Windows of Opportunity for Skillful Forecasts Subseasonal to Seasonal and Beyond

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Abstract

There is high demand and a growing expectation for predictions of environmental conditions that go beyond 0-14 day weather forecasts with outlooks extending to one or more seasons and beyond. This is driven by the needs of the energy, water management, and agriculture sectors, to name a few. There is an increasing realization that, unlike weather forecasts, prediction skill on longer timescales can leverage specific climate phenomena or conditions for a predictable signal above the weather noise. Currently, it is understood that these conditions are intermittent in time and have spatially heterogeneous impacts on skill, hence providing strategic windows of opportunity for skillful forecasts. Research points to such windows of opportunity, including El Niño or La Niña events, active periods of the Madden-Julian Oscillation, disruptions of the stratospheric polar vortex, when certain large-scale atmospheric regimes are in place, or when persistent anomalies occur in the ocean or land surface. Gains could be obtained by increasingly developing prediction tools and metrics that strategically target these specific windows of opportunity. Across the globe, re-evaluating forecasts in this manner could find value in forecasts previously discarded as not skillful. Users' expectations for prediction skill could be more adequately met, as they are better aware of when and where to expect skill and if the prediction is actionable. Given that there is still untapped potential, in terms of process understanding and prediction methodologies, it is safe to expect that in the future forecast opportunities will expand. Process research and the development of innovative methodologies will aid such progress.

Capsule Summary

Research points to strategic windows of opportunity for skillful forecasts on subseasonal, seasonal, and longer timescales with benefits to users when forecasts are increasingly geared accordingly.

Body Text

There is high demand for predictions of meteorological conditions that extend beyond 2 weeks. Outlooks at subseasonal to seasonal (S2S) and seasonal to decadal (S2D) timescales are met with growing expectations, driven by the needs of the energy, water management, agriculture, and emergency sectors, among others. Across the globe, users desire forecasts out to several weeks with the skill of a 5-day weather forecast. In the U.S. expectations have been set by a recent report by the National Academies of Sciences, Engineering and Medicine (NASEM hereafter; NASEM 2016) which suggested that S2S forecasts would, in 10 years, be used like weather forecasts are today. Accordingly, a U.S. public law[1] now includes a mandate for concerted efforts to develop S2S forecast products which provides fresh impetus and new focus to the endeavor. More broadly, decades of past research results provide the scientific basis to guide forecast development and inform future research needs for S2S/S2D forecasts. This includes research under the auspices of the World Climate Research Programme (WCRP) and the World Weather Research Programme (WWRP); programs like CLIVAR and GEWEX; a WCRP/WWRP jointly organized S2S Prediction Project now in its second 5-year phase (Vitart et al. 2017; WMO 2018); and the NOAA Climate Program Office S2S Prediction Task Force (Mariotti et al. 2019). Research indicates that skillful S2S/S2D forecasts can leverage the existence of particular initial or climate conditions for predictability beyond the predictable weather range of 1-14 days. The skill of weather predictions is flow dependent (Frame et al.

[1] Weather Research and Forecasting Innovation Act of 2017. Public Law No: 115-25

2013; Ferranti et al. 2015). The fluctuations in skill increase as the forecast ranges get longer. As such, S2S/S2D skill is increasingly intermittent and can be best exploited by an approach to forecasting, product development, and evaluation that strategically targets such windows of opportunity. The idea of windows of opportunity is analogous to the fact that there is an annual cycle in weather forecast skill (i.e., winter forecasts generally tend to have more skill than summer forecasts, although this depends on the timescale, lead time, and prediction system; e.g. Beverley et al. 2019). This same idea applies to S2S/S2D forecasts but other intermittent sources of skill are considered such as, for example, the Madden-Julian Oscillation (MJO) and the El Niño-Southern Oscillation (ENSO). Such an approach, also recommended by the above mentioned NASEM report, would more adequately address users' expectations for skillful forecasts and actionable information.

Currently, much of the production and evaluation of S2S/S2D forecasts still reflects the heritage of weather forecasting. Forecasts are provided for predefined lead times and for specific regions of interest, depending on an organization's mission requirements. The assessment of mean forecast skill is accomplished by comparing observations to retrospective forecasts for a historical period (i.e., hindcasts; typically over the preceding 2-3 decades). While this makes sense for weather forecasts, for which there is always a certain level of predictability tied to the initial conditions, the case is different for longer-lead forecasts. Here, predictability crucially relies on both initial conditions and slowly evolving coupled interactions among the Earth's components that can serve to constrain the chaotic evolution of the atmosphere. Such crucial coupled processes are often intermittent and have regionally dependent impacts (e.g., Vitart 2017; Lovejoy 2018). Whether they are at play, how non-linear and non-stationary they might be, and how they interact with each other, determines whether potential skill exists beyond the 2-

week weather predictability limit, i.e., whether a forecast opportunity exists. Having forecast tools that strategically target such windows is key for making the most of such opportunities.

1. Processes That Provide Forecast Opportunities

The intermittency of opportunities for skillful long-lead predictions is already evident from long-lead weather forecasts, with those initiated from some atmospheric flow configurations being more skillful than others. Intrinsic predictability levels of different atmospheric states can be estimated from forecast ensembles[2]. In reliable and well calibrated[3] prediction systems, the spread among ensemble members quantifies forecast uncertainty and the underlying predictability. At times when the forecast uncertainties are relatively small we deduce that the atmosphere is more predictable; higher predictability means a window of opportunity for more skillful forecasts. If we can identify processes and conditions that lead to these predictable conditions, we can potentially provide more useful S2S and S2D forecasts.

Mid-latitude Atmospheric Processes Mid-latitude atmospheric processes can lead to circulation patterns or weather regimes that affect predictability. For example, studies of flow-dependent verification based on Euro-Atlantic mid-latitude weather regimes indicate that European blocking is the regime associated with the least accurate medium range weather forecasts over Europe, while the negative phase of the North Atlantic Oscillation (NAO) leads to the most skillful predictions (Ferranti et al. 2015). In another example, forecasts for Europe made

[2] A forecast ensemble consists of several multiple independent forecasts (ensemble members) with perturbed initial conditions and/or perturbed model physics.

