Response

Anonymous Referee #1:

This is an excellent and interesting study. The authors have adequately addressed all the comments raised by previous reviewers.

Thank you very much for the positive comments.

Just one minor point. I think in the Introduction, the authors should appreciate the latest advances in the seasonal hydroclimate forecast using hybrid dynamic-statistical approaches, such as Wanders et al. (2017). Seasonal forecast is also key for drought impact reduction, e.g., related to food security and water resources management (He et al., 2019; Sheffield et al., 2014; He et al., 2021).

Refs.

He, X., Estes, L., Konar, M., Tian, D., Anghileri, D., Baylis, K., Evans, T.P. and Sheffield, J., 2019. Integrated approaches to understanding and reducing drought impact on food security across scales. Current Opinion in Environmental Sustainability, 40, pp.43-54.

Wanders, N., Bachas, A., He, X.G., Huang, H., Koppa, A., Mekonnen, Z.T., Pagán, B.R., Peng, L.Q., Vergopolan, N., Wang, K.J. and Xiao, M., 2017. Forecasting the hydroclimatic signature of the 2015/16 El Niño event on the Western United States. Journal of Hydrometeorology, 18(1), pp.177-186.

Sheffield, J., Wood, E.F., Chaney, N., Guan, K., Sadri, S., Yuan, X., Olang, L., Amani, A., Ali, A., Demuth, S. and Ogallo, L., 2014. A drought monitoring and forecasting system for sub-Sahara African water resources and food security. Bulletin of the American Meteorological Society, 95(6), pp.861-882.

He, X., Bryant, B.P., Moran, T., Mach, K.J., Wei, Z. and Freyberg, D.L., 2021. Climate-informed hydrologic modeling and policy typology to guide managed aquifer recharge. Science advances, 7(17), p.eabe6025.

Thank you very much for the constructive comment. We have improved the introduction and incorporated these references into the revision:

"Seasonal hydroclimatic forecasts are important for agricultural scheduling, water management and drought mitigation (Sheffield et al., 2014; Anghileri et al., 2016; Peng et al., 2018; He et al., 2019; Zhao et al., 2019). Performing hydroclimatic forecasting into the future, the uncertainty generally arises from catchment initial conditions and future climate forcings (Wood and Lettenmaier, 2006; Yuan et al., 2014; Huang et al., 2020). In a short lead time up to about one month, initial conditions tend to outweigh climate forcings; at longer lead times, climate forcings become a more important contributor (Li et al., 2009; Yossef et al., 2013). Therefore, besides remote sensing-based estimations of initial conditions of snow cover, soil moisture and groundwater storage (Mei et al., 2020; Xu et al., 2020b; Sheffield et al., 2014), efforts have been devoted to developing sub-seasonal to seasonal hydroclimatic forecasts of temperature and precipitation (Schepen et al., 2020; Strazzo et al., 2019; Bennett et al., 2016; Cash et al., 2019; Li et al., 2017). While temperature forecasts have been improved substantially in the past decades, the generation of skilful precipitation forecasts remains a challenging task (Becker et al., 2022).

Climate indices, in particular El Niño–Southern Oscillation (ENSO) (Mason and Goddard, 2001), have been conventionally used in hydroclimatic forecasting (Hamlet and Lettenmaier, 1999; Hidalgo and Dracup, 2003; Peel et al., 2004). Teleconnections with climate indices generally reflect slowly varying and recurrent components, such as sea surface temperature (SST), of atmospheric circulations that link climate anomalies over large distances in both the tropics and extratropics (Webster and Yang, 1992; Mason and Goddard, 2001; Lim et al., 2021). As one of the most remarkable teleconnections, ENSO affects the global climate through eastward propagating Kelvin waves, westward propagating Rossby waves and Walker circulations that span the tropical Pacific, Indian and Atlantic Oceans (Yang et al., 2018; Webster and Yang, 1992). For regions exhibiting teleconnection patterns, various forecasting models have been developed, including historical resampling methods (Hamlet and Lettenmaier, 1999; Wood and Lettenmaier, 2006; Lim et al., 2021), statistical (Bayesian) methods (Hidalgo and Dracup, 2003; Strazzo et al., 2019; Emerton et al., 2017) and machine learning methods (Xu et al., 2020a; Li et al., 2021).

Major climate centers develop global climate models (GCMs) to generate operational forecasts of global climate (Bauer et al., 2015; Saha et al., 2014; Khan et al., 2017; Johnson et al., 2019a; Kirtman et al., 2014). For example, the United States National Centers for Environmental Prediction (NCEP) runs the Climate Forecast System version 2 (CFSv2) (Saha et al., 2014) and the European Centre for Medium-Range Weather Forecasts operates the fifth-generation seasonal forecast system (SEAS5) (Johnson et al., 2019b). In contrast to teleconnections that are generally “statistical”, GCM forecasts are “dynamical” in that GCMs assimilate observational information to reduce initial state uncertainty and couple atmosphere, land, ocean and sea ice modules to formulate complex interactions among different components of the earth system

(Bauer et al., 2015; Corti et al., 2015; Becker et al., 2022). Previous studies found that GCM forecasts tend to be skilful in regions subject to prominent ENSO teleconnection and also highlighted that GCM forecasts can be skilful in some extratropical regions where there is limited ENSO teleconnection (Johnson et al., 2019b; Kirtman et al., 2014; Delworth et al., 2020).

Conventional ENSO-based statistical forecasts and emerging GCM dynamical forecasts generally represent two different sources of information (Wood and Lettenmaier, 2006; Bauer et al., 2015; Emerton et al., 2017; Delworth et al., 2020; He et al., 2021). While both of them are valuable and they can further be combined to generate improved forecasts (Madadgar et al., 2016; Wanders et al., 2017; Strazzo et al., 2019), it is not yet known to what extent their information overlaps or differs. Small overlap and large difference highlight that GCM forecasts do offer new information comparing to ENSO teleconnection, while large overlap and small difference imply that GCM forecasts might not provide additional information. Zhao et al. (2021) investigated the overlapping information to attribute GCM forecast correlation skill to ENSO teleconnection. In this paper, we build a Set Operations of Coefficients of Determination (SOCD) method upon Zhao et al. (2021) to furthermore account for the differing information. As will be demonstrated through the methods and results, besides the overlapping information, there exist two types of differing information, i.e., the differing information in GCM forecasts from ENSO and the differing information in ENSO from GCM forecasts. The three types of information facilitate eight patterns to disentangle the close but divergent association of GCM correlation skill with ENSO teleconnection." (Pages 1 to 3, Lines 27 to 69)