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The Skills of the Probabilistic Forecast for Meteorological Drought over the United States

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ABSTRACT

In this study, we evaluated the skills of probabilistic forecast for meteorological drought based on the precipitation forecast from Northern American Multi-model Ensemble (NMME). The total sixty ensemble members are selected from six NMME participated forecast models for the meteorological drought forecast. The NMME forecasts are downscaled to the 0.5 degree CONUS grid and bias corrected with BCSD method. The meteorological drought forecast, based on the standardized precipitation index SPI6 (six months accumulation), is computed and converted to the corresponding drought categories. The grand mean (GM) index summarize the mean state of drought from the all NMME ensemble members. The probabilistic information for each drought category, which is measured by the concurrence at each ensemble member, is computed to quantify the uncertainties of the drought forecast. The total 29 years hindcasts, during 1982-2010, are evaluated against observed drought categories. The assessments show that the meteorological drought forecasts based on the NMME display robust skills, both in grand mean and probabilistic forecast. More than half areas of USCONS are still skillful for lead four month forecast. The skills of probabilistic forecast over climatological forecast are obviously and decreasing with leading time. However, they only indicate very slight skills over the short-leading random ESP forecast that initial drought information dominated. With increasing the lead time, the values of climate forecast begin emerging.

1. Objectives

Drought occurred in the US had the major societal, economical, and environmental impacts. The current objective drought forecasts based on dynamical model, such as the forecasts from the NMME (Kirtman *et al.* 2014) *etc*., however, exist large differences in the drought forecast, in particular to classify the drought into the drought categroies Dx (x=0-4) (Mo 2008). And also, current forecast has no estimation of the uncertainty and doesn't give risk manager or decision maker the best or worse scenarios. Since the chaotic nature of climate system, the demand for probabilistic information of drought forecast is undeniable.

2. Data and procedures

As prescribed by Xu and Mo (2018), we selected six representive models in NMME forecast set, i.e. CanCM3 model, CanCM4 model, GFDL_FLOR model, NASA GEOS5 model, NOAA CFSv2 model and NCAR CCSM4 model.. Each model was selected only 10 ensemble members which are closest to the common forecast initial time (the day 01 at each month). The hindcasts come back for every month from 1982 to 2010 (total 29 years), obtained from the NMME historical archives. The real-time forecast start from 2011 up to recently, issued the precipitation and temperature at the first of each month.

The precipitation (P) forecast for lead 1-6 months from NMME are firstly downscaled to 0.5 degree CONUS grid, by bilateral interpolation. The downscaled P forecasts are then bias corrected by the bias correction and spatial downscaling (BCSD) method (Yoon *et al*. 2012) with leave-one-out cross-validation, which guarantee the target year is removed from the training pool to avoid the overfitting problem. This step is critical for the drought forecast since any forecast bias will cause SPI error in the next computation with

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observed P data. The corrected P forecast, combined with the CPC unified P observations back to 50 years historical record, are utilized to calculate six month accumulated standardized precipitation index (SPI6), as the predictant for meteorological drought. The SPI6 could well capture the short-term drought signal and also balance the persisted long-term drought. The SPI6 forecasts from 60 ensemble members in the leading time 1-6 months, are then transferred to the uniform distribution (percentile) from the original normal distribution.

The sixty ensemble member for drought forecasts in percentile (uniform distribution) are mathematically averaged to the grand mean (GM) for the drought category Dx forecast. This percentile-mean method will reduce the "ensemble mean error" due to uneven distribution of SPI at "the long tail of normal distribution", in particular for the extreme events such as droughts. However, due to the offset effect (cancel out) of the arithmetic mean, the GM index will serious underestimated the drought intensity (Mo and Lettenmaier 2014). We remapped the grand mean index again to the uniform distribution based on the 29 year historical values. The probabilistic information for each drought category Dx, *i.e.* D0-D4, is measured by counting the concurrence of all sixty ensemble member in each drought category.