[3] In a reliable ensemble, forecast probabilities match the observed frequencies. An ensemble system can be made more reliable through statistical calibration, which aims to relabel the forecast probabilities, so that they match the observed frequencies.

when the westerly jet across the Atlantic is displaced to the north (Atlantic Ridge) tend to be less accurate (Frame et al. 2013). The physical processes that can reduce forecast skill are generally associated with atmospheric instabilities and weather regime transitions. At longer ranges, weather regimes play an increasingly important role. Their low frequency, large spatial scale, and sensitivity to tropical and stratospheric conditions point to processes that can matter for subseasonal predictions and beyond. For example, a persistent winter ridging was associated with California drought during 2013-2016, even though the underlying causes have not been robustly established (e.g. Teng and Branstator 2017; Swain et al. 2017).

Quasi-stationary Rossby waves during boreal summer can also condition the skill of subseasonal predictions and impact the predictability of boreal summer climate extremes including heat waves, flooding events, and short-term droughts. Recent examples of such linkages include the 2003 European heat wave, the 2010 Russian heat wave, and the 2012 flash drought in the U.S. Great Plains (e.g., Schubert et al. 2011; Wang et al. 2014). Similar mechanisms are also at play in the Southern Hemisphere during its summer and similarly impact extremes such as the 2009 Australian heat wave (Parker et al. 2014). These waves often manifest as nearly circumglobal teleconnections in which the summer jets act as wave guides (e.g., Ding and Wang 2005; Beverley et al. 2019), sometimes resulting in a synchronization of extremes over distant parts of the globe. While such waves appear to be mainly forced by sub-monthly vorticity transients with limited predictability (Schubert et al. 2011), there is mounting evidence that tropical processes (e.g., Newman and Sardeshmukh 1998; Watson et al. 2016), land forcing (e.g., Koster et al. 2014), or even internal atmospheric resonance processes (Kornhuber et al. 2017), can amplify and sustain these planetary waves. Such processes could increase the predictability of associated extremes, such as heat waves over the U.S. and other continental regions, well beyond 2 weeks. Taking full advantage of the potentially enhanced predictability associated with quasi-stationary Rossby waves at sub-seasonal and longer timescales requires better understanding of their growth and persistence along with improved simulation and prediction of associated processes.

Tropical Processes Tropical processes involving interactions within the atmosphere, and between the atmosphere and the ocean, provide a primary source of predictability on subseasonal timescales and beyond. Regions of organized deep convection in the tropics excite large-scale atmospheric teleconnection patterns through a variety of mechanisms: the linear dispersion of Rossby waves (e.g., Hoskins and Karoly 1981), modification of the background flow and Rossby wave breaking (e.g., Moore et al. 2010), and planetary wave propagation into the stratosphere (e.g., Smith and Kushner 2012; Plumb 2010). The potential for S2S predictability from tropical sources lies in the "slow" and predictable evolution of large-scale tropical convection patterns, the 1-2 week timescale for the extratropical atmosphere to respond fully to tropical convective heating (e.g., Matthews et al. 2004), and the several weeks for stratospheric-tropospheric interactions to occur.

The MJO (Madden and Julian 1994), when active, is a tropical phenomenon that provides a major source of predictability on subseasonal timescales. During an MJO event, regions of large-scale convection propagate eastward along the equator on a 30-60 day timeframe (Matthews 2008), generating Rossby waves along the way that propagate poleward, producing a delayed response in the extratropics 1-2 weeks later. The MJO impacts over North America, in particular, are strongest and most consistent for MJO phases having an east-west dipole of convective heating in the Indian and western Pacific Oceans (Ting and Sardeshmukh 1993; Lin et al. 2010; Tseng et al. 2018) and may, when modulated by ENSO (Arcodia et al. 2019), potentially persist up to five weeks (Riddle et al. 2013). More broadly, the MJO impacts S2S predictability across the Tropics, including the Maritime Continent, and the Indian, Australian, and West African Monsoon regions (e.g., Wheeler et al. 2009; Ventrice 2011; Taraphdar et al. 2018); and parts of China (e.g., Song et al. 2019). Especially promising is that current dynamical models now exhibit significant MJO skill beyond 30 days (Vitart 2017). Recent studies (Benedetti and Vitart 2018) show that there may be additional predictability associated with the MJO effect on atmospheric aerosols. While the MJO creates opportunities for skillful S2S forecasts, important caveats exist. In particular, it is now clear that not all phases of the MJO provide equal forecast opportunities, and only specific regions of the world are affected during certain times of the year (e.g., Garfinkel and Schwartz 2017). There is also evidence that the MJO effects are modulated by other climate phenomena (see below), and that models still exhibit significant weaknesses in their representation of the MJO and its teleconnections.

ENSO, a tropically coupled ocean-atmosphere climate phenomenon, is another leading source of predictability. Once active, its effects are felt on the S2S to multi-annual timescales (DiNezio et al. 2017). During warm ENSO events, also known as El Niño, the eastern tropical Pacific is anomalously warm, while the eastern Indian Ocean and western tropical Pacific are anomalously cold. Opposite conditions exist during cold ENSO events, known as La Niña. These conditions evolve over the course of months to years and tend to be quite predictable, depending on the phase of ENSO (e.g., Zheng et al. 2016). Studies have shown additional predictability of El Niño events following large volcanic eruptions due to the ocean-dynamics thermostat mechanism described by Clement et al. (1996) and Eddebbar et al. (2019). Sea surface temperature anomalies associated with ENSO induce patterns of organized anomalous tropical convection from which emanate global teleconnections via Rossby wave propagation, mid-latitude jet alterations, and other mechanisms. ENSO predictability influences forecast skill from months to years, e.g., influencing MJO teleconnections on subseasonal timescales (e.g., Leroy et al. 2008), while modulating the mid-latitude background flow on seasonal and longer timescales. ENSO-related predictability stems from the duration, strength, and location of specific ENSO events and the lags of remote teleconnections. ENSO impacts, and therefore ENSO-related predictability, are regionally and seasonally dependent, particularly outside the tropics.

It is particularly promising that current climate prediction systems are now able to predict the development of an ENSO event with some skill out to at least a year ahead depending on the initial conditions (Barnston et al. 2017). On the other hand, the ability of models to predict the details (e.g., spatial structure and amplitude of the SST anomalies) and exact timing of individual ENSO manifestations including the associated global teleconnections, is still limited at those forecast leads (e.g., Kim et al. 2012; Wang et al. 2009). As such, we are still far from taking full advantage of ENSO-related predictability.

