Subseasonal Precipitation Forecasts of Opportunity over Southwest Asia

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Introduction

- Subseasonal (weeks 3-8 lead time) forecasts of precipitation are highly desirable but are not always skillful over land (de Andrade 2018; Pegion et al. 2019).
- Instead, identifying the smaller portion of forecasts that *are* skillful, so-called **'subseasonal forecasts of opportunity' (SFOs)**, has become a goal of ongoing research.
- Tropical processes such as the El Niño-Southern Oscillation (ENSO) and Madden-Julian Oscillation (MJO) can impart signals in the extratropics and are often associated with SFOs (Albers and Newman 2021; Mayer an Barnes 2021; Albers et al. 2022; Breeden et al. 2022a,b).

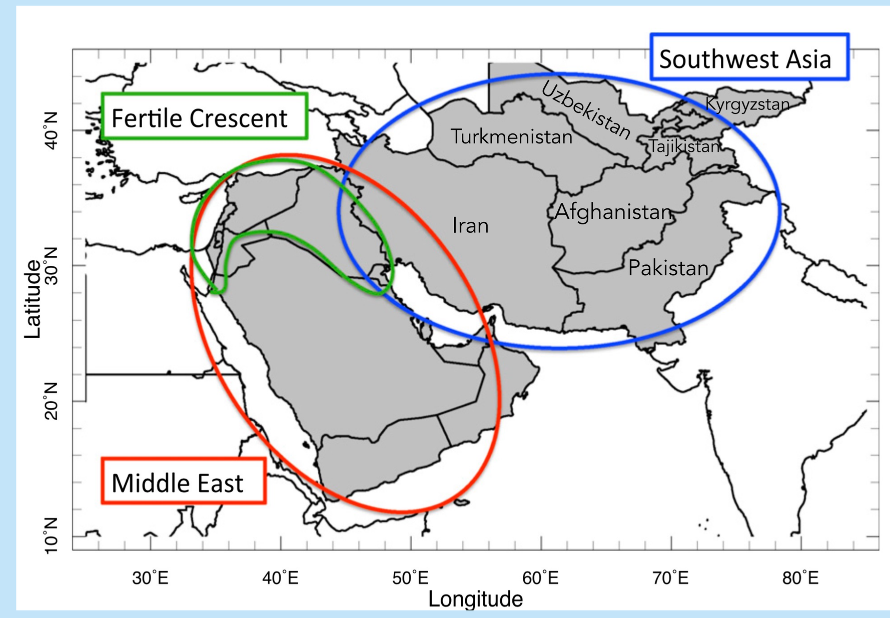

Figure 1: Region of focus, southwest Asia. *From Barlow et al. 2016.*

In this study, we consider **subseasonal precipitation forecast skill over southwest Asia** (Fig. 1; SWA), a region including several food insecure countries that rely heavily on winter precipitation as a key water source for agricultural production. Forecasts are generated by a machine learning model called a **linear inverse model** (LIM, Penland and Sardeshmukh 1995, see below for details), which is also used to identify SFOs and relate them to ENSO and the MJO.

