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Meteorological Drought Prediction Using a Multi-Model Ensemble Approach

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1. Introduction

In the United States, drought is among the costliest natural hazards, with an annual average of 6 billion dollars in damage (NCDC 2013). Drought prediction from monthly to seasonal time scales is of critical importance to disaster mitigation, agricultural planning, and multi-purpose reservoir management. Started in December 2012, NOAA Climate Prediction Center (CPC) has been providing operational Standardized Precipitation Index (SPI) Outlooks using the North American Multi-Model Ensemble (NMME) forecasts, to support CPC's monthly drought outlooks and briefing activities. The current NMME system consists of six model forecasts from U.S. and Canada modeling centers, including the CFSv2, CM2.1, GEOS-5, CCSM3.0, CanCM3, and CanCM4 models (Kirtman *et al.* 2013). Detailed information about the NMME project and forecasts can be found on CPC website (http://www.cpc.ncep.noaa.gov/products/NMME). In this study, we conduct an assessment of the meteorological drought predictability using the retrospective NMME forecasts for the period from 1982 to 2010. The standardized precipitation index, which measures precipitation deficits over a period of time, is used to predict meteorological drought.

2. Methodology

The current NMME SPI prediction framework is similar to the CFSv2 SPI prediction system that developed by Yoon *et al.* (2012). For each model, monthly-mean precipitation (P) forecasts were first bias corrected and spatially downscaled (BCSD) to regional grids of 0.5-degree resolution over the contiguous United States based on the probability distribution functions (PDFs) derived from the hindcasts. As a result, BCSD scheme corrects both the climatological mean and standard deviation of the hindcasts. Specifically, for each month and lead time, the PDF at each grid point is computed based on model hindcasts excluding the target year. The bias-corrected percentile for the target year is then obtained from the inverse PDF of the P analysis based on the percentile calculated from the PDF of the hindcasts. The BCSD method was applied to each member and each lead of the P hindcasts. The corrected P forecasts were then appended to the CPC Unified Precipitation Analysis (Chen *et al.* 2008) to form a P time series for computing 1-month, 3-month, 6-month, and 12-month SPIs. The NMME-ensemble SPI forecasts are the equally weighted mean of the six model forecasts. Two performance measures, the anomaly correlation coefficient (ACC) and root-mean-square errors (RMSE) against the observations, are used to evaluate forecast skill. In this study, CPC Unified Precipitation Analysis is used as the observations for forecast evaluation.

3. Results and discussions

Figure 1 shows the relation of SPI forecast skill to lead time for January and July. In this figure, color lines are for model forecasts and the bold black line is for the ensemble forecasts. The values plotted in the figure are the averages over the continental U.S. For 3-month SPI (SPI3), skill quickly drops and is very close to the P forecast skill after Lead 3, when observations are no longer included in the 3-month window. Similar results are observed for 6-month SPI (SPI6). When P observations are no longer included in the 6-month window at Lead 6, SPI6 forecast skill converges to the P forecast skill. We also notice that when there are more observations include in the time window, for example, Month-1 SPI6 forecasts include 5 months of observations, its skill is higher than Month-1 SPI3 forecasts, which include 2 months of observations. Therefore, P observation is a dominant factor contributed to the SPI forecast skill and the small differences

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among models. Similar results are observed for using ACC and RMSE as performance measures and for different months.

Another thing we notice from this figure is that for both SPI3 and SPI6, the ensemble forecasts, which are on top of most model forecasts in the ACC plots and on the lower end of most model forecasts in the RMSE plots, have higher skill than that from individual models, but the differences are not large. If we use 0.5 as a threshold for ACC and 0.8 as a threshold for RMSE to determine skillful forecasts, both ACC and RMSE suggest similar results that SPI6 forecasts are skillful out to four months.

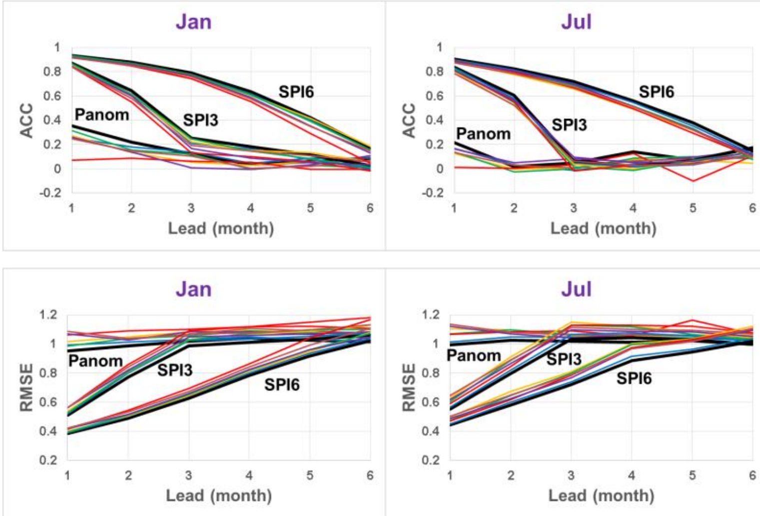

Fig. 1 Relation of SPI forecast skill to lead time for January and July.

