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TECHNICAL REPORT

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PREFACE

It is our pleasure to present to you the APEC Climate Center (APCC)'s Technical Report 2012, which reports the core outcomes of our research activities from the past year.

Since 2005, APCC, as a hub of climate information in the Asia-Pacific region, has strived to share our analysis and prediction of abnormal climate and to apply this information to regional development. The Center has established the most extensive Multi-Model Ensemble (MME) system for seasonal prediction in the world through its international science network and has provided value-added products to various stakeholders. Recently, APCC has expanded its mandate to include enhancing the capacity of APEC member economies to respond effectively to climate change and variability through better application of climate information.

In 2012, APCC continued to make an effort to improve the quality and quantity of our short-term climate forecasts and our online climate information systems, as information dissemination tools. Additionally, APCC began its endeavor to produce more applicable climate information through interdisciplinary research among various sectors, such as agriculture and hydrology. The following technical report provides more information about our research outcomes from 2012.

In 2013, following APCC's goal to enhance socioeconomic well-being through better utilization of climate information, APCC will continue to improve the quality and accuracy of its climate information, recognizing that the utility of this information is only as good as its quality. We would like to make the best use of our research outcomes in various scientific and application areas. We welcome any feedback on this report or on our services.

My best and warmest regards to all of you.

Dr. Chin-Seung Chung

Director/APEC Climate Center

CONTENTS

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Long-Lead Multi-Model Ensemble Prediction of a Drought Index Sensitive to Global Warming

Dr. Soo-Jin Sohn

ABSTRACT

The potential of using a dynamical-statistical method for long-lead drought prediction was investigated. In particular, the APEC Climate Center (APCC) 1-Tier multi-model ensemble (MME) was downscaled for predicting the standardized precipitation index (SPI) and the standardized precipitation evapotranspiration index (SPEI) over 60 stations in South Korea. SPEI depends on both precipitation and temperature and can incorporate the impact of global warming on the balance between precipitation and evapotranspiration. It was determined that 1-Tier MME has difficulties in capturing the local temperature and rainfall variations over extratropical land areas and has no skill in predicting the two hydrological indices during boreal winter and spring. Conversely, temperature and precipitation predictions were substantially improved in the downscaled MME (DMME). In conjunction with variance inflation, DMME can give reasonably skillful six-month-lead forecasts of SPI and 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 in addition to better disaster mitigation and climate adaptations.

1. INTRODUCTION

Precipitation deficits affect several hydrological sectors such as groundwater, 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 the mid-latitudes of the Northern Hemisphere can also be attributed to atmospheric teleconnections related to tropical sea surface temperature (SST) 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 springtime drought conditions. Capturing hydrological variations from winter to spring is therefore essential for properly predicting droughts in South Korea.

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 multi-variable standardized precipitation evapotranspiration index (SPEI) has been proposed to quantify drought severity [Vicente-Serrano *et al.,* 2010]. SPEI can incorporate the effect of hydrological balance between potential evapotranspiration (PET), which is sensitive to air temperature, and precipitation. Figure 1 shows the anomalous surface air temperature and precipitation in values for the December-to-May period of 1983–84 to 2003–04 over South Korea, which are highly variable and fluctuate with comparable timescales. In fact, the air temperature is positively correlated with rainfall with a correlation coefficient of 0.56, exceeding the 99% significance level. This result implies that changes in precipitation can occur with those in temperature; hydrological extremes as identified by the multi-variable SPEI may therefore differ from those based on the single-variable SPI. Moreover, a robust warming trend is apparent in the temperature record, which generally increases drought severity due to increased evapotranspiration. Thus, it is imperative to consider the effects of both temperature and precipitation variability on extreme drought and flood assessment to accurately define long-term hydrological variations over South Korea.

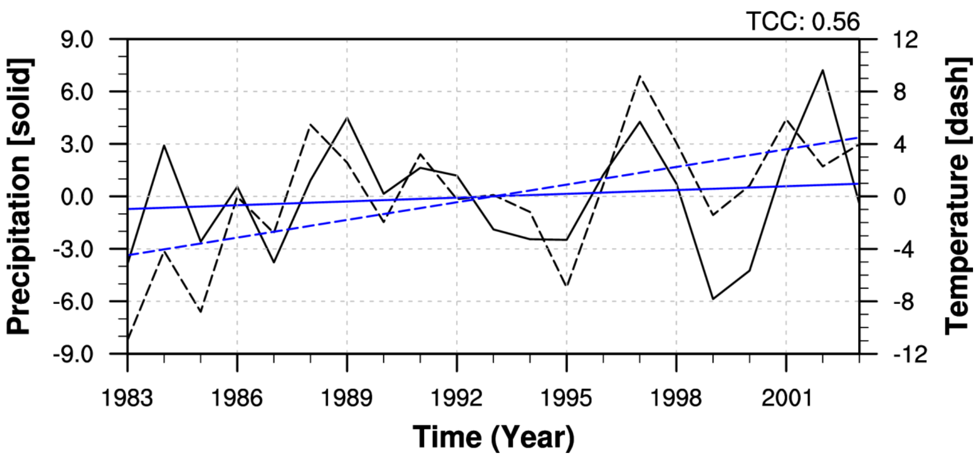

Figure 1 Time series of observed December-to-May anomalous precipitation (black solid line) and surface air temperature (black dashed line) during 1983–84 through 2003–04, which were averaged over 60 station locations in South Korea. The correlation between these two time series exceeds the 99% significance level; its value appears at the upper right. Blue solid and dashed straight lines show linear trends of precipitation and temperature measurements, respectively.

To predict extreme hydrological droughts, it is necessary to acquire reliable forecasts of precipitation deficits or surpluses with a lead time of six months or beyond. Predicting the summer mean precipitation over the Asian summer monsoon region, even with one-month lead, however, remains challenging for climate models [Wang *et al.*, 2007, 2008a, 2008b; Kug *et al.*, 2008; Lee *et al.*, 2010, 2011]. This study evaluates the potential of using 1-Tier multi-model ensemble (MME) products for long-lead drought predictions. Kang *et al*. [2009] employed statistically downscaled global model outputs to derive regional climate information. In the present study, we developed a six-month-lead prediction system for hydrological extremes over 60 stations in South Korea on the basis of downscaled MME (DMME) rainfall and temperature products. In the remaining sections of this report, the datasets and methodology being used in this study will be described, and the performance of the six-month-lead DMME prediction system in capturing hydrological extremes over South Korean will be presented, followed by concluding remarks.