ENSO and MJO Teleconnections to Southwest Asia Precipitation

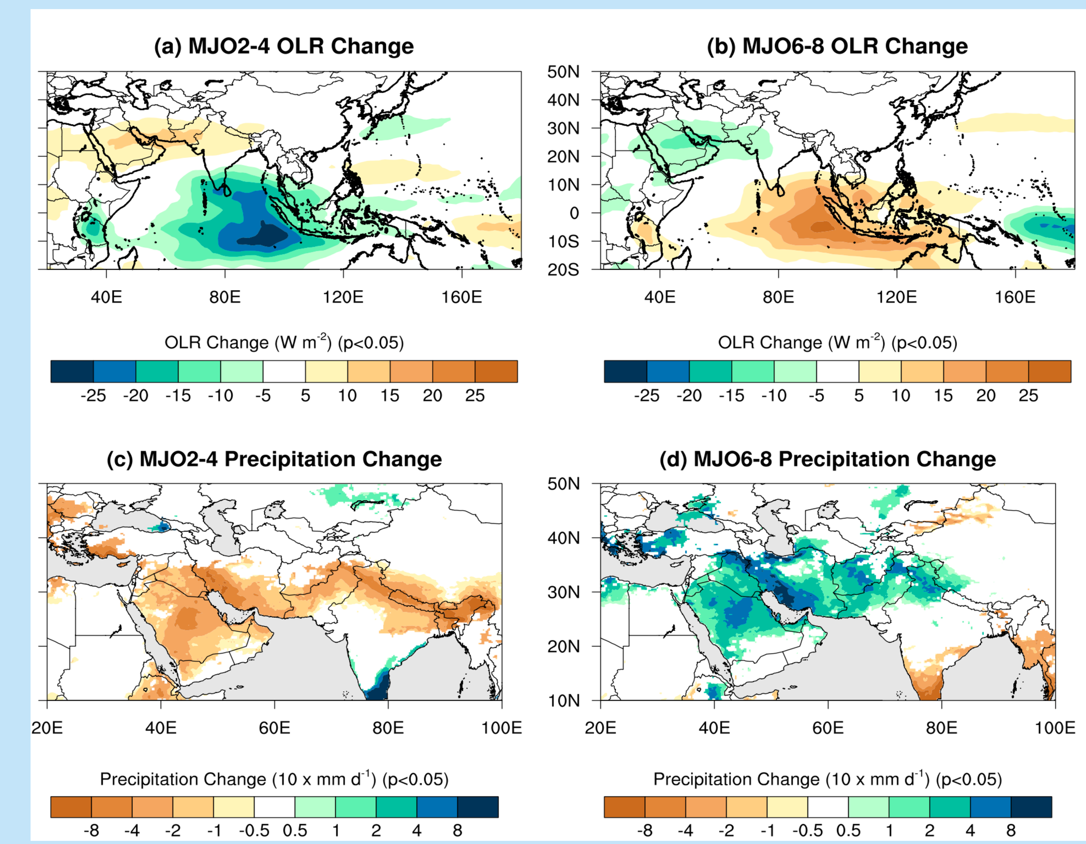

Figure 2: Composite outgoing longwave radiation and precipitation associated with MJO phases 2-4 (a,c) and 6-8 (b,d). *From Hoell et al. 2018a.*

