View Letter

Dear Editor and Reviewers:

Many thanks for the review comments that we received with respect to our paper. Those valuable comments have significantly enhanced our paper. We have carefully addressed the reviewers' comments and suggestions, which lead to significant revisions in many parts of the paper.

Below we hereby provide our point by point responses to the reviewer's comments.

COMMENTS FROM EDITORS AND REVIEWERS

Responses to comments of Referee #1:

This study investigates seasonal drought predictability and forecast skill over a semiarid river basin. While the forecast skill evaluation is routine, the predictability is analyzed by both using a perfect model assumption and the reverse ESP framework. It is an interesting study, and the paper is easy to follow. I have a few minor comments below, basically for clarifications.

Response: Thank you for your review and comments.

1. Given that the predictability has been quantified by both using AC with a perfect model assumption and RMSE within the reverse ESP framework, I would suggest distinguishing them in the abstract and conclusion sections. The former refers to the upper limit of forecast skill (potential skill/predictability), while the latter is usually used for quantifying the role of initial hydrological conditions (IHCs).

Response: Thank you for your suggestions. We have distinguished them in the abstract and conclusion sections.

> *The predictability for meteorological drought was quantified using AC and BS with a "perfect model" assumption, referring to the upper limit of forecast skill. The hydrological predictability was to distinguish the role of initial hydrological conditions (ICs) and meteorological forcings, which was quantified by root-mean-square error (RMSE) within the ESP (Ensemble Streamflow Prediction) and reverse ESP framework.*
>
> *Here, meteorological predictability refers to the upper limit of forecast skill using a "perfect model" assumption, while hydrological predictability is to quantify the role of initial hydrological conditions (ICs) and meteorological forcings.*

2. Figures 7-8 regarding human influence on hydrological predictability is interesting. Yuan et al. (2017) also found human interventions can outweigh the climate variability for the hydrological drought forecasting over the Yellow River basin. Given that Figs. 7-8 only show the unconditional results (including dry and wet conditions) while the main focus of the paper is drought condition, a brief discussion regarding the human influence on drought predictability is encouraged.

Response: Thank you for your suggestions. We have added the discussion regarding the human influence on drought predictability.

Considering droughts (i.e., dry conditions), human activities could also increase hydrological drought predictability mainly by reasonable reservoir regulation. When droughts happen, discharge from reservoir plans to increase to guarantee water supply for irrigation and ecological flow, which will decrease the hydrological variability during dry periods. Therefore, human activities can outweigh meteorological variability and play a more important role on hydrological predictability. The results are similar to Yuan et al. (2017), which found human interventions can outweigh the climate variability for the hydrological drought forecasting over the Yellow River basin.

Yuan, X., Zhang, M., Wang, L., and Zhou, T.: Understanding and seasonal forecasting of hydrological drought in the anthropocene, Hydrol. Earth Syst. Sci., 21, 5477-5492, 2017.

3. Figures 5-6, are the human influence included for the reference forecast (i.e., ESP)? If so, how about the results if the human activities module is switched off?

Response: Thank you for your suggestions. We have added the results when the human activities module is switched off.

How do human activities influence hydrological drought forecast skill? Figures 9-10 show NMME-based hydrological drought forecast skill against ESP in terms of AC and BSS, when the human activities module is switched off. The forecast skill for NMME-based and ESP-based hydrological forecasts without influence of human activities (Fig. 9) are higher than that with human intervention (Fig. 5), especially in the midstream. The influence of human activities mainly occurs in the spring and early summer. Comparing Fig. 6 and Fig. 10 shows that NMME-based drought predictions have more skill improvement over the ESP-based predictions when human activities are involved. The improvement can be attained at lead times of 1-4 months in the winter, and longer lead times during April-September in the midstream. That means human activities have reduced the influence of ICs on hydrological *drought predictions.*