2. DATASETS AND PREDICTION PROCEDURE

2.1 Datasets

The precipitation and surface air temperature data used for calibrating and validating SPI and SPEI predictions were based on observations obtained from 60 stations in South Korea, shown in Figure 2a. The two main ridges in South Korea are the Taebaek and Sobaek Mountains. The former ridge is located along the eastern edge of the Korean Peninsula and runs along the East Sea with an average elevation of approximately 1,000 m. The latter cuts across the southern Korean Peninsula, diverges from the Taebaek range, and trends southwest across the center of the peninsula.

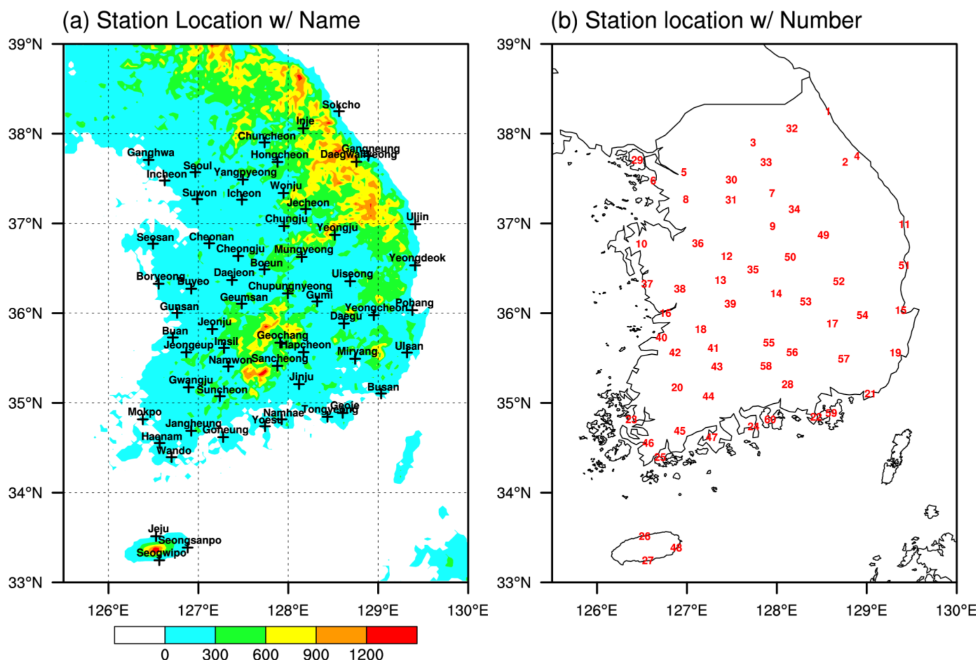

Figure 2 Locations of the 60 stations in South Korea used in this study listed by (a) topography (shaded; unit: m) and name and by (b) identification number.

For model data, historical retrospective forecasts from five different coupled models participating in the APEC Climate Center (APCC) 1-Tier MME six-month prediction were considered. The APCC 1-Tier MME comprises the APCC seasonal prediction system based on the Community Climate System Model (CCSM3) [Jeong *et al.*, 2008], Predictive Ocean Atmosphere Model for Australia (POAMA) from the Bureau of Meteorology Research Center (BMRC) [Wang *et al.*, 2008c], the National Centers for Environmental Prediction (NCEP) Coupled Forecast System (CFS) [Saha *et al.*, 2006], and coupled general circulation models from Seoul National University (SNU) [Ham and Kang, 2010] and Pusan National University (PNU) [Sun and Ahn, 2011]. All historical predictions were initiated in November and targeted for December to May, with the common hindcast period of 1983–84 to 2003–04. A brief summary of the model experiments is shown in Table 1.

Table 1 Description of the models used in this study.

Institute	Model	AGCM	Resolution	OGCM	Resolution	ENS. Member
APCC	CCSM3	CAM3	T85 L26	POP1.3	gxlv3 L40	5
BMRC	POAMA	BAM3	T47 L17	ACOM2	0.5-1.5°lat x 2°lonL25	10
NCEP	CFS	GFS	T62 L64	MOM3	1/3°lat x 5/8°lonL27	15
PNU	PNU	CCM3	T42 L18	MOM3	0.7-2.8°lat x 2.8125°lonL29	5
SNU	SNU	SNU	T42 L21	MOM2.2	1/3° lat x 1°lon L32	6

2.2 Statistical downscaling

To predict hydrological extremes, MME outputs were statistically downscaled on the basis of the coupled pattern projection method with an optimal predictor selection [Kang *et al.*, 2009; Sohn *et al.*, 2012]. The novelty of this approach is the use of model output statistics (MOS) [Wilks, 1995] for predicting meteorological variables on the station scale. Pattern projection is based on the premise that local variation is related to the variation in large-scale patterns that are well simulated by dynamical models; hence, local precipitation forecasts may be retrieved from the information in the coupled pattern by using a proper transfer function. Suppose that the predictand and predictor are $Y(t)$ and $X(i,j,t)$, respectively. Here, $Y(t)$ represents local observations, and $X(i,j,t)$ represents model-predicted large-sale variables in the grid point (i,j) for the same period. Then,

$$Y(t) = aX_p(t) + \beta,$$

where $X_p(t)$ is the projection of the predictor in an optimal window. The optimal window refers to the area in which the sum of the correlation coefficients of the predictand at the target stations when the predictor field reaches its maximum:

$$X_p = \Sigma_{i,j} COR(i,j) \times (i,j,t).$$

The correlation coefficient based on the training period is obtained as

$$COR(i,j)=\frac{\frac{1}{N}\sum[Y(t)-Y_m]\times[X(i,j,t)-X_{m(i,j)}]}{\sigma_x(i,j)\times\sigma_y}$$

where *N* is the training year; *m* is the average of the variable during the training period; and σ is the variance [Kug *et al*. 2007; Kang *et al*. 2007].

Previous downscaling studies that use APCC MME products focus mainly on products from atmospheric general circulation models [Kang *et al*., 2009]. However, our pool of predictors is composed of atmospheric variables including sea-level pressure, 2 m air temperature, 500 hPa geopotential height, 850 hPa temperature, 850 hPa winds and 200 hPa winds in addition to the oceanic variable of SST. The latter is included because of the potential linkage between tropical SSTs and hydrological variations at mid-latitudes. Moreover, appropriate inflation was applied to correct the small variance of MME and regression-based downscaled outputs [Sohn *et al*., 2012].