This objective probabilistic forecast is computed at the 10th day of each month, after collect all the six NMME forecasts initialized at the beginning of that month. The objective forecast could be delivered to drought forecasters, before the drought briefing, the seasonal drought overlook at the middle of the month and monthly drought overlook at the end of the month. Figure 1 shows an example of the probabilistic drought forecast for January 2019 based on the NMME forecast initialized at Dec 1, 2018. The top panel is the Grand Mean (GM) drought index that gives the mean state of drought by averaging all sixty ensemble member. The bottom four panel display the detail of probabilistic information for the Dx category or worse drought event (Dx and above). For instance, the "D0 and above" show the probabilistic for the "abnormally dry" or worse drought event (percentile < 30%). Similarly, the "D3 and D4" indicate the "extreme drought" (percentile <5%) and "exceptional drought" (percentile <2%). This objective forecast will help the forecaster to prepare the first guess map of the monthly drought overlook. Similarly, Fig. 2 shows the probabilistic drought forecast

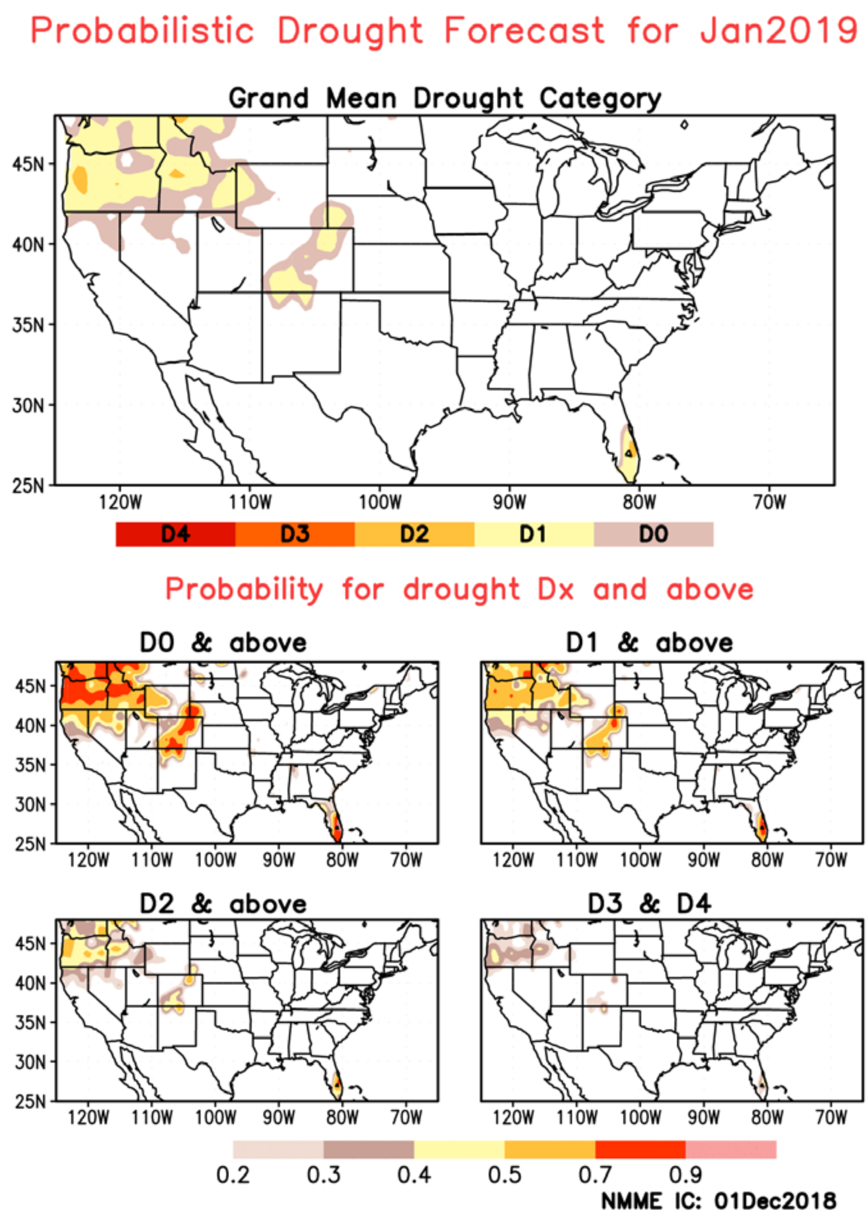

Fig. 1 The probabilistic drought forecast for January 2019 based on the NMME forecast initialized at Dec 01 2018.

for March 2018 based on the NMME forecast initialized at Dec 1, 2018. This map could help the operational seasonal drought overlook issued at the middle of each month.

3. Evaluations

Observed drought events are defined by the same SPI6 indices based on the observed rainfall analysis from CPC unified precipitation data. The rank correlation (Spearman Rho) is used to assess the GM index and Rank Probability Skill Score (RPSS) is used for the probabilistic forecast.

For skill assessment, the reference forecasts are defined to isolate the forecast skill origin from initial condition or climate forecast information. The persistent forecast is defined as the forecast map that prescribes the last month precipitation anomalous for the next six months. The climatological forecast are defined based on the drought categories definition, the 30% probability for “D0 and above” droughts, the 20% probability for “D1 and above” droughts, the 10% probability for “D2 and above” droughts, the 5% probability for “D3 and above” droughts and then 2% probability for D4 droughts. The random forecast, similar to the hydrological “ESP” type forecast, are calculated according to the random retrieved historical precipitation observation time series to computer the SPI forecast.

