME is much better than the original MME for both variables. It is also noteworthy that the improvement in the forecast skill brought about by downscaling actually increases as the lead time increases (compare, e.g., Figures 2a and 2f). The skill improvement in most locations can be attributed to the station-dependent optimal predictor selection in the downscaling procedure. In fact, DMME results averaged over all predictors lead to no obvious increase of skill for precipitation, as well as to a decrease of skill for air temperature predictions (see Supporting Information, Figure A1). Overall, this suggests that DMME has the potential

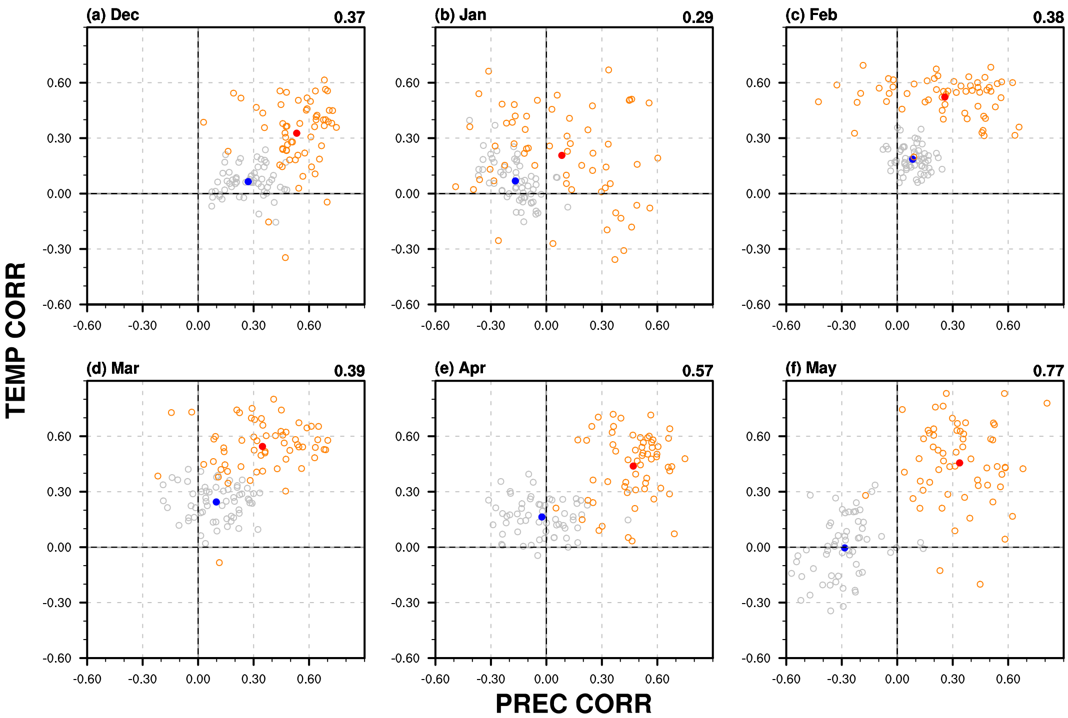

Figure 2. Scatter plots of TCCs between the observed and predicted precipitation (x axis) and temperature (y axis), for the target month of (a) December, (b) January, (c) February, (d) March, (e) April, and (f) May. Each orange (gray) point represents the results based on downscaled (raw) MME predictions for one station location. The blue and red dots denote the TCC values averaged over 60 stations in South Korea for raw and DMME, respectively. The "distance" between the downscaled and raw MME results is given at the upper right of each panel. See text for details.