2.3 SPI and SPEI

SPI identifies the standardized precipitation surplus or deficit within a period of time and is determined 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]. This index involves computing the accumulated deficit or surplus of the climate water balance, which is the difference between precipitation and PET, and the adjustment to a log–logistic probability distribution. Following Vicente-Serrano *et al*. [2010], PET is calculated empirically from air temperature [Thornthwaite, 1948]. Although the commonly used PDSI is also based on the soil water balance, it assumes autoregressive characteristics with a fixed temporal scale between 9 and 12 months. Thus, PDSI may not be suitable for monitoring shorter-term drought and flood events [Guttman, 1998]. Here, we employed the inflated DMME temperature and rainfall products for station-scale SPI and SPEI predictions over South Korea. Temporal correlation [Barnston, 1994] as well as the linear error in probability score (LEPS) [Potts *et al.*, 1996], which measures the error in the probability space rather than in the actual measurement space, were used to assess the skill of extreme predictions.

2.4 Climatic water balance and PET

The climate water balance is defined as the difference between precipitation and PET. The latter is the amount of water that could be evaporated from land, water, and plant surfaces if soil water were in unlimited supply. PET strongly correlates with the distribution of forest types and, to some degree, susceptibility of the landscape to fire. We have calculated PET for 60 stations in South Korea by using the water balance method [Thornthwaite, 1948]. In particular, the value of PET is given by the following formula:

$$E = 1.6\left(\frac{10T}{I}\right)^{a},$$

where E is the monthly potential evapotranspiration (in cm), T is the monthly mean temperature (in °C), and I is the heat index for a given location, which is the sum of 12 monthly values of the index i such that i = $(\frac{T}{5})^{1.514}$. The exponent a is given by the following empirical formula:

$$a = 6.75*10^{-7I^{3}} - 7.71*10^{-5I^{2}} + 1.79*10^{-2}I + 0.49.$$

This method is able to provide reasonably accurate estimates of potential evapotranspiration [Palmer and Havens, 1958].

3. SIX-MONTH-LEAD DMME PREDICTION FOR HYDROLOGICAL EXTREMES IN SOUTH KOREA

3.1 Model simulated hydrological extremes

To assess the prediction skill based on raw MME outputs, temporal correlation coefficients (TCC) between the observed and model-predicted December-to-May SPI and SPEI values were computed; the results are shown in Figure 3. It is evident that MME is skillful in predicting SPI over several eastern coastal locations in China, the northern part of China bordering Mongolia, and southern Japan. In these locations, however, MME has no skill in capturing the SPEI value. The poorer performance in predicting SPEI might be related to latter's dependence on two variables, rainfall and temperature, rather than one as for SPI. It is also noteworthy that raw MME shows no skill in either SPI or SPEI predictions in any South Korean locations, which highlights the challenges in predicting local hydrological extremes, even with the use of state-of-the-art MME seasonal prediction systems.

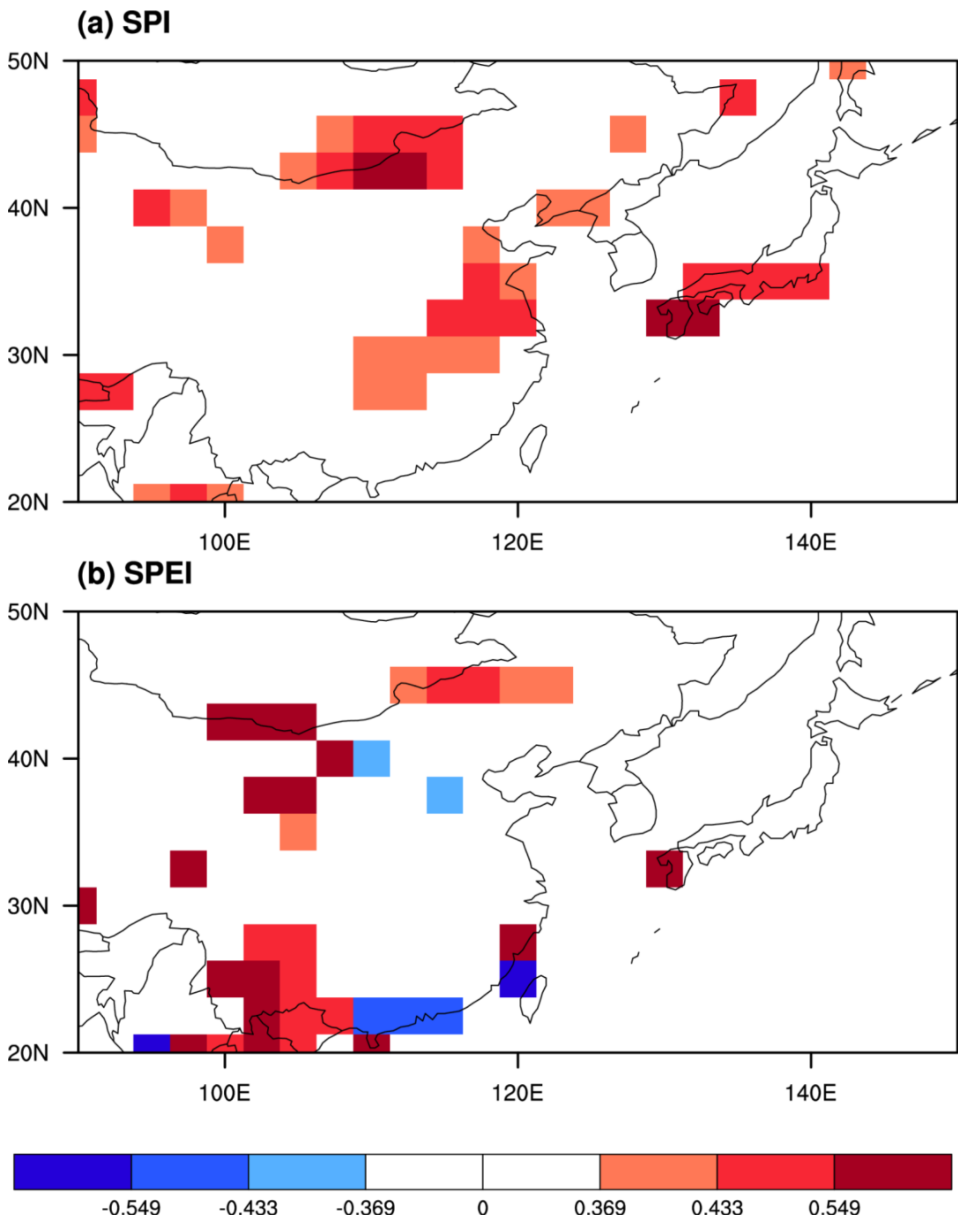

Figure 3 Temporal correlation coefficient (TCC) between the observed and multi-model ensemble (MME)-predicted (a) standardized precipitation index (SPI) and (b) standardized precipitation evapotranspiration index (SPEI) for the December-to-May season from 1983–84 to 2003–04. Shading indicates locations with TCC values above the 90% significance level based on a two-tailed t-test.