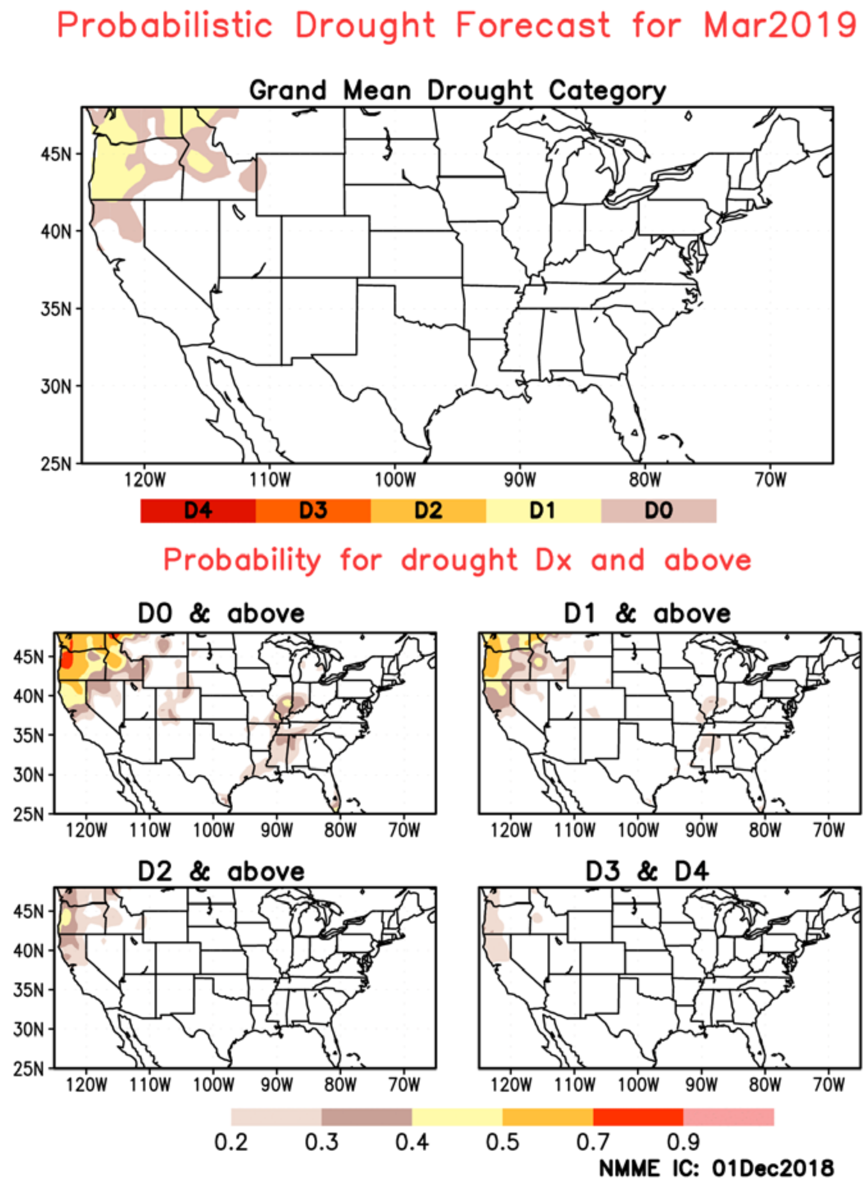

Fig. 2 The same as Fig. 1, but for March 2019.

3.1 Grand mean forecast

The grand mean forecast are the summary the mean drought state over the total 60 ensemble member. The rank correlation (Spearman Rho) is used to evaluate the GM forecast against the observed SPI indices based on the CPC unified precipitation. Figure 3 shows the Spearman Rho for January 01, April 01, July 01 and October 01 initialized forecast (from top to bottom), during 1982-2010 hindcast period.

As Fig. 3 shows, in the lead one month forecast (left column), the rank correlations are very high over the most area of USCONS. Except limited area in the Great Plain at April initialized forecast and some southwest area at July and October initialized forecast, Spearman Rho over the most area of USCONS are over 0.8. This indicates the GM forecast could well catch the drought situation at a short leading time, due to the strong persistence in the nature of the drought. For the lead-3 month forecast, the spearman Rho decrease with the lead