Interplay of Troposphere-Stratosphere Processes Tropical processes providing opportunities for S2S/S2D predictability extend to interactions with the stratosphere. Specifically, the stratospheric Quasi-Biennial Oscillation (QBO; Baldwin et al. 2001) can modulate the predictability of the wintertime MJO and its teleconnections (e.g., Marshall et al. 2016; Zhang and Zhang 2018) as well as ENSO teleconnections (Garfinkel and Hartmann 2010). The QBO oscillates at a longer timescale than the MJO, around 28 months, with alternating easterly and westerly equatorial wind states that develop in the upper stratosphere and propagate downwards until dissipating at the tropical tropopause. The modulation of mid-latitude S2S extremes by the

MJO depends on QBO phase. This effect has been demonstrated in the context of U.S. West Coast atmospheric rivers (ARs; Baggett et al. 2017). Times when the QBO and MJO are both active provide windows of opportunity for improved forecasts of S2S extremes. Skillful empirical forecasts using only the MJO and QBO to forecast S2S extremes have already been realized (e.g., Mundhenk et al. 2018; Nardi et al. 2019).

Stratospheric processes associated with the winter stratospheric polar vortex also provide opportunities for enhanced S2S predictability. The polar vortex describes the climatological circumpolar stratospheric westerly winds that circle the pole in wintertime (Waugh et al. 2017). About once every other year the Northern Hemisphere polar vortex is disrupted by tropospheric wave forcing and also by internal resonance of stratospheric waves (Birner and Albers 2017). When this happens, it can either be displaced off of the pole or split into two smaller vortices, and the stratosphere rapidly warms in a few days in an event called a "sudden stratospheric warming" (SSW; e.g., Butler et al. 2017). The anomalous winds and temperatures then slowly descend to the tropopause via wave-mean flow interactions and ultimately influence the tropospheric jet stream over a period of weeks to months (Baldwin and Dunkerton 2001). Typically, these impacts manifest as an increase in synoptic cyclone tracks over Europe and a decrease over the Russian Arctic, a tendency for colder-than-normal temperatures over Eurasia and the eastern United States, wetter conditions over Southern Europe, and warmer temperatures over eastern Canada and subtropical Asia and Africa (see Fig. 1). In the Southern Hemisphere, stratospheric polar vortex variations have an impact on Australian hot and dry extremes (Lim et al. 2019). Deterministic predictability of SSW events is limited to 10-20 days (e.g., Karpechko 2018). Probabilistic SSW prediction likely depends on the state of the MJO, QBO, and ENSO, among other factors (e.g., Domeisen et al. 2019a). ENSO, for example, can modulate both the strength of the polar vortex via its stratospheric teleconnection, and the impact of SSWs on surface weather over the North Atlantic via its tropospheric teleconnection (Domeisen et al. 2019b).

Once a SSW has occurred, the associated extreme stratospheric conditions can constrain the evolution of the atmosphere through wave-mean flow interactions. Since recovery to climatological conditions after a SSW occurs on radiative timescales (several weeks in mid-winter) the impacts of SSWs are long-lived, potentially allowing increased surface predictive skill 3-6 weeks after an event (Sigmond et al. 2013). When the anomalous stratospheric conditions are simulated in a numerical weather prediction model, the extended period of anomalous wave-mean flow interactions can also shift a forecast away from climatology (Scaife et al. 2016) and into weather regime states with enhanced predictability (e.g., Charlton-Perez et al. 2018). Other types of extreme stratospheric variability, such as vortex intensification, may also provide opportunities for predictability (Tripathi et al. 2015).

Land-Atmosphere Interactions The land surface responds to sustained anomalies in the atmosphere on S2S time scales and can thus amplify and sustain anomalies to enhance predictability (Koster and Suarez 2001; Dirmeyer et al. 2018). Positive land-atmosphere feedback processes may exacerbate associated extremes (Koster et al. 2014) and enhance the persistence of major droughts (e.g., Vautard et al. 2007) and heat waves (e.g., Ford and Quiring 2014). Beyond these extremes, the land surface plays a role in S2S climate variations. In fact, any time and place that three specific conditions are met, the process chain for land-atmosphere feedbacks offers an opportunity for enhanced predictability (e.g., Dirmeyer et al. 2015). The first condition is sensitivity of the atmosphere to land surface state variations via changes in surface fluxes; the second is sufficient magnitude of variability in land surface states to drive a significant atmospheric response. These first two conditions are both in force in the so-called “hot spot” regions of land-atmosphere coupling such as the Great Plains of North America, the Sahel of Africa, the Indus River basin, much of Australia, southern Africa, and the Pampas of South America (Koster et al. 2001). The third necessary condition for land-driven predictability on S2S time scales is memory or persistence of land surface anomalies. The greatest memory tends more toward arid regions, but memory can also persist and deliver anomalies across seasons when coupling emerges (e.g., Guo et al. 2011). Effects may be non-local, as the same circulation systems that can initiate anomalies in the land surface can serve to advect their effects downwind to other locations (Koster et al. 2014; Koster et al. 2016). When these three factors are combined and accounted for in the forecast models, there is opportunity for improved S2S prediction skill stemming from land-atmosphere interactions (e.g., Koster et al. 2011; Dirmeyer et al. 2018).

Mid-to-High Latitude Ocean-Atmosphere Interactions In addition to ENSO and MJO related ocean-atmosphere processes, other oceanic dynamics and feedbacks outside the Tropics more broadly provide opportunities for enhanced S2S predictability. For instance, Arctic sea-ice anomalies have been linked with high-to-mid latitude atmospheric anomalies (e.g., Alexander et al. 2004) and enhanced predictive skill (He et al. 2018). During years with low seasonal sea ice concentrations (when there's more heat loss from more exposed open water), the north-south differences in atmospheric temperatures across the Barents Sea are reduced. These conditions have been linked to wintertime cyclones travelling further south into western Europe, instead of their tendency to move eastwards towards Siberia, as well as more frequent cold winter extremes at middle latitudes (Petoukhov and Semenov 2010; Inoue et al. 2012; Mori et al. 2014). There is evidence for predictive skill for high-latitude climate due to midsummer sea ice extent anomalies (He et al. 2018). Predictability associated with sea-ice processes, derives both from lead-lag relationships between the sea-ice anomalies and the high-to-mid latitude response, and also from our increasing capability to predict sea-ice anomalies themselves a season ahead (e.g., Stroeve et al. 2014).