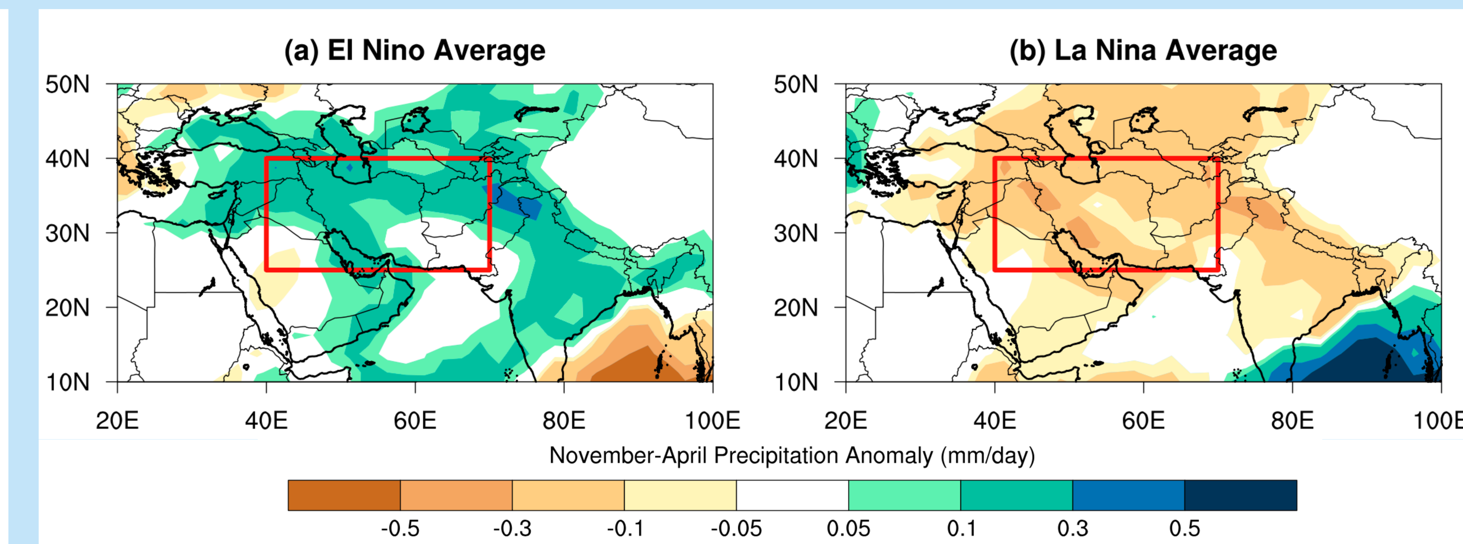

Figure 3: Mean precipitation anomaly from November – April associated with a) El Niño conditions and b) La Niña conditions. *From Hoell et al. 2018b.*

Research Questions

1. Can precipitation SFOs over southwest Asia be objectively identified at time of forecast?
2. Are these SFOs associated with ENSO or the MJO?

- MJO phases track the eastward movement of subseasonal tropical convection from the Indian Ocean to the central Pacific. Phases 2-4 reflect anomalous convection in the Indian Ocean (Fig. 2a,c) and reduced precipitation over SWA. Phases 6-8 reflect suppressed convection in the Indian Ocean (Fig. 2b,d) and enhanced precipitation over SWA.
- ENSO is the leading interannual mode of tropical convection, which also greatly impacts subseasonal convection and the associated teleconnections. El Niño conditions are associated with enhanced precipitation, and La Niña conditions with reduced precipitation (Fig. 3).

Method and Results

The LIM is an empirical dynamical model in which the dynamics are determined from the observed instantaneous and lagged covariance between a selected subset of climate anomalies relevant to SWA precipitation. Similar to output from numerical forecast models, for each initialization and lead time, the LIM generates unbiased forecasts of temperature and precipitation by propagating the initial conditions forward in time (Fig. 3).

Precipitation (22-48 N, 50-80 W)
2-m Temperature (0-50N, 0-120W)
200-hPa Streamfunction (0-90 N, 0-360 W)
Tropical Heating (20 S – 20 N, 0-360 W)
Tropical SST (20 S – 20 N, 0-360 W)

Table 1: Variables and domains used to create the SWA precipitation LIM. Forecasts are available at 3-day lag: https://www.psl.noaa.gov/forecasts/s2s_international/.

- LIM is trained on daily mean data with a 7-day running mean applied, for January-February-March (JFM), 1981-2020.
- The Japanese Reanalysis-55 dataset is used for all variables except precipitation.
- The Climate Hazards InfraRed Precipitation with Stations dataset is used for precipitation.