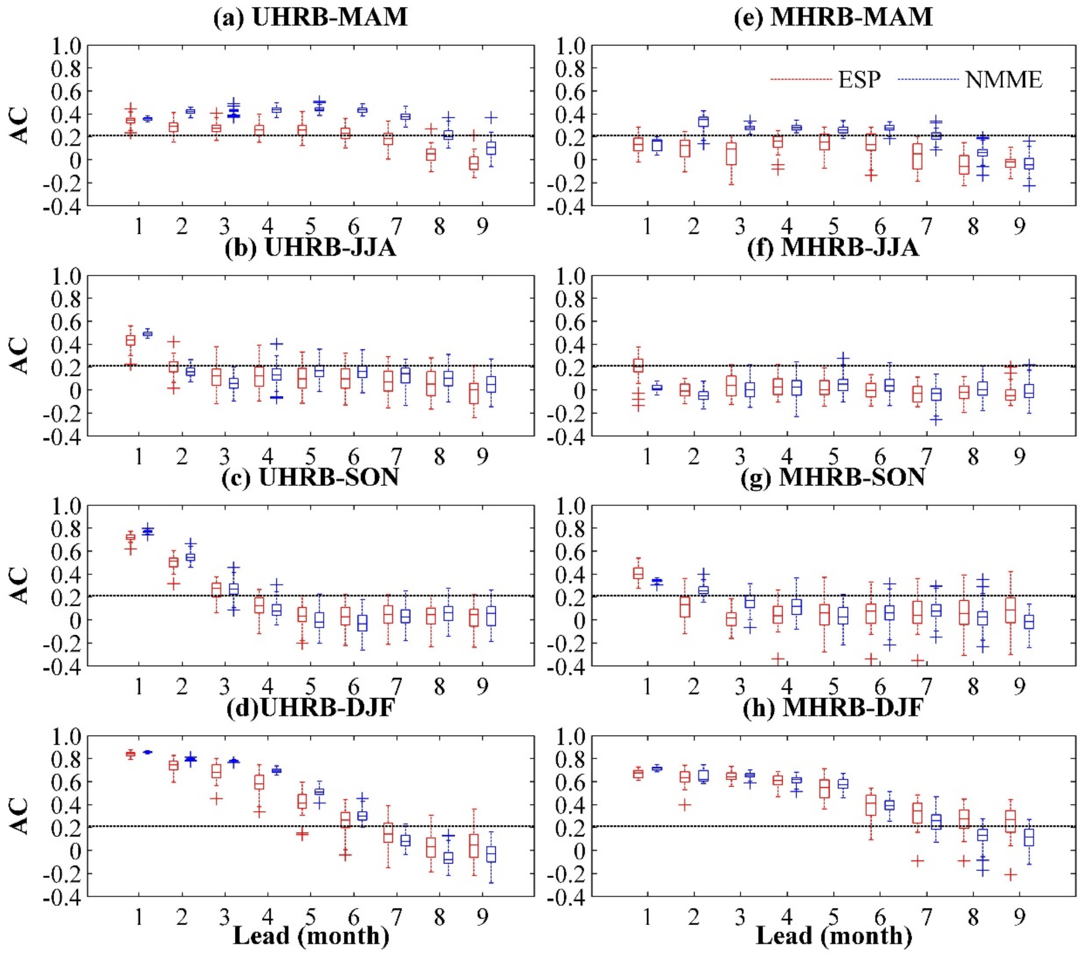

Figure 5. *Anomaly correlation (AC) of forecast of seasonal SSI1. The red boxplots show the spread of AC of each member from NMME, and the blue boxplots show that from ESP. The blue (red) crosses show the outliers for NMME (ESP) forecast skill. The dashed black line indicates the threshold (AC=0.21) of 95% confidence intervals calculated from t-test.*