3.2 Long-lead station-scale climate prediction from downscaling

To obtain more reliable SPI and SPEI predictions, we used temperature and precipitation products from DMME. The long-lead station-scale climate prediction for precipitation and temperature was developed following Sohn *et al.* [2012]. For the coupled pattern projection method for downscaling, the linkage between observed station data and each of the nine potential predictors was first revealed on the basis of correlation analysis. It was determined that for the same predictand, the most signal-bearing predictor can differ among stations (Figure 4). This result is consistent with that different factors are responsible for inter-annual climate variations at different station locations, owing to the influence of local terrain [Kang *et al*., 2009]. The use of a single predictor therefore may not be adequate for specifying climate variations for all stations. Moreover, to avoid overestimation of skill scores, this downscaling procedure was conducted on the basis of a “leave-one-out” cross-validation framework [Kang *et al*., 2009; Sohn *et al*., 2012]. Finally, cross-validated correlation coefficients were computed to assess the skill on the basis of each individual predictor, and the best predictor as well as the associated transfer function was adopted for statistical downscaling. By repeating this protocol for all years, a full set of downscaled predictions was obtained.

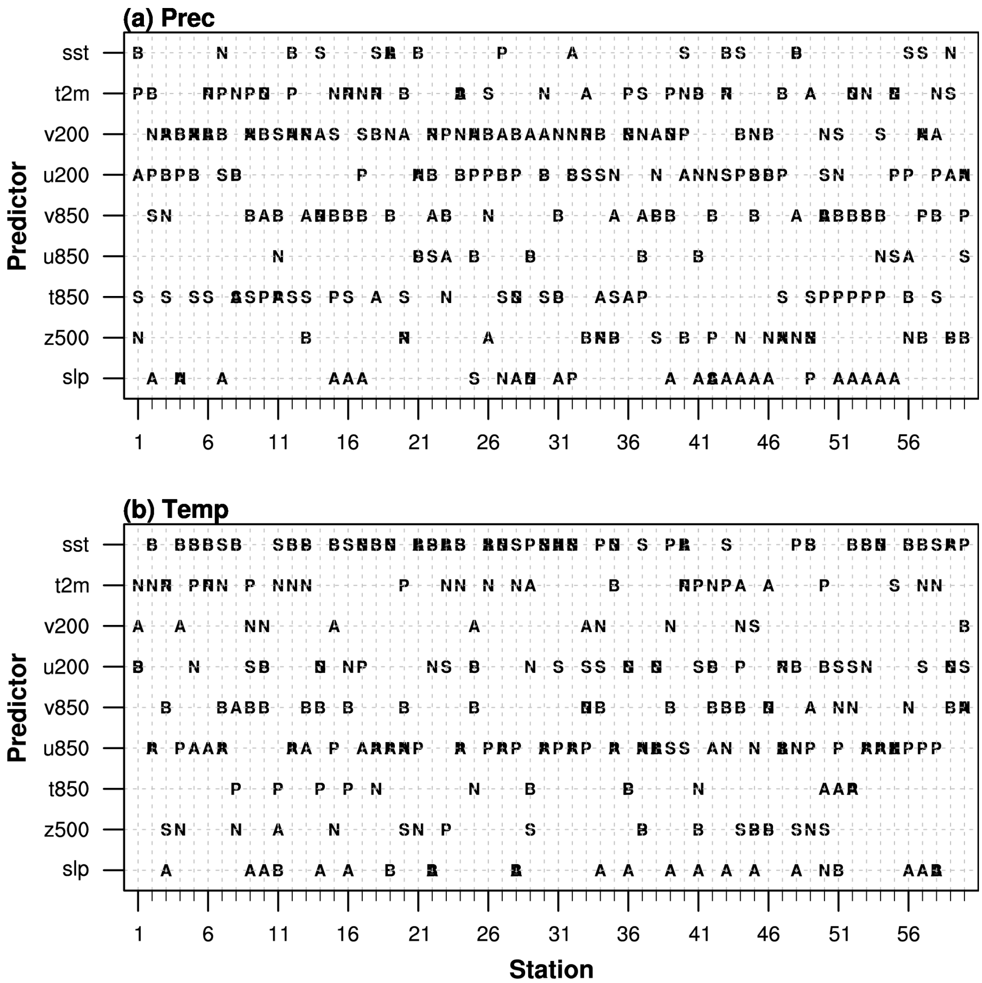

Figure 4 Best predictors selected on the basis of entire hindcast skill in producing six-month accumulated (a) precipitation and (b) temperature at each station. A, B, N, S, and P correspond to APEC Climate Center (APCC), Bureau of Meteorology Research Center (BMRC), National Centers for Environmental Prediction (NCEP), Seoul National University (SNU), and Pusan National University (PNU), respectively.

As previously mentioned, we applied a cross-validation method, in which both the regression equation development and the best predictor selection were cross-validated. Figure 5 shows the TCCs between the observed and predicted temperature and precipitation at various station locations over South Korea. It is evident that the interpolated raw MME products include large errors, especially for precipitation (Figure 5a). The cross-validated temporal correlation of the DMME prediction, based on all predictors, is comparable with that from raw MME for this variable (Figure 5b). DMME with the best predictor, however, can correct a large part of the systematic error in many stations and can greatly enhance the forecast skill for precipitation (Figure 5c). Similar results are apparent in the comparison between temperature prediction from the raw MME and DMME with the best predictor (Figures 5d and 5f).

