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A Hybrid Dynamic-Statistical Approach to Link Predictive Understanding to Improve Seasonal Prediction of Rainfall Anomalies at the Regional Scale

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1. Introduction

Seasonal prediction of summer rainfall anomalies over the United State (US) Great Plains (GP) is central for drought early warning and society preparedness. Yet, current dynamic models' predictions have failed to predict recent extreme droughts in 2011 and 2012 and shown virtually no skills for seasonal prediction of the summer rainfall anomalies (*e.g.* Quan *et al.* 2012; Hoerling *et al.* 2014). In addition, whether summer rainfall anomalies, especially droughts, are intrinsically predictable without oceanic forcing, if so, what are the underlying physical mechanisms, are still debatable. Namias (1982) have observed a persistent circulation anomaly from March to June for 1980 and 1988 summer droughts. He suggested that such persistence can provide reasonably good seasonal predictability. Fernando *et al.* (2016) have shown that 13 out of 18 severe-to-extreme summer droughts over the US southern GP since 1895 were linked to dry spring, only 3 summer droughts occurred after wet springs. There is a significant correlation between soil moisture anomalies and the 500 hPa geopotential height anomalies 2-4 weeks later that is stronger than the autocorrelation of the 500 hPa geopotential height anomalies. Thus, the observed drought persistence is likely due to land surface feedbacks, as suggested by previous studies (*e.g.* Carson and Sangster 1981; Dirmeyer 1994; Myoung and Nielsen-Gammon 2010; Oglesby and Erickson 1989). However, soil moisture feedbacks in the current dynamic models can only sustain drought memory for about a month. Why soil moisture memory in these models is so short lived compared to that appears in observation is not clear. In addition, the apparent drought memory can be a result of a sequence of random weather events induced by stationary Rossby waves (*e.g.* Hoerling *et al.* 2014, Schubert *et al.* 2011). Whether soil moisture memory plays a significant role in sustaining the dry anomalies between these random dry spells is not clear. Furthermore, soil moisture anomalies can lead to Rossby wave like large-scale circulation anomalies (*e.g.* van den Dool *et al.* 2003; Koster *et al.* 2014). Our research is motivated by these outstanding questions, focusing on the role of land-atmospheric coupling processes in determining the observed spring to summer drought persistence, its implication for seasonal predictability and potential causes of the inadequate representation of the spring to summer drought memory.

2. Data and model products

We have used the monthly precipitation of Precipitation Reconstruction over Land (Chen *et al.* 2002; hereafter PRECL) from National Oceanic and Atmospheric Admiration (NOAA) from 1948 to present at 1° by 1° resolution, the European Centre for Medium-Range Weather Forecasts (ECMWF) Interim Re-Analysis (ERA-Interim) (Dee *et al.* 2011) for the moisture budget analysis (Erfanian and Fu 2019) and the radiosonde profiles provided by the Department of Energy (DOE) Atmospheric Radiation Measurement (ARM) at its southern GP site. In addition, we have used the Climate Forecasting System Version 2 (CFSv2) real time forecasts and the CFS reanalysis (CFSR) products to train a Canonical Correlation Analysis (CCA) based statistical model provided by Climate Predictability Tool (CPT) of the International Research Institute for Climate and Society at Columbia University. The predictors of this model are the anomalous large-scale atmospheric circulation (500 hPa geopotential height), convective inhibition energy (CIN) and soil moisture anomalies in April. The predictant is the rainfall anomalies during May-July.

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3. Highlight of the results

What process initiates the summer droughts over the US GP? Figure 1 suggests a connection between rainfall deficit over the southwestern (SW) US in spring (March-May) and rainfall deficit over the US GP in summer (June-August), through anomalous zonal advection of drier air. In particular, Fig. 1a shows a significant positive correlation between rainfall anomalies over SW US and the zonal moisture advection anomalies into the GP during March-May. The dry anomalies over the SW US in spring is often induced by La Niñas (*e.g.* Leathers *et al.* 1991)). Figure 1b shows a significant positive correlation between the zonal moisture advection anomalies into the GP in spring and the rainfall anomalies over the GP in summer. Figure 1c shows persistent dry zonal advection anomalies to the GP during 2012 in the lower troposphere (900 – 600 hPa) started in March, and intensified in May-June. This persistence is in contrast to the zonal moisture advection in the middle and upper troposphere, which changed between dry and wet anomalies, presumably influenced by random large-scale circulation anomalies associated with the Rossby waves. Thus, the persistent dry advection to the GP due to rainfall deficits over the SW US from late winter to early summer plays a significant role in initiating the summer rainfall deficit over the US GP, as illustrated schematically in Fig. 1d. This result has been reported as part of the publication (Erfanian and Fu 2019).