In another example, oceanic processes associated with western boundary currents, such as the Kuroshio and the Gulf Stream currents, are being explored as sources of atmospheric predictability (e.g., Smirnov et al. 2015). Such currents, bringing warm water from the Tropics poleward, are associated with sharp oceanic temperature gradients. At the exit of such currents, are mesoscale eddies which carry anomalous warm SST as they propagate out of the formation region. Hence the evolution of currents and eddies in areas of sharp temperature gradients is associated with ocean-atmosphere heat flux anomalies that can potentially affect the weather on S2S timescales (Chelton and Xie 2010; Jia et al. 2019). For example, Haarsma et al. (2019) showed that resolving oceanic mesoscale features (eddies and fronts) near the North Atlantic storm-track translates into enhanced seasonal prediction skill compared to forecast systems that do not resolve oceanic mesoscale features.

Beyond S2S While our primary focus here is on the S2S prediction problem, the windows of opportunity framework similarly applies to longer timescales. There is of course no clear spectral gap between variability at S2S time scales and the variability at decadal and longer time scales. In fact, while some phenomena already discussed for S2S, such as the MJO, have spectral peaks at subseasonal timescales, several others have substantial impacts beyond one season (e.g., ENSO or QBO). There are other processes that operate on multi-year and even multi-decadal time scales that are particularly relevant to prediction at these longer time scales. Processes that involve slow ocean dynamics or long-lived atmospheric constituents, which affect S2S forecasts, can also lead to enhanced predictability on longer timescales, provided we can adequately capture underpinning processes in forecast models. As an example, the Atlantic Meridional Overturning Circulation (AMOC) evolves on multi-decadal timescales, and may provide potential predictability if it can be adequately simulated in prediction systems (e.g., Zhang and Zhang 2015). Also, particular Atlantic conditions may be especially conducive to higher prediction skill. For example, when the Atlantic Ocean heat transport around 50°N is strong at the initialization of a hindcast, SST skill in the northeast Atlantic at lead years 2–9 is significantly increased (Borchert 2019). Also, when focusing on decadal hindcast skill in the North Atlantic subpolar gyre, skill is higher during strong multi-year trends, especially during the warming period of the 1990s, and lower in the absence of such trends (Brune et al. 2018).

The sudden injection of aerosols into the troposphere and stratosphere by a major volcanic eruption can alter climate for years (e.g., McCormick et al. 1992), while also influencing shorter term weather (Reale et al. 2011; Reale et al. 2014). While volcanic eruptions are not predictable, once they occur and their impact is captured in the initial conditions, they can enhance predictability across a variety of timescales (Benedetti and Vitart 2018). In addition, anthropogenic aerosols may also present a source of decadal predictability (Bellucci et al. 2017). Similarly, long-term increases in greenhouse gas concentrations and associated warming trends are a major source of predictability for surface air temperature and other surface meteorological variables, affecting the skill of climate forecasts at S2S timescales and beyond (e.g., Luo et al. 2011; Boer et al. 2013). For instance, Arctic sea-ice anomalies due to polar amplification of long-term surface temperature increase have been linked to changes mid-latitude weather (e.g., Cohen et al. 2014; Zhang et al. 2012). More broadly, there is a growing body of research examining the effects of climate variability and change on the predictability of extremes across the globe (e.g. Herring et al. 2019).

2. From Windows of Opportunities to Forecast Tools

Knowing which processes (e.g., atmospheric circulation, climate patterns, ocean dynamics, etc.) offer predictability is relevant for forecast interpretation as well as the development of new forecast tools. In fact, this knowledge must be reflected in our forecast models if we are to use them to identify opportunities for enhanced skill.

A Priori Identification of Forecast Opportunities Providing an objective measure of the expected forecast accuracy is very valuable (e.g., Kalnay and Dalcher 1987; Molteni and Palmer 1991). There are several examples of flow-dependent verification based on weather regimes. This approach has been applied to Euro-Atlantic weather regimes, as discussed above (Ferranti et al. 2015). Also, Vigaud et al. (2018a) used daily wintertime 500 hPa geopotential height fields to classify four weather regimes over the Pacific-North American sector that can be used to identify windows of high forecast opportunity in the midlatitudes by highlighting persistent episodes in real time and in the forecasts. A prototype system has been set up at IRI to do this on a daily basis using the NOAA CFSv2 model. Forecast characteristics are plotted according to target day and lead time, permitting the visualization of a large number of forecast runs in a way that emphasizes forecast timing and consistency from one forecast to another (Tippett et al. 2012; Carbin et al. 2016). Similarly, cluster analysis of daily circulation/convection types and related modes of subseasonal predictability, has also been applied over South Asia (Moron et al. 2012), the Maritime Continent (Moron et al. 2015), West Africa (Vigaud and Giannini 2018), the Caribbean (Vigaud and Robertson 2017), and South America (Muñoz et al. 2015; 2016; Doss-Gollin et al. 2018).

Tools are being developed to predict the skill of climate forecasts during windows of opportunity. Because of the fundamentally nonlinear and chaotic nature of the atmosphere, inherent nonlinear interactions act so rapidly that much of their effects are unpredictable on S2S time scales and beyond. What predictability remains can be well-approximated by much simpler linear dynamics and a residual random “noise” (e.g., Hasselman 1976; Penland and Sardeshmukh 1995). This approximation, empirically determined using the “linear inverse model” (LIM) technique (Penland and Sardeshmukh 1995), generates S2S forecasts about as skillful as those from operational dynamical models at both NCEP and ECMWF (e.g., Newman et al. 2003; Albers and Newman 2019). The LIM technique also allows identification of high skill cases or forecasts of opportunity ahead of time (Albers and Newman 2019; see example in Fig. 2). Such higher skill depends upon the similarity of the forecast initialization to patterns leading to the most rapidly amplifying anomalies within the LIM. For example, Newman et al. (2003) found that Week 3 forecast skill of the 250 hPa extratropical stream function was largely related to how strongly the initialization matched varying combinations of only three patterns, which together represented ENSO, the MJO, and the Pacific North American (PNA) teleconnection pattern.

North American Week 3-4 Temperature and Precipitation The combined influence of ENSO and the MJO significantly impacts the wintertime general circulation over North America for lead times up to at least 4 weeks. Based on these relationships, probabilistic 2-m temperature and precipitation forecasts over North America are now generated solely on the basis of the climatological linear trend associated with each variable along with their statistical relationships with the initial state of the MJO and ENSO (Johnson et al. 2014). Such forecasts, now used as part of the NOAA operational forecast suite (experimentally for precipitation), exhibit substantial skill for some regions and some initial states of the MJO and ENSO out to a lead time of approximately 4 weeks. The highest temperature forecast skill tends to follow MJO phases 2-3 and 6-7 owing to the strong extratropical response to the dipole convective heating anomalies associated with these phases (Lin et al. 2010; Tseng et al. 2018), although the precise MJO phases and regions with maximum skill are sensitive to the state of ENSO (Johnson et al. 2014).