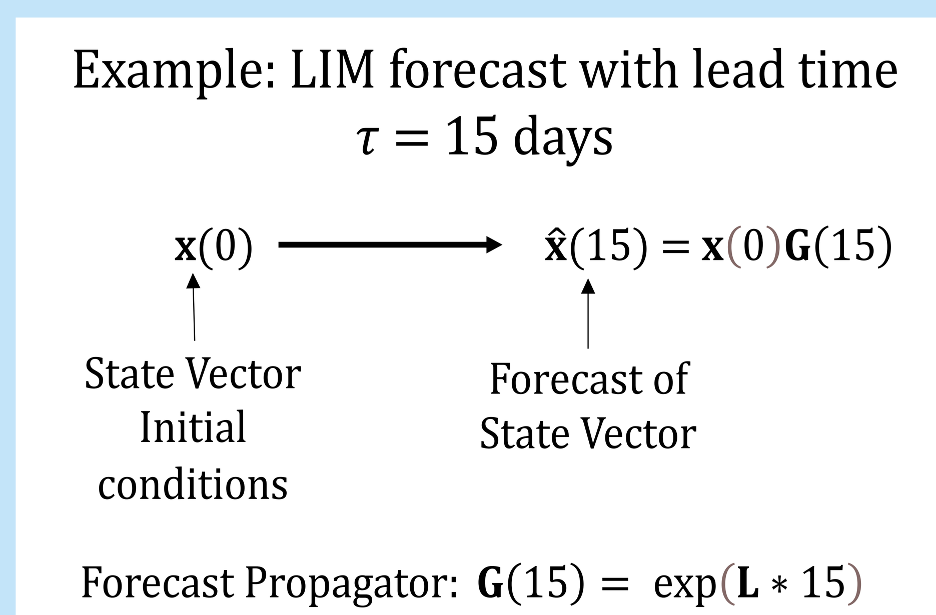

Figure 3: Schematic showing how the LIM generates a 15-day forecast using the dynamic operator, L. *From Breeden et al. 2022.*

- Theoretical LIM expected skill, a function of the forecast signal-to-noise ratio, is used to assess the confidence of the forecasts and identify SFOs (Fig. 4).

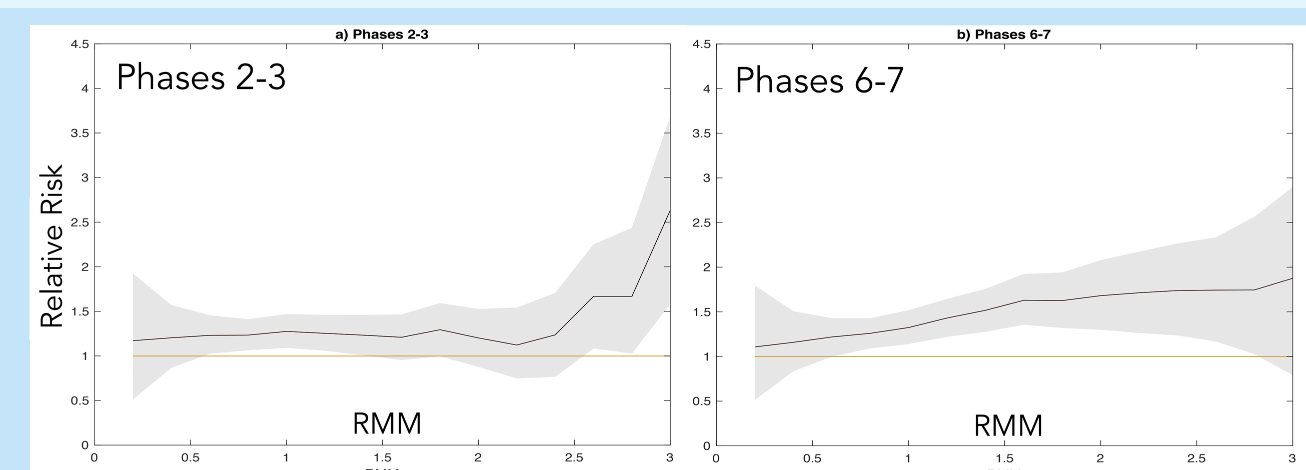

Figure 5: Relative risk a weeks 3-4 lead time SFO is identified, relative to the risk one occurs on any given day, as a function of RMM index amplitude and phase. *From Breeden et al. 2022.*