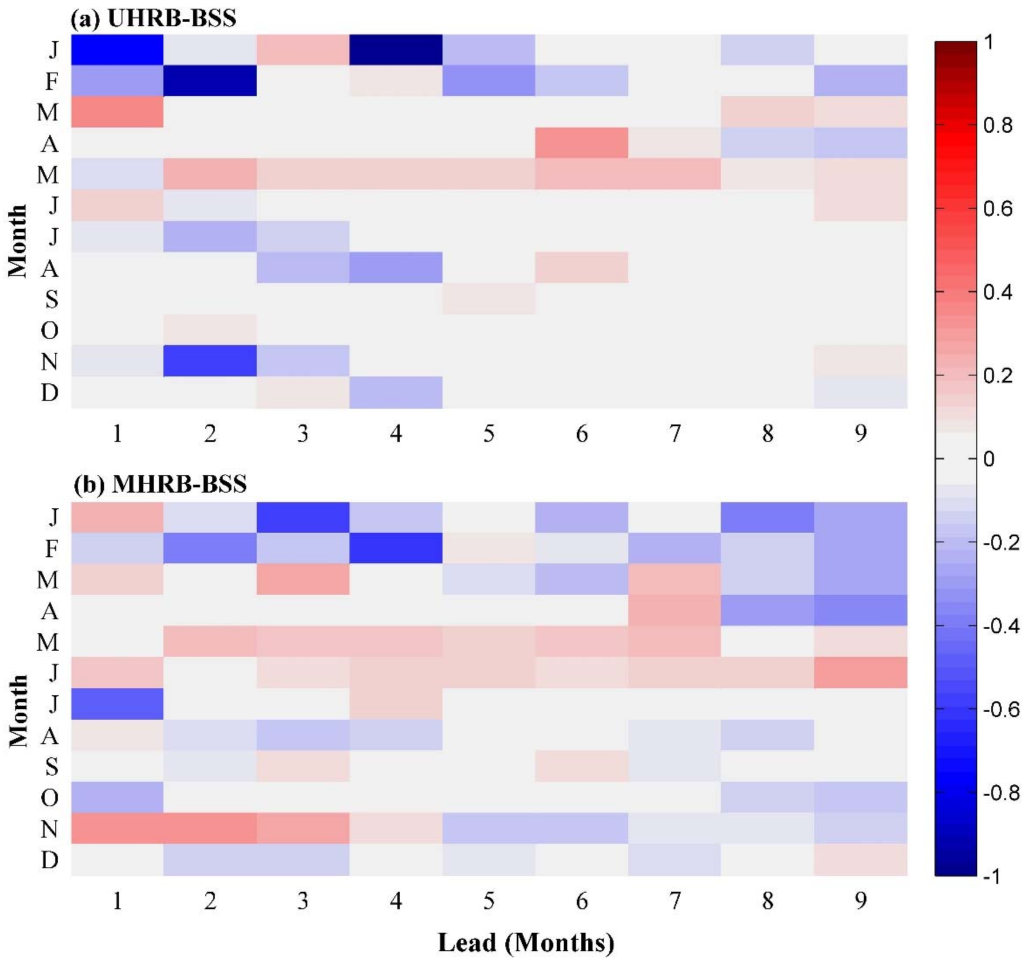

Figure 6. *Brier Skill score (BSS) of NMME forecast for hydrological drought events. Here, a hydrological drought event happens when the SSI1 value is below -1. The reference forecasts are simulations from ESP experiment.*