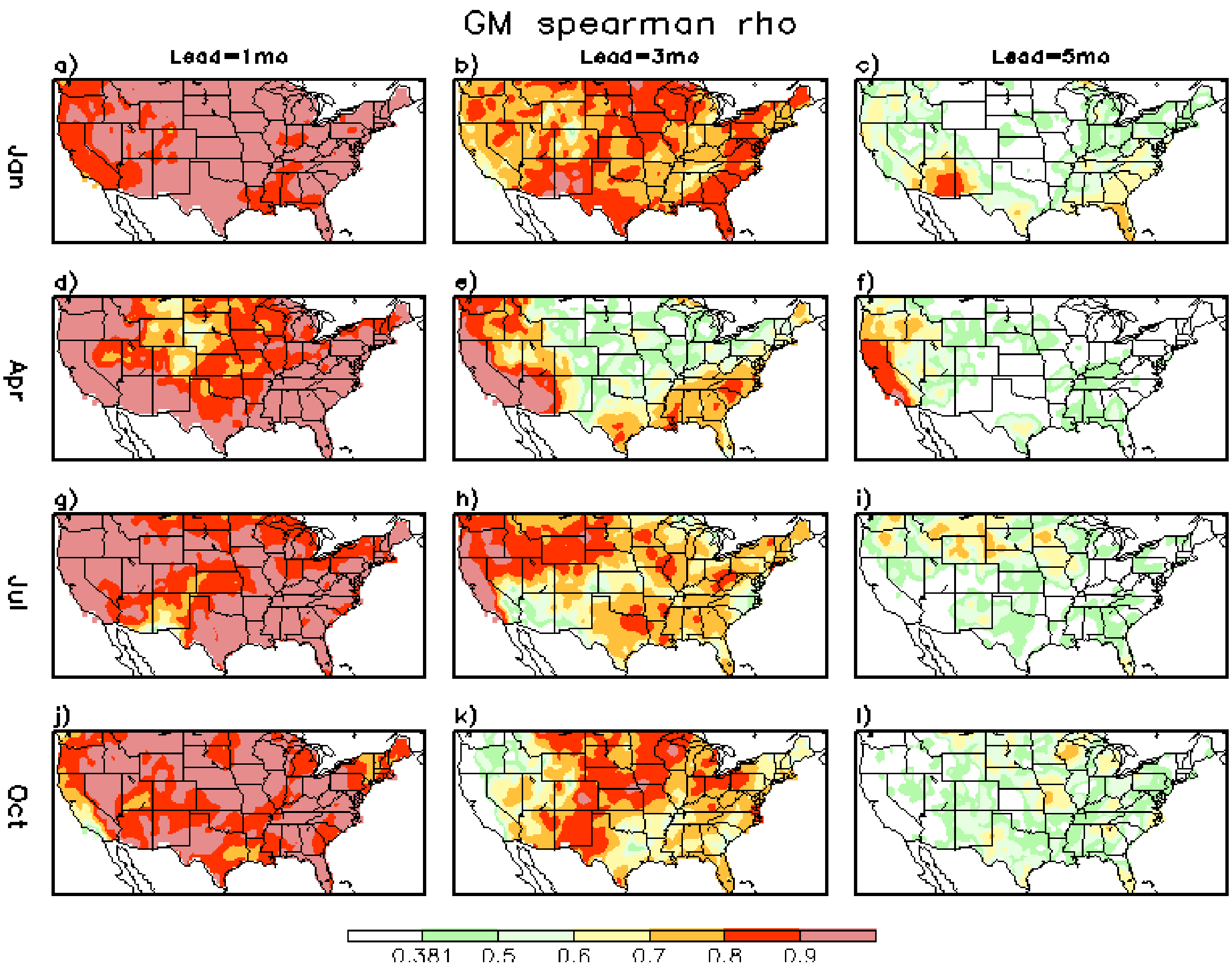

Fig. 3 The Spearman rank correlation (rho) for the Grand mean (GM) forecast with observed indices, for the January 01, April 01, July 01 and October 01 initialized forecast (from top to bottom) during 1982-2010. The left, central and right columns are the lead one, three and five months forecast respectively. Only the area where the correlation is 95% significance for student-t testing during 1982-2010 is colored.

time. But, more than half area of USCONS, the Rhos are still over 0.5 implying the useful of forecast. Except some scatter regions in the central plain for April