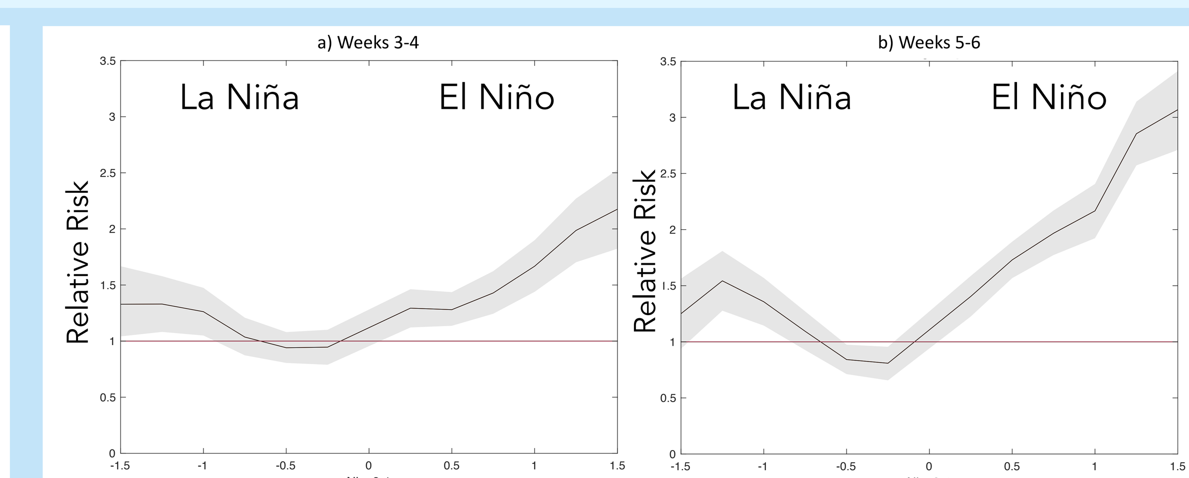

Figure 6: Relative risk a weeks 3-4 (a) or 5-6 (b) lead time SFO is identified, relative to the risk one occurs on any given day, as a function of Niño3.4 amplitude and sign.

Even though the LIM expected skill better ID's SFOs than just considering MJO or ENSO indices (Fig. 4), the likelihood of SFOs increases during strong RMM phases (Fig. 5) and strong Niño3.4 (Fig. 6) phases, consistent with past research (see above).

LIM Skill and Success Identifying SFOs

The southwest Asia JFM LIM hindcast skill is evaluated using anomaly correlation coefficient (ACC; Fig. 4), which is comparable to or higher than other subseasonal models (de Andrade et al. 2019; Pegion et al. 2018). The LIM can also identify periods of elevated forecast skill at the time of forecast, which is achieved using a theory-based metric called **expected skill**. This approach identifies more skillful forecasts (Fig. 4b) than those identified using other methods such as the Niño3.4 index (Fig. 4c) and Realtime Multivariate MJO (RMM) index (Fig. 4d).