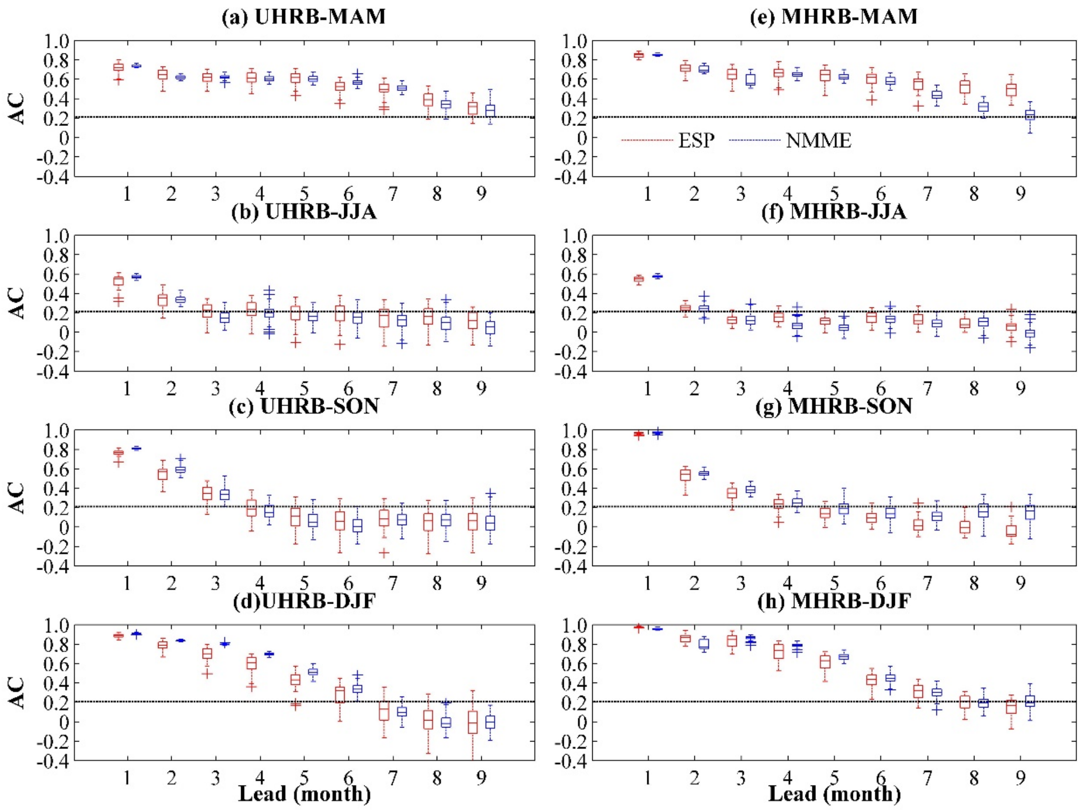

Figure 9. *Anomaly correlation (AC) of forecast of seasonal SSI1. The red boxplots show the spread of AC of each member from NMME, and the blue boxplots show that from ESP. The blue (red) crosses show the outliers for NMME (ESP) forecast skill. The dashed black line indicates the threshold (AC=0.21) of 95% confidence intervals calculated from t-test. The predictions and simulations are carried out with human activities module switched off.*