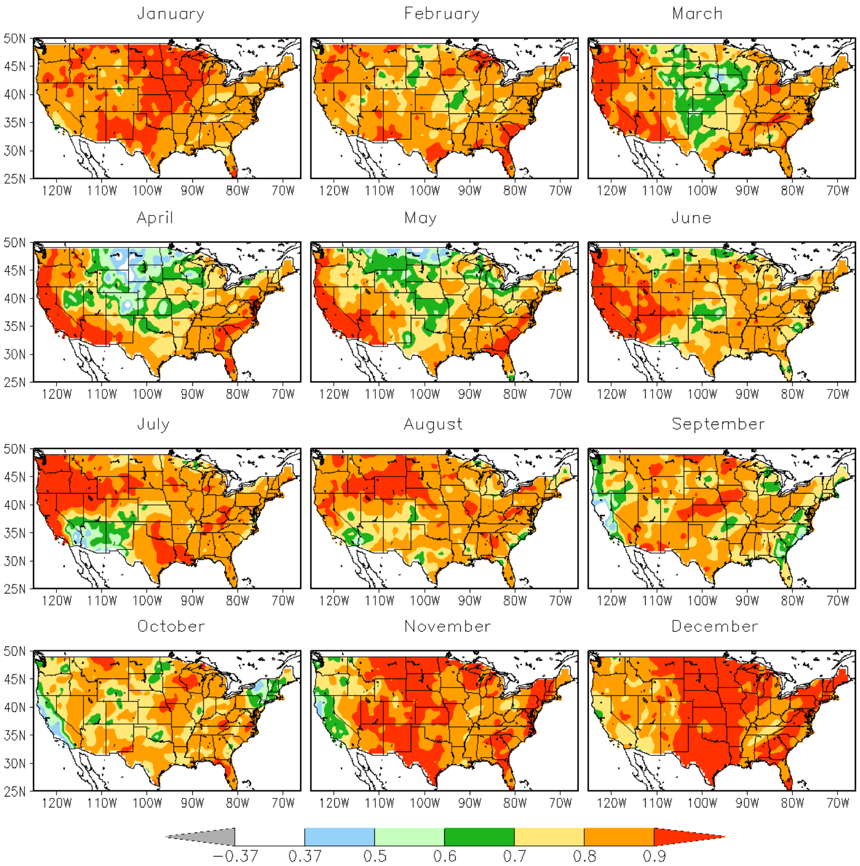

Fig. 2 ACC maps of Month-1 SPI3 forecasts for all 12 months.

Figure 2 shows the ACC maps of Month-1 SPI3 forecasts for all 12 months. We can see that predictive skill is seasonally and regionally dependent. Skill generally is higher for the winter season (*e.g.*, January) and lower in the Spring (*e.g.*, April). Areas with high forecast skill in the month generally correspond to the dry climatology in the region. For example, over central U.S. for January and along the West Coast in July. Areas with low forecast skill in the month generally correspond to the wetter climatology in the region. For example, springtime over the central U.S. is the time of rain showers, and July over the Southwest is their monsoon season.

4. Conclusions

For P forecasts (figures not shown), errors vary among models and predictive skill generally is low after the second month. All model P forecasts have higher skill in winter and lower skill in summer. BCSD improves RMSE for both P and SPI forecasts, but the differences in ACC between with and without BCSD are marginal (and not statistical significant). Most RMSE improvements are over the western mountainous regions and along the Great Lake. Although P forecast skill is not large and quickly drops after one month, SPI predictive skill is high and the differences among models are small. Generally, model with lower P forecast skill has lower SPI forecast skill. The skill mainly comes from the P observations appended to the model forecasts. This factor also contributes to the similarity of SPI prediction among the six models. Still, NMME SPI ensemble forecasts have higher skill than those based on individual models or persistence.

Overall, SPI predictive skill is regionally and seasonally dependent, and NMME SPI6 forecasts are skillful out to four months. SPI forecast skill at a region corresponds to local rainfall climatology and variability. Dynamical models improve SPI predictive skill from baseline skill when and where P forecasts are skillful. The improved skill of SPI prediction during the wet seasons spanning roughly late autumn to early spring over the Southwest and Gulf Coast region is attributed to the known impacts of ENSO signals on these regions' cold-season precipitation, which is consistent with the findings by Quan *et al.* (2012) from CFSv2 SPI prediction.

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