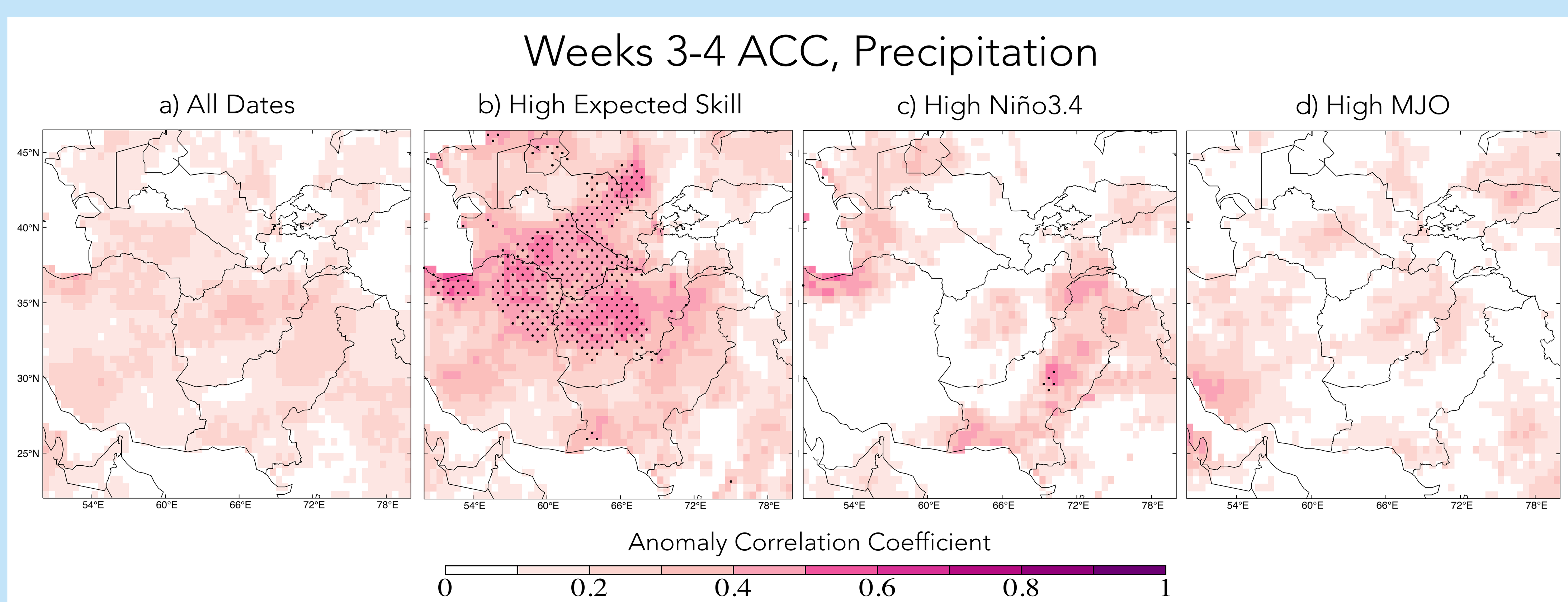

Figure 4: ACC for weeks 3-4 forecasts, evaluated from January – March 1982-2020. Panel a) shows ACC for all dates in the record, b) ACC for the 20% of forecasts initialized with the highest expected skill, c) ACC for the 20% with the highest Niño3.4 amplitude, and d) ACC for the 20% with the highest RMM amplitude. The black stippling indicates where the skill of the top 20% of forecasts in each group is statistically significantly different from the skill of the remaining 80% of forecasts at the 95% confidence level. *From Breeden et al. 2022.*

Research Questions

A1: Yes! The LIM can identify, at time of forecast, the ~20% of forecasts with significantly elevated precipitation skill, indicating SFOs.

A2: SFOs *are* significantly more likely in forecasts initialized on days with strong El Niño, La Niña and MJO phases 2-3 and 6-7 conditions.

References

1. de Andrade, F. M., C. A. S. Coelho, and I. F. A. Cavalcanti, 2019: Global precipitation hindcast quality assessment of the Subseasonal to Seasonal (S2S) prediction project models. *Climate Dyn.*, 52, 5451–5475, https://doi.org/10.1007/s00382- 018-4457-z.
2. Pegion, K., *et al.*, 2019: The Subseasonal Experiment (SubX): A multi-model subseasonal prediction experiment. *Bull. Amer. Meteor. Soc.*, https://doi.org/10.1175/BAMS-D-18-0270.1.
3. Albers, J. R. and M. Newman, 2021: Subseasonal predictability of the North Atlantic Oscillation, *Environmental Research Letters*, **16** (4), 044024.
4. Breeden, M. L., Albers, J. R., A. Hoell, 2022a: Subseasonal precipitation forecasts of opportunity over southwest Asia, Wea. Clim. Dynam., 3, 1183–1197, https://doi.org/10.5194/wcd-3-1183-2022.
5. Albers, J. R., Newman, M., Hoell, A., Breeden, M. L., Wang, Y., and Lou, J., 2022: The February 2021 Cold Air Outbreak in the United States: A Subseasonal Forecast of Opportunity, Bulletin of the American Meteorological Society, 103(12), E2887-E2904.
6. Breeden, M. L., Albers, J. R., Butler, A. H., and Newman, M., 2022b: The Spring Minimum in Subseasonal 2-m Temperature Forecast Skill over North America, Monthly Weather Review, 150(10), 2617-2628, 2022.
7. Hoell, A., M. Barlow, T. Xu, and T. Zhang, 2018a: Cold Season Southwest Asia Precipitation Sensitivity to El Niño–Southern Oscillation Events. Journal of Climate, 31, 4463-4482, 10.1175/JCLI-D-17-0456.1.
8. Hoell, A., F. Cannon, and M. Barlow, 2018b: Middle East and Southwest Asia Daily Precipitation Characteristics Associated with the Madden–Julian Oscillation during Boreal Winter. J. Climate, 31, 8843–8860, https://doi.org/10.1175/JCLI-D-18-0059.1.
9. Penland, C. and P. D. Sardeshmukh, 1995: The optimal growth of tropical sea surface temperature anomalies *J. Clim.* **8**, 1999–2024.