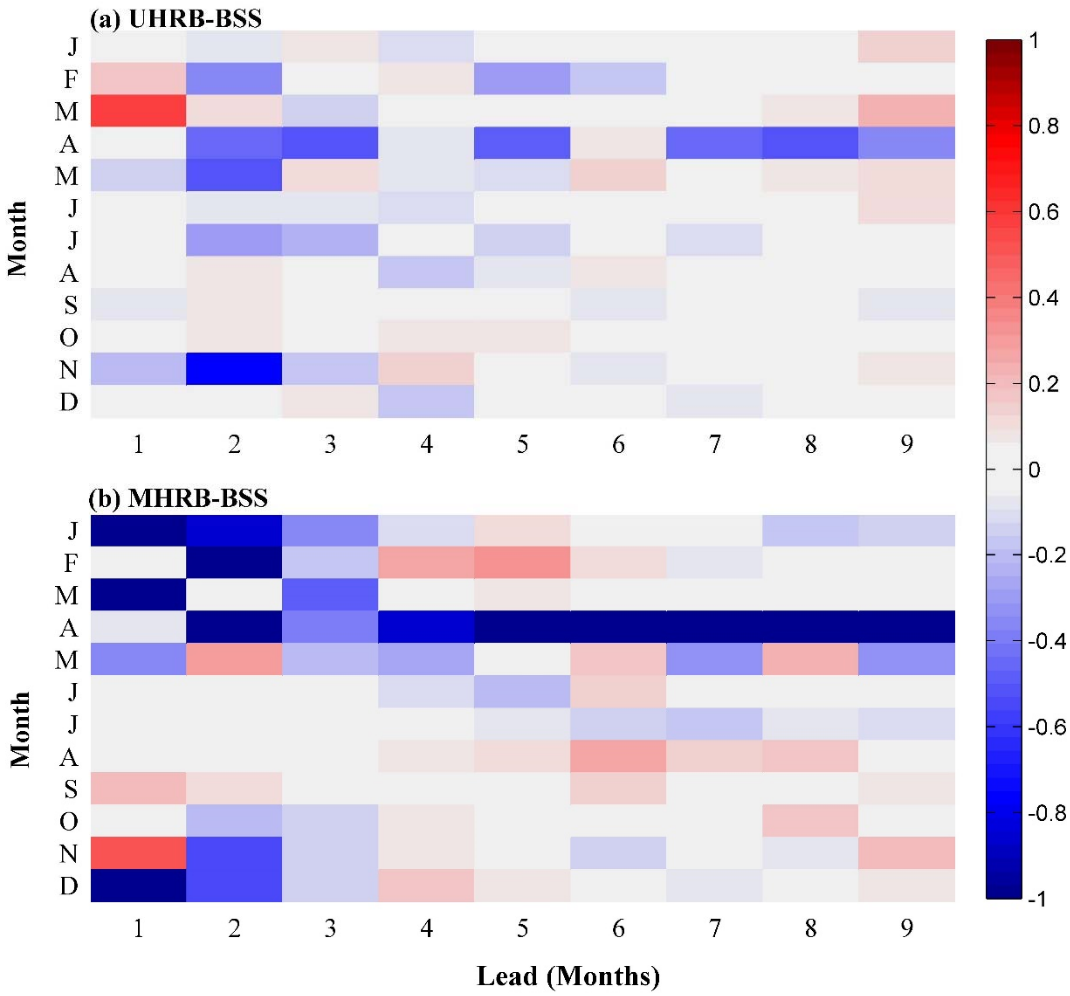

Figure 10. *Brier Skill score (BSS) of NMME forecast for hydrological drought events. Here, a hydrological drought event happens when the SSI1 value is below -1. The reference forecasts are simulations from ESP experiment. The predictions and simulations are carried out with human activities module switched off.*

4. A careful proofreading is necessary. I list a few typos or errors, but they may not be the complete list. L19, there's -> there are; L57, is subjected to -> is subject to; L58, intensifying -> intensified; L120, 0.5-drgree -> 0.5-degree; L233, may linked -> may be linked;

Response: Thank you for your suggestions, we have checked all manuscript and corrected all errors.

During wet seasons, there are no skillful hydrological predictions since lead-2 month because the dominant role of meteorological forcings.

However, the basin is subject to serious drought problems historically and in *recent decades related to climate change and intensified human activities (Zhang et al., 2016).*

Finally, the 0.5-degree bias-corrected daily hindcasts were bilinearly interpolated into 181 sub-basins to drive the hydrological model over the HRB.

During spring, the improvement of hydrological drought predictions was the most significant as more streamflow was generated by seasonal snowmelt.

However, drought remains one of the least understood natural hazards that is affected by many contributing factors, including meteorological anomalies, land-atmosphere interaction and human activities (Van Loon et al., 2016a, b), which makes accurate drought prediction a challenge (Hao et al., 2018).

Daily temperature and precipitation data at 0.5° spatial resolution (Zhao and Zhu, 2015) are obtained for 1961-2016, which were interpolated using thin plate spline (TPS) and 3D geospatial information from 2472 meteorological stations by the National Meteorological Information Center, China Meteorological Administration (CMA) (Hutchinson, 1998a, 1998b).

Hydrological data (1982-2011) used in this study was monthly streamflow datasets from Yingluoxia (YLX) and Zhengyixia (ZYX) hydrologic stations that are located at the outlet of UHRB and MHRB.

The data for hydrological model (the Distributed Time-Variant Gain Hydrological Model (DTVGM) in this study) setup and calibration was mainly obtained from Chinese Academy of Sciences, Gansu Water Resources Bulletin, and Statistical Yearbooks, which is presented in Ma et al. (2018) in detail.

In this study, meteorological drought forecasting was produced using NMME climate forecasts, and hydrological drought forecasting makes use of a hydrological model forced by NMME climate forecasts (Figure 2).

The 1-degree monthly NMME precipitation and temperature hindcasts were interpolated into 0.5-degree with bilinear interpolation over the Heihe River basin.

Topographic influence on regional and local weather and climate cannot be resolved by GCMs, for example local ascending motion affected by Qinghai-Tibet plateau exists and has considerable impact on precipitation over the HRB (Sun et al., 2011).