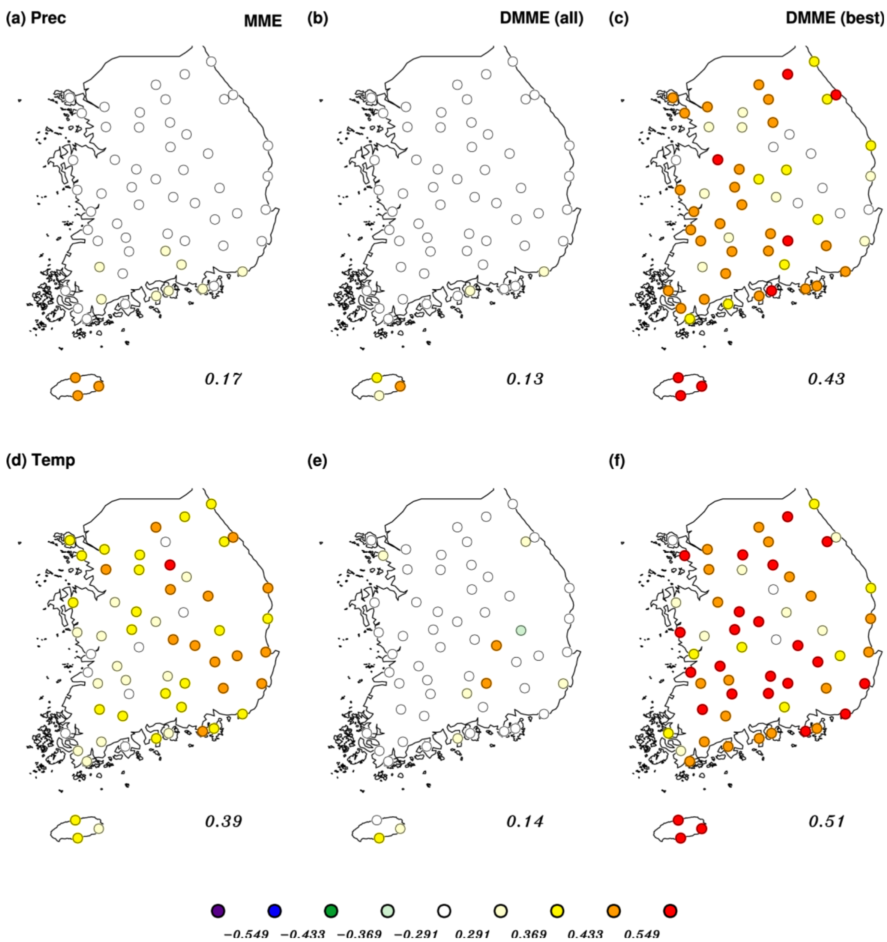

Figure 5 Temporal correlation coefficients (TCCs) between the observed and predicted (a, b, c) precipitation and (d, e, f,) temperature from December to May according to (a, d) raw multi-model ensemble (MME) and downscaled MME (DMME) based on (b, e) all predictors and (c, f) optimal predictors for each station. Values with magnitudes of 0.549, 0.433, 0.352, and 0.291 represent the 99, 95, 90, and 80% significant levels, respectively. The temporal correlation averaged over the 60 examined stations is shown at the bottom right of each panel.

Figure 6 compares TCC between the observed and raw MME monthly mean rainfall and temperature and those 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 downscaled MME skill scores, defined as the square root of the sum of squares of averaged TCCs, are also shown in the figure 6. The overall skill of DMME is much better than that of the original MME for both variables. It is also noteworthy that the improvement in the forecast skill as a result of downscaling actually increases as the lead time increases, as shown in a comparison of Figures 6a and 6f. The skill improvement at most locations can be attributed to the station-dependent optimal predictor selection in the downscaling procedure. In fact, DMME results averaged over all predictors led to no obvious increase (decrease) of skill for precipitation (air temperature) predictions (Figure 5). Overall, these results suggest that DMME has the potential for providing reliable station-scale precipitation and temperature signals with long forecast lead time.

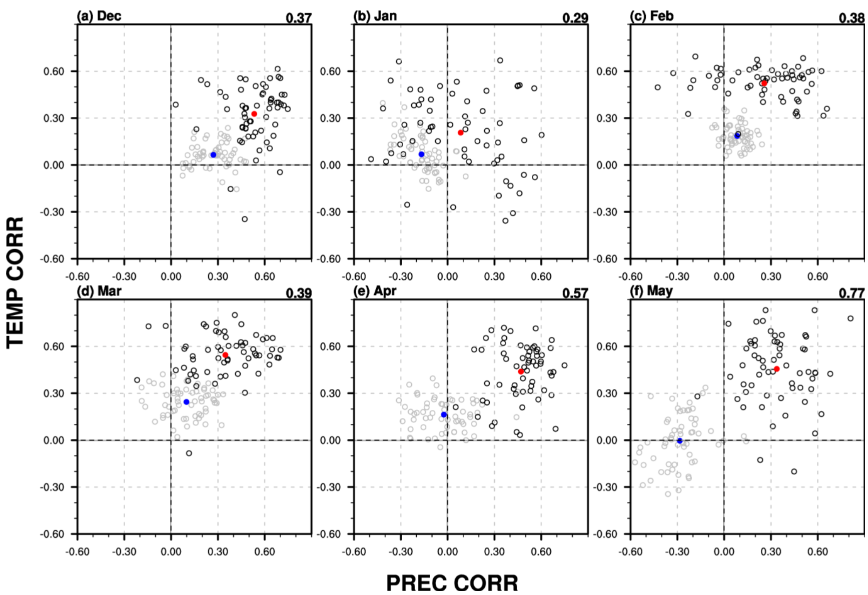

Figure 6 Scatter plots of temporal correlation coefficients (TCCs) between observed and predicted precipitation (x-axis) and temperature (y-axis) for target months of (a) December, (b) January, (c) February, (d) March, (e) April, and (f) May. Each black (gray) point represents the results based on downscaled (raw) MME predictions for one station location. Blue and red dots denote the TCC values averaged over 60 stations in South Korea for raw and downscaled MME, respectively. The "distance" between the downscaled and raw MME results is shown at the upper right of each panel.

Before using the DMME products for computing SPI and SPEI, their values were inflated to match the realistic amplitudes of the anomalous precipitation and temperature data, following Sohn *et al.* [2012] (Figures 7 and 8). Moreover, the MME average showed very low variance in both precipitation and temperature (Figures 7 and 8), compared with observations. Further, very little regional variation was evident (Figure 7). DMME showed larger variability; however, the variance of the downscaling product was much less than the observed value. To compensate for such low variance, inflation was employed to adjust the amplitudes of the DMME products (Figures 7 and 8). The inflation method simply rescales the variance of the predicted variable to that based on climate records at each station [Sohn *et al.*, 2012]. The inflated DMME gives a spread comparable to the observed values and is able to capture the amplitudes of extreme events.