initialized forecast, and part of southwest region for July and October initialized forecast, most area of Rho are still significant at 95% in student t testing. However, for the lead-5 month forecast, the forecast signals are serious weakened at most area (the Rho less than 0.5) and the area with significant correlation has greatly decreased.

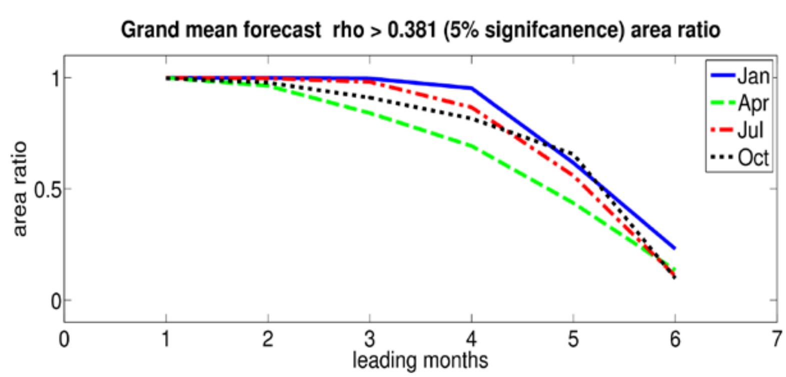

Fig. 4 The area ratio of the grid-points over USCONS with 95% significance in the Spearman rank correlation (rho) during 1982-2010 (larger than 0.381) , for the GM forecast initialized at January 01, April 01, July 01 and October 01.