Risk of Severe Cold Spells Over Europe Forecast skill of the NAO has been shown to be conditioned on the presence of an MJO or SSW in the initial conditions (e.g., Sigmond et al. 2013; Tripathi et al. 2015; Ferranti et al. 2018). By inferring surface weather through large-scale flow patterns, forecasters try to identify the spatial extent of temperature anomalies that are predictable at subseasonal time scales. For example, reliable subseasonal forecasts of the NAO and blocking are used to assess the risk of severe cold spells over Europe (Ferranti et al. 2018). Current S2S models can deliver skillful forecasts for some large-scale patterns 2 weeks ahead, and longer in certain cases. This suggests that subseasonal predictions have the potential to support early warnings of severe cold events over Europe. The success of predicting weeks ahead the changes in large-scale flow leading to cold spells depends on the type of regime transitions. For example, the ECMWF ensemble provides reliable probabilities of cold spells associated with the establishment of Greenland blocking (NAO-) well beyond one week (e.g., Ferranti et al. 2018). The predictive skill of such events can be significantly enhanced during MJO activity via tropical–extratropical teleconnections. Using the ensemble spread rate of change[4] with lead time as a measure of predictability, it is possible to show that the NAO− circulation regime exhibits a higher level of inherent predictability than the European blocking regime (Ferranti et al. 2018).

Atmospheric Rivers and Extreme Weather Activity As previously discussed, two modes of tropical variability offer windows of opportunity to forecast aspects of North America's extreme weather at subseasonal lead times. Specifically, the MJO has been shown to modulate springtime hail and tornado activity (Thompson and Roundy 2013; Barrett and Gensini 2013), along with west coast snowpack (Guan et al. 2010), while the MJO and QBO have been shown to modulate wintertime AR frequencies (Baggett et al. 2017). Baggett et al. (2018) developed an empirical model using the current state of the MJO to forecast hail and tornado activity over the U.S. Plains and found skillful forecasts of opportunity out to 5 weeks. A similar empirical model was developed by Mundhenk et al. (2018) that utilized both the states of the MJO and QBO to predict AR activity along the U.S. West Coast. This empirical model also produced skillful forecasts with lead times out to 5 weeks for specific combinations of MJO and QBO phases (see Fig. 3 for an example of derived forecast tools following Nardi et al. (2019)). Dynamical models, by comparison, show skillful forecasts only out to ~2 weeks for similar variables (e.g., Carbin et al. 2016).

[4] The ensemble spread, of a well-constructed ensemble prediction system, is an indicator of forecast uncertainties and the rate at which the spread grows is an estimate of predictability. As the ensemble spread grows rapidly with lead time, so does the forecast uncertainty, indicating reduced predictability. Conversely, as the ensemble spread grows slowly with lead time, so does the uncertainty, implying a smaller reduction in predictability.

Atmospheric Rivers and Western U.S. Water Availability The California Department of Water Resources and its research partners are exploring opportunities for skillful S2S forecasts to aid in the management of western U.S. water availability and related hazards under extreme conditions. Efforts have mainly targeted wintertime ARs as a major source of freshwater input and on ridging as a dominant way ARs are restricted. Relationships between weekly AR occurrence, ridging, and certain phases of ENSO, the Arctic Oscillation, the PNA, and the MJO (DeFlorio et al. 2018; Guirguis et al. 2018) have formed the basis for predictability considerations. An experimental prediction framework is being developed to predict weekly AR frequency (DeFlorio et al. 2018; DeFlorio et al. 2019) based on hindcast and forecast information from the S2S Prediction Project (Vitart et al. 2017). Results indicate conditional useful skill 1-3 weeks ahead. Forecast tools under development focus on ridging types and persistence, as they relate to distinct characteristics and opportunities for enhanced predictability and skill; they also examine the integrated water vapor transport in a given week associated with ARs over the U.S. West Coast. Guirguis et al. (2018) identified circulation anomaly patterns associated with AR activity along the North American West Coast and showed how seasonal variation in the prevalence of these weather types is associated with interannual variability in AR landfalls. Such knowledge is providing the basis for new experimental tools built on historical analogs.

Climate Extremes: Operational centers currently produce forecasts for extremes or hazards on weather timescales, such as severe weather or heat extremes. Generally, such operational forecasts have not been extended into climate timescales. Examples of climate extremes include monthly or seasonal temperatures or accumulated precipitation amounts that have occurred infrequently in the climate record, which may be defined using the tails of the observed distribution. These extremes can be the result of internal variability and can also be modulated by forcings such as increasing greenhouse gases. An example of a forecast of opportunity for climate extremes is that of flooding probabilities in Peru conditioned on ENSO states, given the heavy rains that typically accompany El Niño events. These forecasts of opportunity are now informing the development of potential early action plans. At seasonal forecast leads, these early action plans would be triggered with a high degree of confidence if several forecast criteria are met, such as El Niño SST anomalies (Niño region “1+2”) exceeding 3°C or ensemble probabilities for precipitation above the 90th percentile exceeding 40% (Bazo et al. 2018). Interestingly, some studies have identified that subseasonal and seasonal climate models can more skillfully predict events with greater anomalies than events with anomalies closer to the mean (Becker et al. 2013; Becker et al. 2018). These results suggest that useful outlooks for extreme events could be developed.

3. Challenges and Benefits

While experimental tools that build on windows of opportunity are being developed, such an approach is not without challenges. At the outset, it is a question of culture. Recognizing that a forecast tool has scientific standing and practical value even if it provides information only when the opportunity arises is not customary. On the user side, both forecast centers and forecast users are accustomed to expecting forecasts on time, all the time. Adapting to an approach that provides probabilistic forecasts with information only in certain conditions requires a significant mindset shift. In seasonal forecasting, the approach to skill-intermittency has been to issue probabilistic forecasts calibrated in order to yield climatological probabilities in the absence of a forecast signal (Mason et al. 1999). This approach provides users with a forecast “all the time” which can be acted upon when and where the probabilities deviate from climatology, provided the forecasts are well calibrated to issue reliable probabilities (e.g., for tercile categories or exceedance/non-exceedance of user-defined thresholds; Barnston and Tippett 2014). This approach has recently been applied to subseasonal forecasts of precipitation and temperature (e.g., Vigaud et al. 2017a; Vigaud et al. 2019), and discussed in the context of monsoonal climates (Vigaud et al. 2017b; Robertson et al. 2019), and East Africa/West Asia (Vigaud et al. 2018b). On subseasonal timescales, the NOAA Climate Prediction Center generates probabilistic forecasts following similar approaches for the calibration of dynamical model output (Unger et al. 2009; Strazzo et al. 2019). However, for subseasonal forecasts of particular meteorological variables such as precipitation, calibrated probabilities will often deviate very little from climatology, dependent on the region, season, and lead time. Furthermore, such methods of calibration may underestimate reliable probabilities of forecasts during periods of enhanced predictability. These could potentially be targeted more purposefully as part of a forecast of opportunity framework approach.