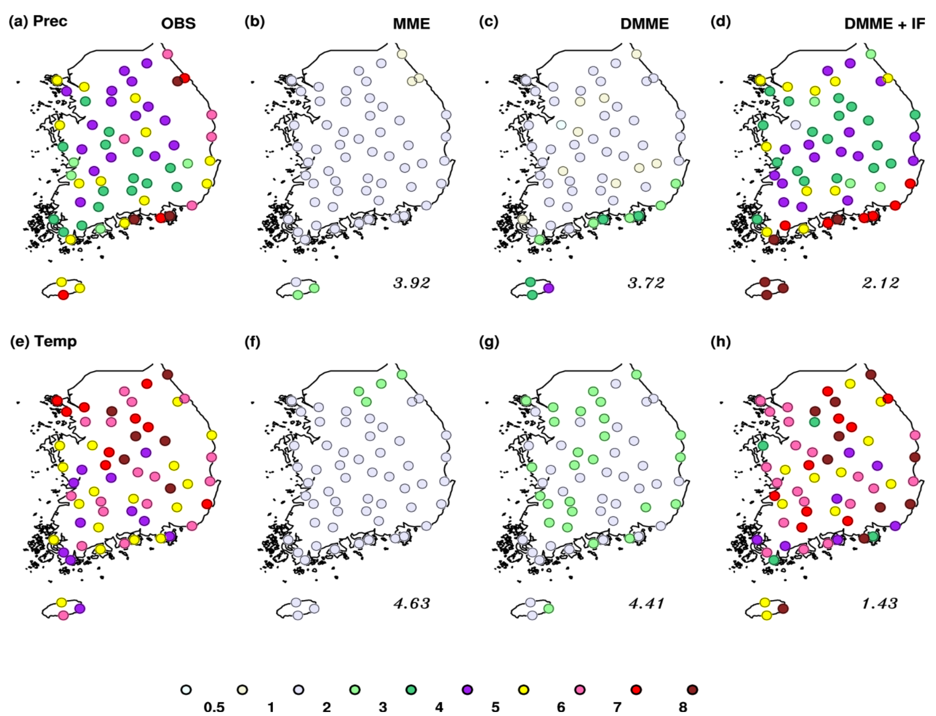

Figure 7 Interquartile ranges (IQRs) for the December-to-May (a, b, c, d) precipitation and (e, f, g, h) temperature from (a, e) observations, (b, f) raw multi-model ensemble (MME), (c, g) non-inflated downscaled MME (DMME), and (d, h) inflated DMME predictions. The root mean square difference (RMSD) between IQRs of observations and predictions are provided the bottom right of panels b–h.

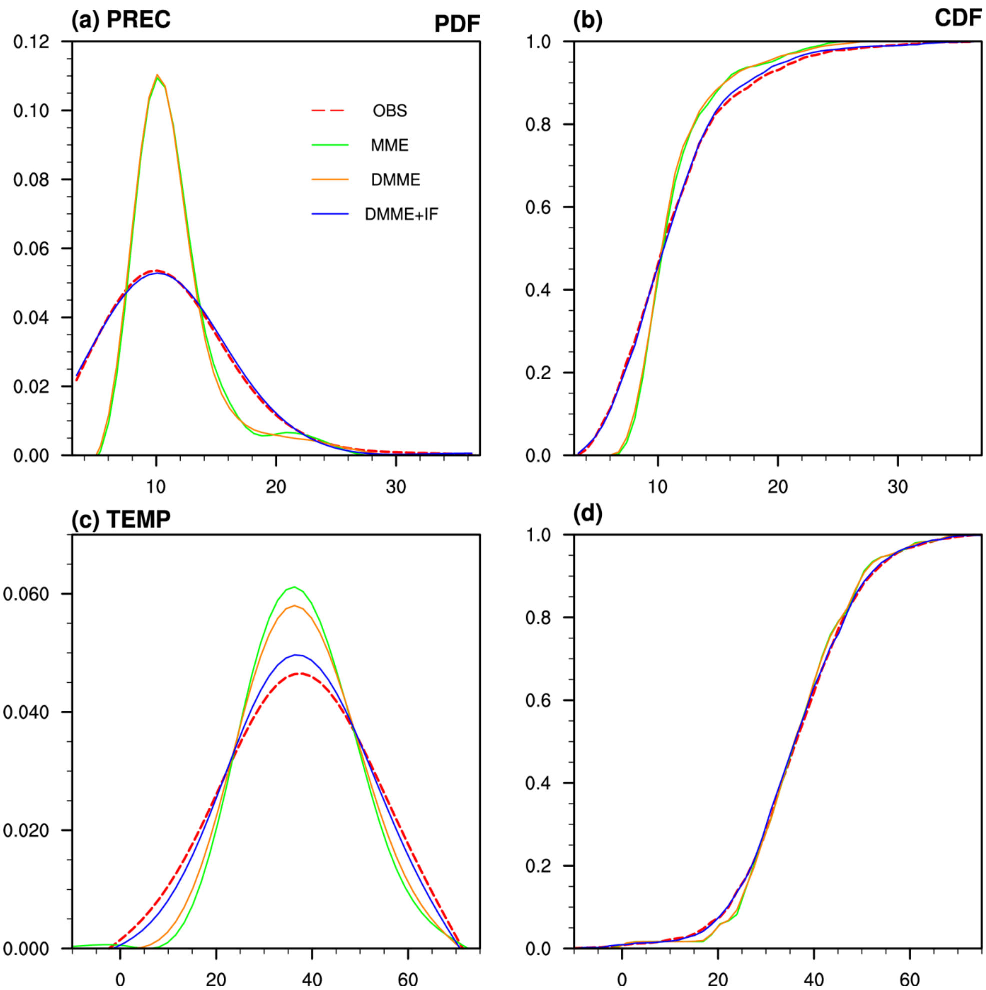

Figure 8 (a, c) Probability density functions (PDFs) and (b, d) cumulative density functions (CDFs) for the December-to-May (a, b) precipitation and (c, d) temperature, averaged over 60 stations, from observations and various prediction schemes.