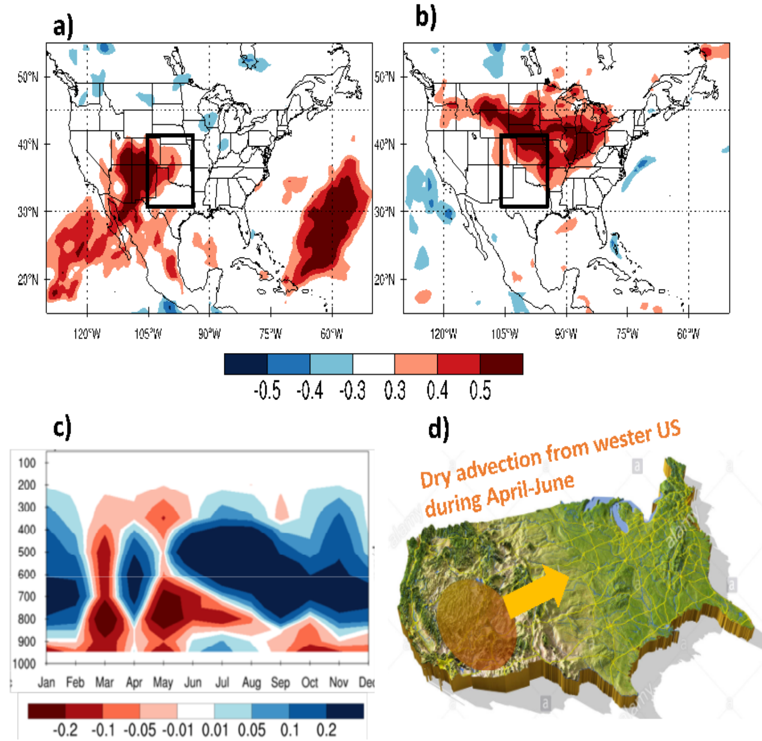

Fig. 1 a) and b) Single point correlation maps between the standardized time series (1979-2018) of the March-May zonal moisture advection at 700 mb averaged over the GP (shown by the black box) with the standardized anomalies of precipitation in (a) the March-May; (b) in June-August. The correlation coefficients greater than 0.3 and 0.4 are statistically significant at the 90% and 98% confidence level, respectively. c) The seasonal evolution of the standardized mean zonal moisture advection anomalies induced by the anomalous moisture gradient as a function of the pressure (hPa) for the 2012 GP drought. d) Schematic illustration of the mechanism that initiates the summer drought over the US GP.

What process intensify the summer droughts over the US GP? In particular, whether the dry anomalies are intensified by a bottom-up land-atmospheric interaction, or by a top-down Rossby wave induced atmospheric circulation anomalies? Figure 2 shows the evolution of the dry atmospheric layers associated with the intensification of the 2011 and 2012 droughts, compared to that of 2013, a non-drought year, based on the radiosonde profiles provided by the Department of Energy (DOE) Atmospheric Radiation Measurement (ARM) at its Southern GP site. As one can see, a drier relative humidity layer started in the atmospheric boundary layer and the lower troposphere (below 3 km in height) in April of 2011, and 2012 (Fig. 2a). The drier layer deepened and reached mid-troposphere (surface to 7 km height) in May (Fig. 2b), and then further deepened and reached to the upper troposphere (surface to 13 km height) in June (Fig. 2c) and July (Fig. 2d) of 2011 and 2012, respectively. Such a gradual deepening of the drier layer from the lower troposphere to the mid-troposphere and then to the upper troposphere suggest that a drier air advection from the US SW in spring reduces shallow convection and increasing land surface dryness, which reduces moisture transport to the mid-troposphere and suppresses convective congests and deep convection (*e.g.* Holloway and Neelin 2009; Zhang and Klein 2010). The latter reduces moisture in the middle and upper troposphere. Fig. 2 suggests that the intensification of the 2011 and 2012 GP droughts is primary contributed by a bottom-up positive land-atmospheric feedbacks.

Could the above discussed mechanisms enable us to improve seasonal prediction of the US GP summer rainfall anomalies? To answer this question, in Fig. 3 we compare the prediction skills of our CCA based statistical model (Figs. 3a-3c) with the skills of the North American Multi-model Ensemble (NMME) seasonal predictions (including all the ensemble members of the seven models, Figs. 3d-3f) for the southern GP, both are initialized in April. The statistical prediction shows overall higher prediction skills than those of the NMME ensemble predictions, as measured by the Spearman's correlation (Figs. 3a, 3d), the Receiving Operating Characteristic (ROC, Figs. 3b, 3e) and Two-Alternative Forced Choice (2AFC, Figs. 3c, 3f), especially over Texas, the central area of the southern GP. The statistical prediction shows less skills than the NMME predictions near the western margin of the domain though. In addition, this statistical model can be used to improve NMME extended seasonal prediction of rainfall anomalies during May-July through a hybrid dynamic-statistical approach. This hybrid system uses NMME ensemble predictions for April as the predictors of the statistical prediction for the rainfall anomalies in May-July. Using the NMME ensemble predictions initialized in January, February and March, respectively, this hybrid dynamic-statistical prediction system can provide extended seasonal prediction with lead-time up to 4-6 months, with the prediction skills higher than those of the NMME prediction of rainfall anomalies initialized in April (not shown here due to page space limit). This result further suggests the importance of the adequate representation of mechanisms that initiate and intensify the summer droughts over the US GP, as suggested by figures 1 and 2. The aforementioned statistical and the hybrid dynamic-statistical prediction systems have been used as an important climate indicator by the Texas Water Development Board (TWDB) in the drought briefing newsletter and at their Water For Texas website since 2015 to support water management decisions (http://waterdatafortexas.org/drought/drought-forecast).