Figure 4 shows the ratio of grid-points where are 95% significance in the Spearman rank correlation (rho) for January 01, April 01, July 01 and October

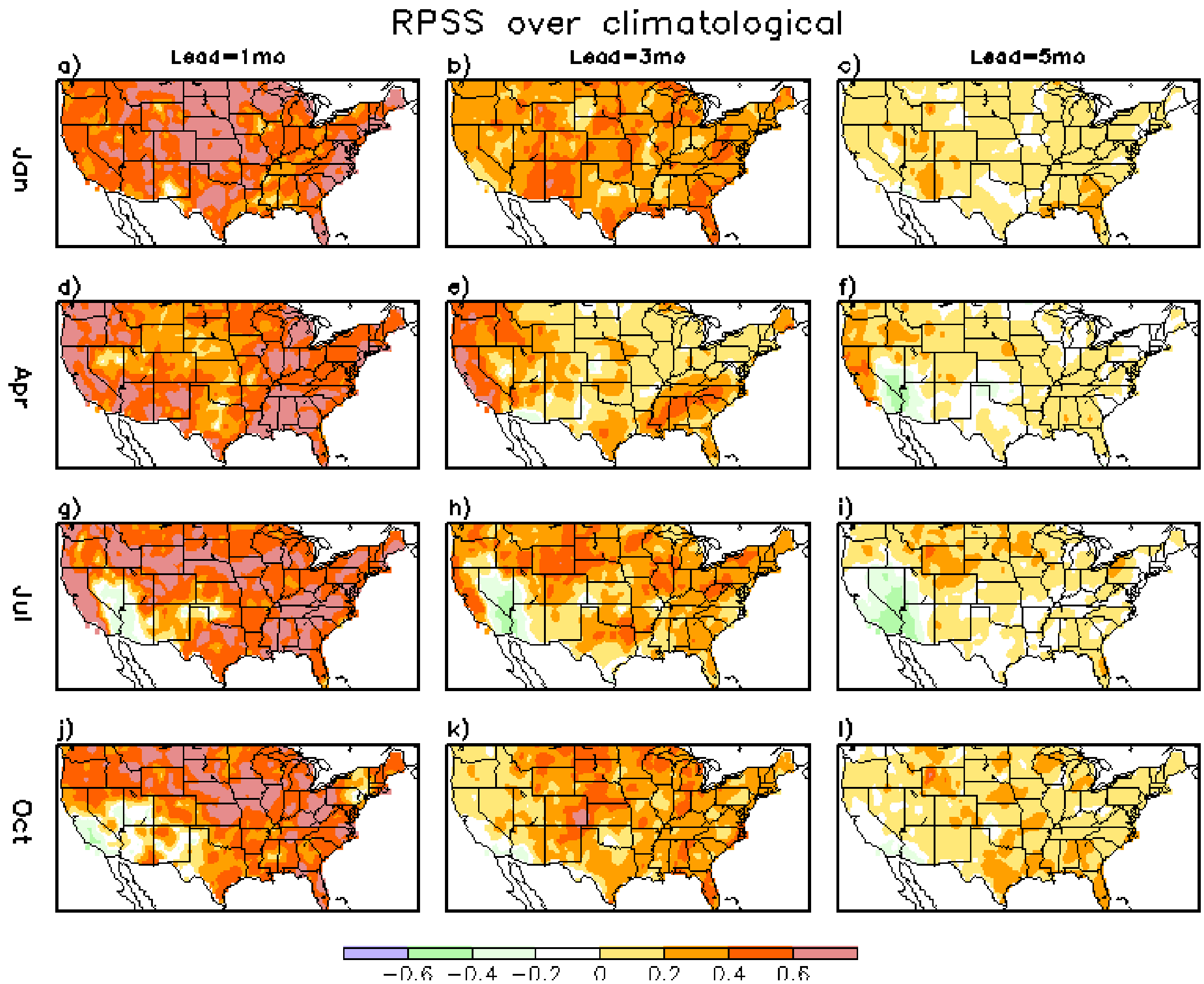

Fig. 5 The same as Fig. 3 but for the RPSS over the climatological forecast.