3.3 Prediction of extreme hydrological drought and flood episodes

Finally, DMME forecasts were applied for local drought and flood predictions. The LEPS skill scores of the six-month SPI and SPEI ending in May from raw and downscaled MMEs are shown in Figure 9. The error in the raw MME forecast was particularly high near the rim of Taebaek Mountain, particularly at stations along the eastern to northeastern coastline which is just to the east of the mountain range (Figures 9a and 9c). The low skill in this region can be attributed to the coarse resolution of dynamical models used [Kang *et al*., 2009]. Conversely, statistical downscaling can correct a large part of the systematic errors even for forecasts with longer lead times, which is evident in Figures 9b and 9d. In addition, relative large error was apparent in the raw MME SPEI forecast to the south near Sobaek Mountain in the southern coastal region of the Korean Peninsula. In contrast, DMME, in conjunction with variance inflation, can significantly improve the skill in the aforementioned region.

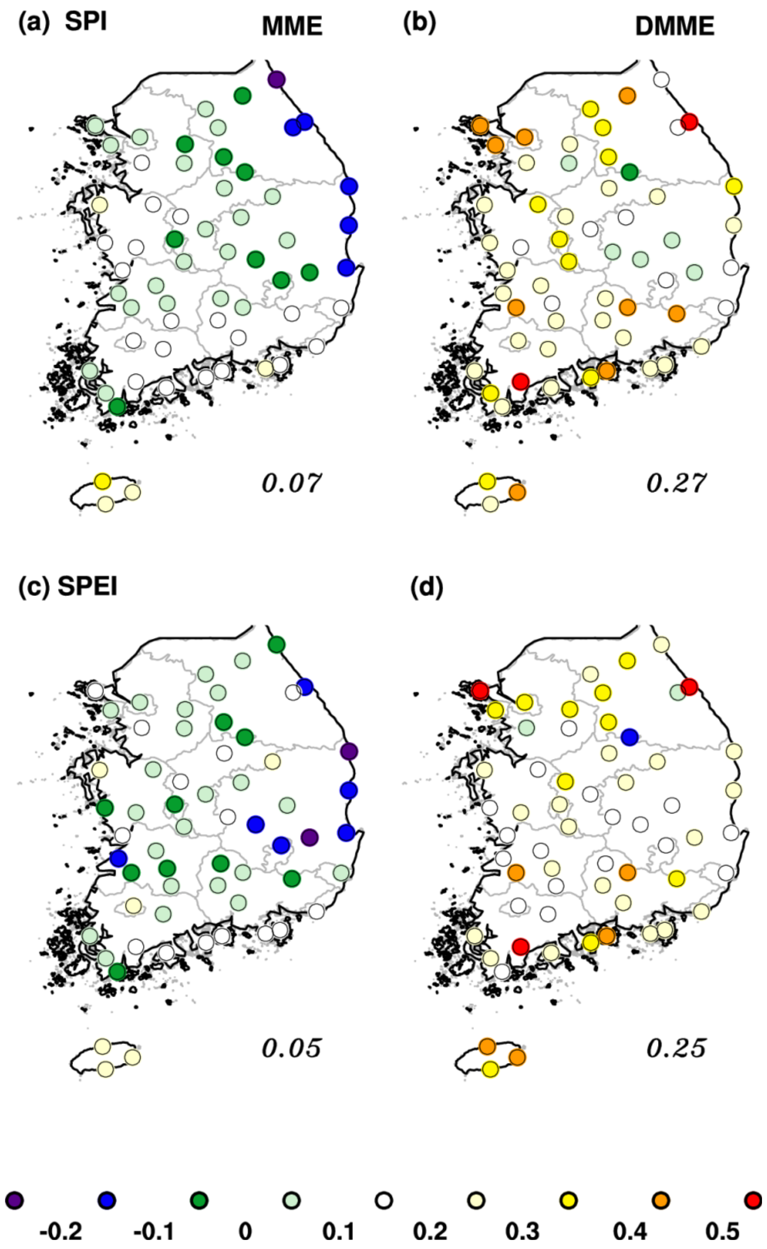

Figure 9 Linear error in probability score (LEPS) between observations and predictions based on (a, c) raw multi-model ensemble (MME) and (b, d) inflated downscaled MME (DMME) predictions for (a, b) standardized precipitation index (SPI) and (c, d) standardized precipitation evapotranspiration index (SPEI). The skill score averaged over 60 station locations is given at the bottom right of each panel. Gray lines indicate the boundaries of administrative areas for South Korea.

We conducted case studies for the extreme springtime drought (flood) episodes in 2000 (2003) to evaluate the performance of our prediction scheme in capturing individual drought and flood episodes. In particular, the predicted SPI and SPEI maps for the extreme cases of 2000 and 2003 were compared with those based on observations (Figures 10 and 11). In 2000, drier-than-normal conditions below 70% for spring persisted across the Korean Peninsula [Kim *et al.*, 2005]. In contrast, South Korea received an unusual precipitation surplus in 2003. The hydrological drought patterns determined from two different indices were consistent with a pattern correlation of 0.88. The flood-like conditions from SPI and SPEI maps for 2003 were also comparable with a pattern correlation of 0.96. It is apparent that DMME in conjunction with variance inflation can provide much more reliable predictions of hydrological extremes than those derived from raw MME products (Figures 10 and 11). Overall, the results show that our method can greatly improve reliability for prediction of hydrological extremes. Moreover, it is interesting to note that the features and strengths of extreme events represented by the multi-variable drought index SPEI differ from those given by the conventional SPI, which is based on precipitation only.