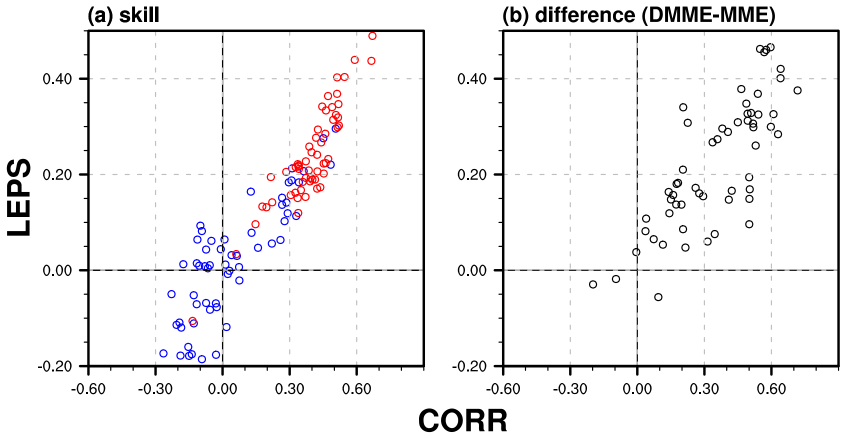

Figure 3. Scatter plots of TCCs (x axis) and linear error in probability scores (y axis) between the observed and predicted 6 month SPEI, for (a) original skills and (b) the difference between DMME and MME. In Figure 3a, each red (blue) point represents the result based on downscaled (raw) MME predictions for one station location.

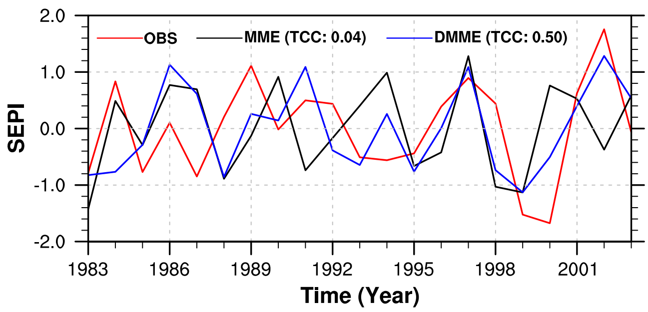

Figure 4. Time series of the observed and predicted 6 month SPEIs during the 1983/1984 to 2003/2004 period, averaged over 60 station locations in South Korea. Straight lines in red, black, and blue indicate observations, raw MME, and DMME predictions, respectively. Correlation coefficients between observations and predictions for the time series of MME and DMME are given in the parentheses following the legends.

in providing reliable station-scale precipitation and temperature signals with long forecast lead time.

[10] Finally, DMME forecasts were applied for local drought predictions. Before using the DMME products for computing SPEI, their values were inflated in order to match the realistic amplitudes of the anomalous precipitation and temperatures following *Sohn et al*. [2012b] (see Supporting Information, Figures A2 and A3). The TCC and linear error in probability skill scores of the 6 month SPEI ending in May from raw and DMME are given in Figure 3. It can be seen that the skill improvement between temperature and precipitation indeed leads the better skill of DMME SPEI. Statistical downscaling can correct a large part of the systematic errors. This can be clearly seen in Figure 3b. Overall, DMME, in conjunction with variance inflation, can significantly improve the skill in most of the regions.

[11] The 1983/04-2003/04 SPEI time series during winter to spring for the whole of South Korea (i.e., averaged over 60 stations) from observation, MME, and DMME are further compared in Figure 4. The correlation coefficient between observations and raw MME is 0.04. For DMME, the correlation is 0.50 (significant at the 95% level). The strong correlation suggests that DMME has better skill than MME in predicting the year-to-year variation of droughts. Consistent with the previous analyses, this suggests that the DMME is able to capture the historical large-scale drought events over South Korea.

4. Concluding remarks

[12] A new dynamical-statistical approach to carry out 6 month–lead forecasts of extreme drought events on the station scale has been developed and evaluated. Extreme droughts were identified by computing the values of SPEI, incorporating the effect of temperature change in the hydrological variation assessment. Local values of temperature and precipitation were taken from the APCC one-tier MME products, which were downscaled based on the best predictor selection, and downscaling was done in a cross-validated framework in order to avoid any overestimation of skill. Finally, SPEI was predicted using the inflated DMME temperature and precipitation. Compared with outputs based on raw MME, this method was found to greatly improve long-lead predictions of droughts over South Korea in boreal winter and spring. There was a pronounced enhancement of skill at station locations that were strongly affected by the local topography. Overall, DMME in conjunction with variance inflation can be a powerful tool for local-scale SPEI prediction.

[13] The newly proposed SPEI, which considers the climatic water balance between precipitation and evapotranspiration, can properly account for the effect of global warming on hydrological variations. It is advantageous to predict such a water balance–based hydrological indicator on the scale relevant to river basin and catchments for facilitating early warning of droughts a few months ahead. Under the background of climate change, advanced information on hydrological extremes will be particularly useful for decision making in water management, disaster mitigation, and better climate adaptation.

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