01 initialized forecast, based on the 29 years hindcast during 1982-2010. This ratio indicates the area with useful forecast. The forecasts initialized at the January are the best. More than half of areas are still useful at lead-5 month forecast. The forecasts initialized in the April are the worst; the forecast signal will reduce less than the half of USCONS in the lead-4 month. The forecasts initialized at the July and October are in the middle, still more than half area are useful at the lead-5 month forecast.

3.2 Probabilistic forecast

For Rank Probability Score (RPS) evaluation, the probabilistic forecast are equally divided by 10% probability as a bin, such as 90%, 80%, 70%....20%, 10%, where total bin n=10,

$$RPS = \sum_{m=1}^{n}(Y_m - O_m)^2, \quad Y_m = \sum_{j=1}^{m} y_j, \quad O_m = \sum_{j=1}^{m} o_j.$$

The RPS is the sum of the square of probabilistic differences at the each bin between forecast (Y_m) and observed (O_m) drought events. The skill score of RPS (RPSS) is the forecast skill with respect to the referrence climatological forecast or random “ESP” type forecast.

$$RPSS = 1 - \frac{\langle RPS \rangle}{\langle RPS_{Cl} \rangle}$$

Figure 5 shows the RPSS for the probabilistic drought forecast over the climatological forecast. With a short lead time (left column), the probabilistic forecast dominantly beat the climatological forecast, with large