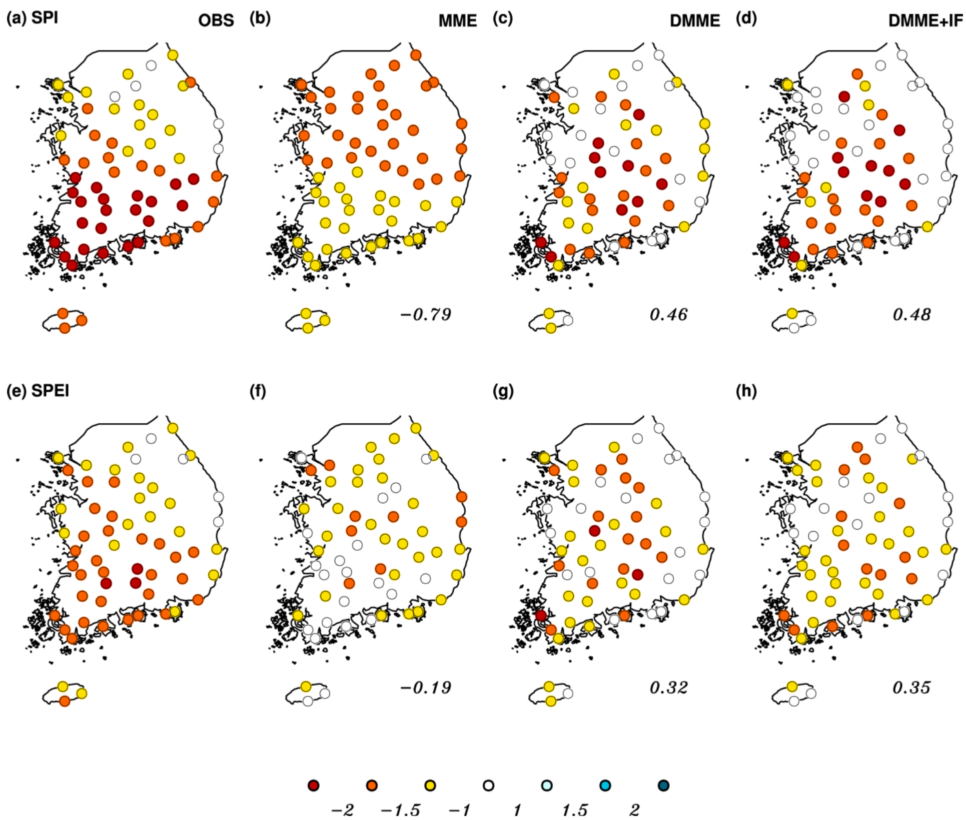

Figure 10 (a, b, c, d) Six-month standardized precipitation indices (SPIs) and (e, f, g, h) standardized precipitation evapotranspiration indices (SPEIs) ending in May 2000 from (a, e) observations, (b, f) raw multi-model ensemble (MME), (c, g) non-inflated downscaled MME (DMME), and (d, h) inflated DMME predictions. The spatial pattern correlation between observations and predictions are provided at the bottom right of (b) to (h).

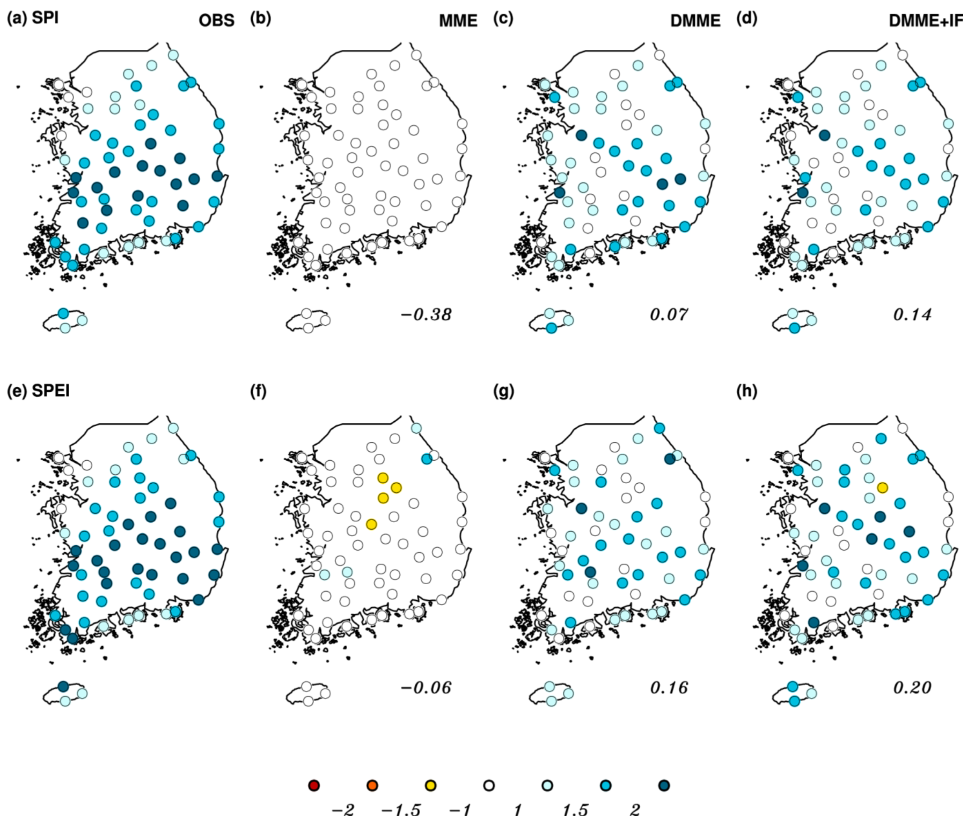

Figure 11 (a, b, c, d) Six-month standardized precipitation indices (SPIs) and (e, f, g, h) standardized precipitation evapotranspiration indices (SPEIs) ending in May 2003 from (a, e) observations, (b, f) raw multi-model ensemble (MME), (c, g) non-inflated multi-model ensemble downscaled MME (DMME), and (d, h) inflated DMME predictions. The spatial pattern correlation between observations and predictions are provided at the bottom right of (b) to (h).

4. CONCLUDING REMARKS

A new dynamical-statistical approach for conducting six-month-lead forecasts of extreme drought and flood events on the station scale has been developed and evaluated. Extreme droughts and floods were identified by computing the values of SPI and SPEI, the latter of which incorporated the effect of temperature change in the hydrological variation assessment. Local values of temperature and precipitation were obtained from the APCC 1-Tier MME products, which were downscaled on the basis of the best predictor selection; downscaling was performed in a cross-validated framework to avoid overestimation of skill. Finally, SPI and SPEI were predicted by using the inflated DMME temperature and precipitation. Compared with that based on raw MME outputs, this method was determined to greatly improve long-lead predictions of droughts and floods over South Korea in boreal winter and spring. Pronounced enhancement of skill was observed at stations that were strongly affected by the local topography. Overall, it was determined that DMME in conjunction with variance inflation can be a powerful tool for local-scale SPI and SPEI prediction.

The newly proposed SPEI, which considers the climatic water balance between precipitation and evapotranspiration, can properly account for the impact of global warming on hydrological variations. This index is advantageous for predicting such a water balance-based hydrological indicator on a scale relevant to river basins and catchments, for facilitating early warning of droughts and floods several months in advance. 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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