Moving towards opportunity-based forecast approaches may not always be practically achievable. Even when predictive linkages between processes and meteorological outcomes have been theoretically established, it is another matter to build forecast tools that exploit such relationships. Among other things, this requires a large enough sample of past events to build statistically sound relationships as the basis of the new prediction tools. Building forecasts of opportunity automatically decreases the sample size as only a particular subset of days are being considered as training data. Sample size issues become particularly challenging for forecasts of events that happen rarely.

Advancing an opportunity-based forecast approach requires both foundational and applied research. This includes furthering our understanding of the processes that can lead to opportunities for enhanced predictability and forecast skill. In turn, this requires having robust observations as the basis of research, including key surface variables such as ocean mixed layer depth, sea ice thickness, snow water equivalent, soil moisture, etc. (NASEM 2016; 2018) along with improved long-term reanalysis products that are consistent across the Earth's climate system. Research outcomes could point to new predictability sources to help alleviate over-reliance on well-established processes such as ENSO, which have limited relevance and applicability. Research is also needed to further develop prediction systems and statistical methodologies that build on observations, process understanding, and models for new opportunity-based forecasts. There is also the need to develop evaluation diagnostics and metrics that optimally evaluate such forecasts to inform the development of opportunity-based prediction tools.

Lastly, but importantly, communication strategies need to be tackled. Given the intermittency in the occurrence of forecast windows of opportunity, their format may differ from typical weather forecasts made by operational centers. However, there are already examples of this approach in weather forecasting, where predictions of the risk of weather hazards are issued only when that risk is enhanced using the "watch" and "warning" progression. Another possible format is currently in operations at the Climate Prediction Center. Probabilistic hazard maps of extreme temperature, wind, and precipitation are issued for a lead time of 2 weeks. Rather than pinpointing exact locations and times as typical weather advisories and warnings do, these maps subsume broad regions over several days where and when probabilities of hazardous weather are elevated. Forecasts of opportunity necessitate a different kind of response from users, who must understand the uncertainty associated with the forecast event. The development of capacity in forecasts of opportunity should be accomplished through the collaboration with potential users to ensure that forecast information is actionable (White et al. 2017).

Despite the challenges, the potential benefits of exploring opportunity-based forecast approaches are tantalizing, especially considering the current alternative of having forecasts with limited skill beyond weather timescales (Malloy and Kirtman 2019). Applying a window of opportunity approach to the examination of observational data and forecast system output could reveal new useful relationships and skill when and where it was thought there was none. This in turn could open the door to a new set of forecast products. With an approach that explicitly builds on specific opportunities, communication, and dissemination tools, users' expectations could be more adequately met, as they are better aware of when and where to expect skill and if the prediction is actionable.

Given that there is still untapped potential, it is safe to expect that in the future the range of forecast opportunities will expand beyond what is currently available. There is much that is unknown. For example, it is conceivable that predictive processes exist that have not yet been detected based on observations or are not fully understood. Moreover, these processes may not yet be well captured in our models and prediction systems that have limited resolution and parameterized physics. There are experimental statistical forecasts tools with consistent forecast skill in certain situations and for certain quantities at a level not yet achieved in our dynamical models based on current process understanding (e.g., for western AR activity, Mundhenk et al. 2018). This is not surprising and, most importantly, it is also suggestive that further dynamical models' skill improvement is to be expected and purposefully sought after. For example, there is much variability in the ocean beyond ENSO that we are still trying to understand, simulate, and exploit for prediction purposes. Indeed, there are recent studies pointing to coupled processes both in the Tropics (e.g., the MJO, the diurnal cycle, and monsoons) and mid-to-high latitudes (e.g., sea-ice, mesoscale frontal interactions) as important to modulate intraseasonal variability (e.g., Taraphdar et al. 2018; Li et al. 2018; Alexander et al. 2004; Smirnov et al. 2015; DeMott et al. 2015; Chelton and Xie 2010; Jia et al. 2019). This is even more true when considering the broader set of Earth system components and interactions that could lead to enhanced predictability. It is logical to build opportunity-based forecasts considering the processes that we understand create favorable conditions for enhanced forecast skill and improve our dynamical prediction systems so they optimally represent them. However, empirical models or dynamical models based on forecast output models (i.e., hybrid models) have already shown promise (e.g., Dobrynin et al. 2018) and may continue to be a synergetic innovative way forward for exploring predictability potential, until underpinning mechanisms can be more fully understood and better simulated by dynamical forecasts systems.

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References

Albers, J. R., and M. Newman, 2019: A Priori Identification of Skillful Extratropical Subseasonal Forecasts. *Geophys Res Lett*, **46,** 12527-12536, https://doi.org/10.1029/2019gl085270.

Alexander, M. A., U. S. Bhatt, J. E. Walsh, M. S. Timlin, J. S. Miller, and J. D. Scott, 2004: The Atmospheric Response to Realistic Arctic Sea Ice Anomalies in an AGCM during Winter. *J Climate,* **17**, 890–905, https://doi.org/10.1175/1520-0442(2004)017<0890:TARTRA>2.0.CO;2.

Arcodia, M. C., B. P. Kirtman, and L. S. P. Siqueira, 2019: Interference between MJO and ENSO Teleconnection Signals Impacts US Rainfall. J Climate (submitted).

Baggett, C. F., E. A. Barnes, E. D. Maloney, and B. D. Mundhenk, 2017: Advancing atmospheric river forecasts into subseasonal-to-seasonal time scales. *Geophys Res Lett*, **44,** 7528-7536, https://doi.org/10.1002/2017gl074434.

Baggett, C. F., K. M. Nardi, S. J. Childs, S. N. Zito, E. A. Barnes, and E. D. Maloney, 2018: Skillful Subseasonal Forecasts of Weekly Tornado and Hail Activity Using the Madden-Julian

Oscillation. *Journal of Geophysical Research: Atmospheres*, **123**, https://doi.org/10.1029/2018jd029059.