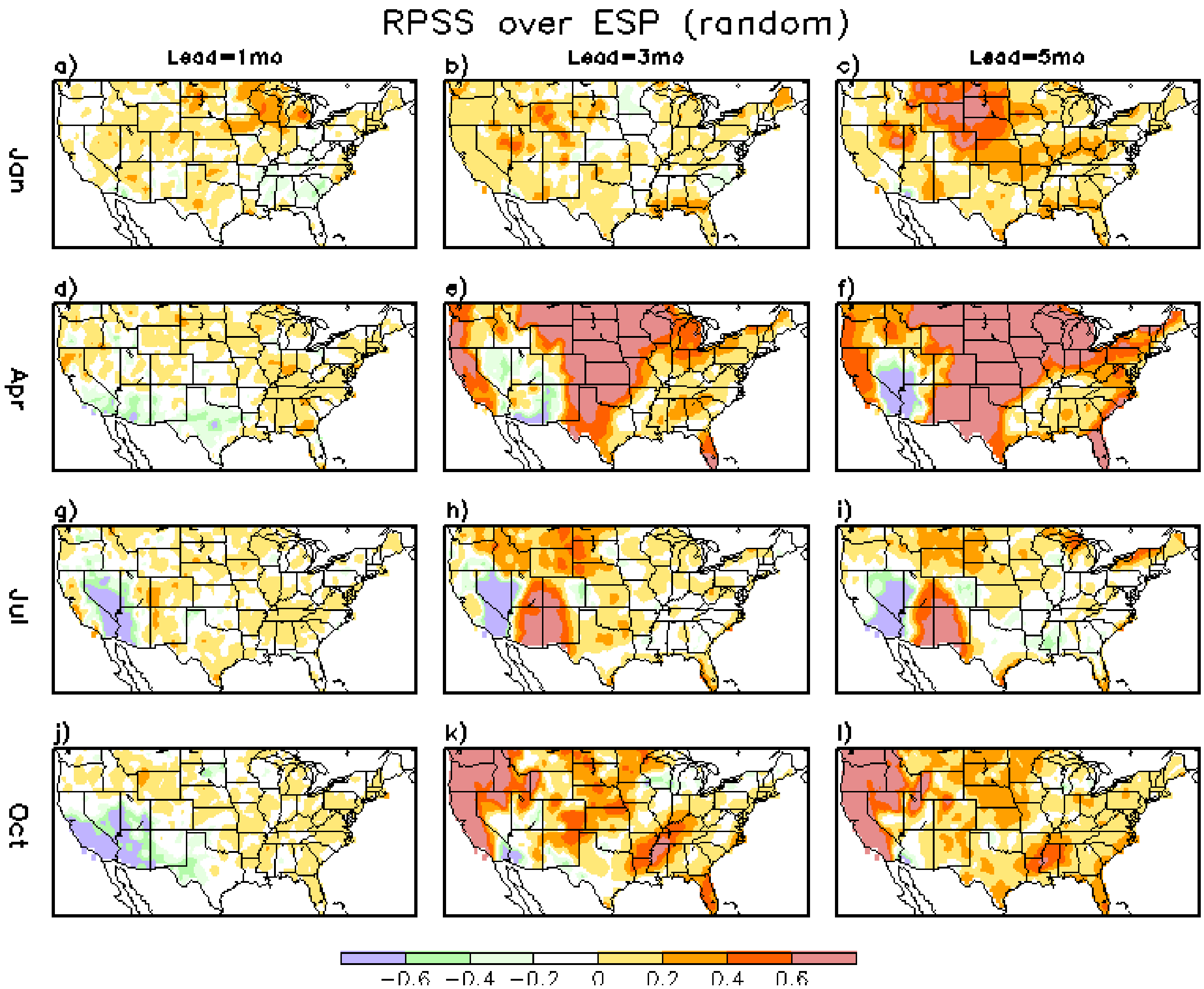

Fig. 6 The same as Fig. 3 but for the RPSS over the random (ESP) forecast.

positive RPSS score. Except limited region at AZ and NM at July and October initialized forecast, most area of USCONS indicated positive skills of probabilistic forecast. With increasing with lead time, the skills over climatological forecast are weakened as expected. However, at lead-5 month forecast, over the majority of USCONS, the skills are still positive. These positive skills indicate the forecasts are better than climatological forecast.

Similarly, Fig. 6 shows skill score RPSS for the probabilistic forecast over the “ESP” forecast, which combined the random retrieved precipitation time series with current drought condition. In the short leading, the probabilistic forecast show very weak skill over the random forecast. This implies the most forecast signal of probabilistic forecast come from the initial condition. With increasing the lead time, the probabilistic forecast show increasing skills over the random forecast, indicating the contribution of initial conditions are reducing and the contributions of forecast information are increasing. With the decreasing the impact of initial condition, the probabilistic forecast gradually display the value from the climate forecast

4. Conclusions

In this study, we evaluated the usefulness of probabilistic forecast for meteorological drought based on the precipitation forecast from Northern American Multi-model Ensemble (NMME). The total 29 years hindcasts, during 1982-2010, are evaluated against observed drought categories based on the CPC unified precipitation. The assessments show the meteorological drought forecasts based on the NMME display strong skills, both at

Grand Mean forecast and probabilistic forecast. The GM forecast show robust rank correlation at the different lead time over the most area of USCONS. The ratio with useful forecast signal (95% significant at student t testing) is more than the half area of USCONS, even at the lead four month forecast. The probabilistic forecast display strong skills over the climatological forecast at lead one to five months. This implies the objective forecast well beat the climatological drought forecast based on the historical occurrence. The probabilistic forecasts also indicate very litter skills over the short leading random ESP forecast that initial information dominated. With increasing lead time, however, the values of climate forecast begin to override the impacts of initial condition.

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