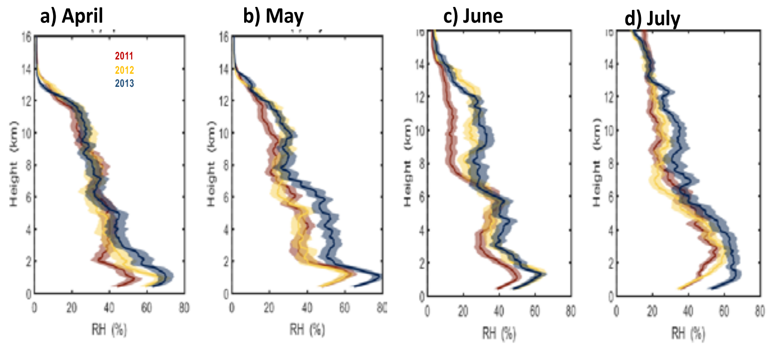

Fig. 2 Monthly mean relative humidity profiles derived from the radiosonde profiles provided by the DOE ARM program at its Southern GP site for a) April, b) May, c) June, and d) July for 2011 (brown curves), 2012 (orange curves) and 2013 (blue curves), respectively. The shades represent the standard error.

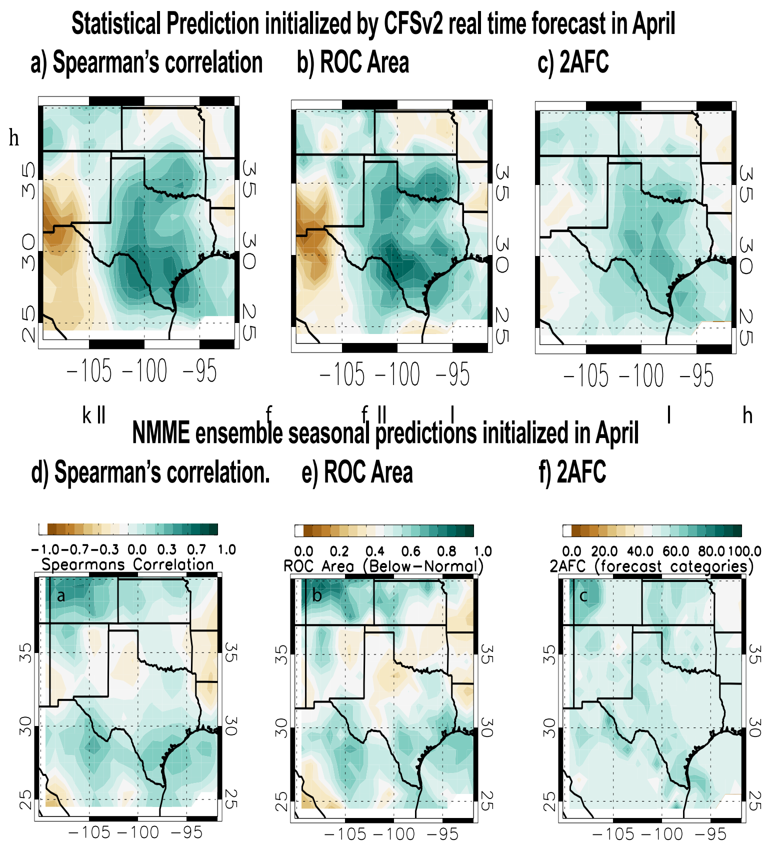

Fig. 3 Maps of the statistical seasonal prediction skills (a-c), compared to those of the NMME multi-model ensemble seasonal predictions for May-July rainfall anomalies initialized in April. The prediction skills are measured by the Spearman's correlation (a, d), ROC Area (b, e), and 2AFC (c, f), respectively. The period of evaluation is 1982-2010 using the 3-point cross-validation (Barnston *et al.*, 1992).

4. Conclusions and Discussion

Our observational analysis supported by the NOAA MAPP program has shown that the reduced westerly moisture transport in the lower troposphere, due to dryness over US SW and the positive feedbacks between surface dryness and large-scale circulation, especially through the coupling between land surface, shallow clouds, deep convection, play important roles in initiating and intensify summer droughts over the US GP. These mechanisms can be used to improve predictability of the summer rainfall anomalies over the US GP, as shown by improved prediction skills of a statistical prediction model based on these mechanisms, over those of the ensemble dynamic seasonal predictions by the NMME. Our hybrid dynamic-statistical seasonal prediction system has shown skills to improve summer rainfall predictions over the US GP using NMME seasonal predictions of the large-scale atmospheric circulation, CIN and soil moisture anomalies in April as predictors for the statistical prediction. Thus, this approach can provide a value-added product of NMME to support NOAA's mission of improving seasonal prediction of regional rainfall over the US to support societal drought preparedness.

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