Baldwin, M. P., and T. J. Dunkerton, 2001: Stratospheric harbingers of anomalous weather regimes. *Science*, **294,** 581-584, https://doi.org/10.1126/science.1063315.

Barnston, A. G., and M. K. Tippett, 2014: Climate information, outlooks, and understanding–where does the IRI stand? *Earth Perspectives*, **1**, https://doi.org/10.1186/2194-6434-1-20.

Barnston, A. G., M. K. Tippett, M. Ranganathan, and M. L. L'Heureux, 2017: Deterministic skill of ENSO predictions from the North American Multimodel Ensemble. *Clim Dynam*, **53,** 7215-7234, https://doi.org/10.1007/s00382-017-3603-3.

Barrett, B. S., and V. A. Gensini, 2013: Variability of central United States April-May tornado day likelihood by phase of the Madden-Julian Oscillation. *Geophys Res Lett*, **40,** 2790-2795, https://doi.org/10.1002/grl.50522.

Bazo, J., R. Singh, M. Destrooper, and E. C. de Perez, 2019: *Pilot experiences in using seamless forecasts for early action: The "Ready-Set-Go" approach in the Red Cross*. Sub-seasonal to Seasonal Prediction, A. Robertston and F. Vitart, Elsevier, Inc., 387-398.

Becker, E. J., H. van den Dool, and M. Peña, 2013: Short-Term Climate Extremes: Prediction Skill and Predictability. *J Climate*, **26,** 512-531, https://doi.org/10.1175/jcli-d-12-00177.1.

Becker, E.J., and H. van den Dool, 2018. Short-term climate extremes: probabilistic forecasts from a multi-model ensemble. Climate Prediction S&T Digest, 42nd NOAA Climate Diagnostics

Prediction Workshop Special Issue. Norman, OK, USA, NOAA, 46-48, https://doi.org/10.7289/V5/CDPW-NWS-42nd-2018.

Bellucci, A., A. Mariotti, and S. Gualdi, 2017: The Role of Forcings in the Twentieth-Century North Atlantic Multidecadal Variability: The 1940–75 North Atlantic Cooling Case Study. *J Climate*, **30,** 7317-7337, https://doi.org/10.1175/jcli-d-16-0301.1.

Benedetti, A., and F. Vitart, 2018: Can the Direct Effect of Aerosols Improve Subseasonal Predictability? *Mon Weather Rev*, **146,** 3481-3498, https://doi.org/10.1175/mwr-d-17-0282.1.

Beverley, J. D., S. J. Woolnough, L. H. Baker, S. J. Johnson, and A. Weisheimer, 2019: The northern hemisphere circumglobal teleconnection in a seasonal forecast model and its relationship to European summer forecast skill. *Clim Dynam*, **52,** 3759-3771, https://doi.org/10.1007/s00382-018-4371-4.

Birner, T., and J. R. Albers, 2017: Sudden Stratospheric Warmings and Anomalous Upward Wave Activity Flux. *Sola*, **13A,** 8-12, https://doi.org/10.2151/sola.13A-002.

Boer, G. J., V. V. Kharin, and W. J. Merryfield, 2013: Decadal predictability and forecast skill. *Clim Dynam*, **41,** 1817-1833, https://doi.org/10.1007/s00382-013-1705-0.

Borchert, L. F., A. Düsterhus, S. Brune, W. A. Müller, and J. Baehr, 2019: Forecast-Oriented Assessment of Decadal Hindcast Skill for North Atlantic SST. *Geophys Res Lett*, **46,** 11444-11454, https://doi.org/10.1029/2019gl084758.

Brune, S., A. Düsterhus, H. Pohlmann, W. A. Müller, and J. Baehr, 2018: Time dependency of the prediction skill for the North Atlantic subpolar gyre in initialized decadal hindcasts. *Clim Dynam*, **51,** 1947-1970, https://doi.org/10.1007/s00382-017-3991-4.

Butler, A. H., J. P. Sjoberg, D. J. Seidel, and K. H. Rosenlof, 2017: A sudden stratospheric warming compendium. *Earth System Science Data*, **9,** 63-76, https://doi.org/10.5194/essd-9-63-2017.

Carbin, G. W., M. K. Tippett, S. P. Lillo, and H. E. Brooks, 2016: Visualizing Long-Range Severe Thunderstorm Environment Guidance from CFSv2. *Bulletin of the American Meteorological Society*, **97,** 1021-1031, https://doi.org/10.1175/bams-d-14-00136.1.

Charlton-Perez, A. J., L. Ferranti, and R. W. Lee, 2018: The influence of the stratospheric state on North Atlantic weather regimes. *Q J Roy Meteor Soc*, **144,** 1140-1151, https://doi.org/10.1002/qj.3280.

Chelton, D., and S.-P. Xie, 2010: Coupled Ocean-Atmosphere Interaction at Oceanic Mesoscales. *Oceanography*, **23,** 52-69, https://doi.org/10.5670/oceanog.2010.05.

Clement, A. C., R. Seager, M. A. Cane, and S. E. Zebiak, 1996: An Ocean Dynamical Thermostat. *J Climate*, **9,** 2190-2196, https://doi.org/10.1175/1520-0442(1996)009<2190:Aodt>2.0.Co;2.

Cohen, J., and Coauthors, 2014: Recent Arctic amplification and extreme mid-latitude weather. *Nat Geosci*, **7,** 627-637, https://doi.org/10.1038/ngeo2234.

DeFlorio, M. J., D. E. Waliser, B. Guan, D. A. Lavers, F. M. Ralph, and F. Vitart, 2018: Global Assessment of Atmospheric River Prediction Skill. *J Hydrometeorol*, **19,** 409-426, https://doi.org/10.1175/jhm-d-17-0135.1.

DeFlorio, M. J., and Coauthors, 2019: Experimental Subseasonal-to-Seasonal (S2S) Forecasting of Atmospheric Rivers Over the Western United States. *Journal of Geophysical Research: Atmospheres*, **124,** 11242-11265, https://doi.org/10.1029/2019jd031200.

DeMott, C. A., N. P. Klingaman, and S. J. Woolnough, 2015: Atmosphere-ocean coupled processes in the Madden-Julian oscillation. *Rev Geophys*, **53,** 1099-1154, https://doi.org/10.1002/2014rg000478.

DiNezio, P. N., C. Deser, Y. Okumura, and A. Karspeck, 2017: Predictability of 2-year La Niña events in a coupled general circulation model. *Clim Dynam*, **49,** 4237-4261, https://doi.org/10.1007/s00382-017-3575-3.

Ding, Q., and B. Wang, 2005: Circumglobal Teleconnection in the Northern Hemisphere Summer. *J Climate*, **18,** 3483-3505, https://doi.org/10.1175/jcli3473.1.

Dirmeyer, P. A., G. Balsamo, and C. D. Peters-Lidard, 2015: Land-Atmosphere Interactions and the Water Cycle. Seamless Prediction of the Earth System: from Minutes to Months, G. Brunet, S. Jones, and P. M. Ruti, World Meteorological Organization, Geneva, Switzerland, 145–154.

Dirmeyer, P. A., S. Halder, and R. Bombardi, 2018: On the Harvest of Predictability From Land States in a Global Forecast Model. *Journal of Geophysical Research: Atmospheres*, **123**, https://doi.org/10.1029/2018jd029103.

Dobrynin, M., and Coauthors, 2018: Improved Teleconnection-Based Dynamical Seasonal Predictions of Boreal Winter. *Geophys Res Lett*, **45,** 3605-3614, https://doi.org/10.1002/2018gl077209.

Domeisen, D. I. V., C. I. Garfinkel, and A. H. Butler, 2019a: The Teleconnection of El Niño Southern Oscillation to the Stratosphere. *Rev Geophys*, **57,** 5-47, https://doi.org/10.1029/2019jd030923.

Domeisen, D. I. V., and Coauthors, 2019b: The role of the stratosphere in subseasonal to seasonal prediction Part II: Predictability arising from stratosphere - troposphere coupling. *Journal of Geophysical Research: Atmospheres*, https://doi.org/10.1029/2018rg000596.

Doss-Gollin, J., Á. G. Muñoz, S. J. Mason, and M. Pastén, 2018: Heavy Rainfall in Paraguay during the 2015/16 Austral Summer: Causes and Subseasonal-to-Seasonal Predictive Skill. *J Climate*, **31,** 6669-6685, https://doi.org/10.1175/jcli-d-17-0805.1.

Eddebbar, Y. A., K. B. Rodgers, M. C. Long, A. C. Subramanian, S.-P. Xie, and R. F. Keeling, 2019: El Niño–Like Physical and Biogeochemical Ocean Response to Tropical Eruptions. *J Climate*, **32,** 2627-2649, https://doi.org/10.1175/jcli-d-18-0458.1.

Ferranti, L., S. Corti, and M. Janousek, 2015: Flow-dependent verification of the ECMWF ensemble over the Euro-Atlantic sector. *Q J Roy Meteor Soc*, **141,** 916-924, https://doi.org/10.1002/qj.2411.

Ferranti, L., L. Magnusson, F. Vitart, and D. S. Richardson, 2018: How far in advance can we predict changes in large-scale flow leading to severe cold conditions over Europe? *Q J Roy Meteor Soc*, **144,** 1788-1802, https://doi.org/10.1002/qj.3341.

Ford, T. W., and S. M. Quiring, 2014: In situ soil moisture coupled with extreme temperatures: A study based on the Oklahoma Mesonet. *Geophys Res Lett*, **41,** 4727-4734, https://doi.org/10.1002/2014gl060949.

Frame, T. H. A., J. Methven, S. L. Gray, and M. H. P. Ambaum, 2013: Flow-dependent predictability of the North Atlantic jet. *Geophys Res Lett*, **40,** 2411-2416, https://doi.org/10.1002/grl.50454.

Garfinkel, C. I., and D. L. Hartmann, 2010: Influence of the quasi-biennial oscillation on the North Pacific and El Niño teleconnections. *Journal of Geophysical Research*, **115**, https://doi.org/10.1029/2010jd014181.

Garfinkel, C. I., and C. Schwartz, 2017: MJO-Related Tropical Convection Anomalies Lead to More Accurate Stratospheric Vortex Variability in Subseasonal Forecast Models. *Geophys Res Lett*, **44,** 10054-10062, https://doi.org/10.1002/2017GL074470.

Guan, B., N. P. Molotch, D. E. Waliser, E. J. Fetzer, and P. J. Neiman, 2010: Extreme snowfall events linked to atmospheric rivers and surface air temperature via satellite measurements. *Geophys Res Lett*, **37,** https://doi.org/10.1029/2010gl044696.

Guirguis, K., A. Gershunov, R. E. S. Clemesha, T. Shulgina, A. C. Subramanian, and F. M. Ralph, 2018: Circulation Drivers of Atmospheric Rivers at the North American West Coast. *Geophys Res Lett*, **45**, https://doi.org/10.1029/2018gl079249.

Guo, Z., P. A. Dirmeyer, and T. DelSole, 2011: Land surface impacts on subseasonal and seasonal predictability. *Geophys Res Lett*, **38,** https://doi.org/10.1029/2011gl049945.

Haarsma, R. J., J. Garcia-Serrano, C. Prodhomme, O. Bellprat, P. Davini, and S. Drijfhout, 2019: Sensitivity of winter North Atlantic-European climate to resolved atmosphere and ocean dynamics. *Sci Rep*, **9,** 13358, https://doi.org/10.1038/s41598-019-49865-9.

Hasselmann, K., 1976: Stochastic climate models Part I. Theory. *Tellus*, **28,** 473-485, https://doi.org/10.1111/j.2153-3490.1976.tb00696.x.

He, S., E. M. Knudsen, D. W. J. Thompson, and T. Furevik, 2018: Evidence for Predictive Skill of High-Latitude Climate Due to Midsummer Sea Ice Extent Anomalies. *Geophys Res Lett*, **45,** 9114-9122, https://doi.org/10.1029/2018gl078281.

Herring, S.C., N. Christidis, A. Hoell, M.P. Hoerling, and P.A. Stott, 2019: Explaining Extreme Events of 2017 from a Climate Perspective. *Bull. Amer. Meteor. Soc.,* **100**, S1–S117, https://doi.org/10.1175/BAMS-ExplainingExtremeEvents2017.1

Hoskins, B. J., and D. J. Karoly, 1981: The Steady Linear Response of a Spherical Atmosphere to Thermal and Orographic Forcing. *J Atmos Sci*, **38,** 1179-1196, https://doi.org/10.1175/1520-0469(1981)038<1179:Tslroa>2.0.Co;2.

Inoue, J., M. E. Hori, and K. Takaya, 2012: The Role of Barents Sea Ice in the Wintertime Cyclone Track and Emergence of a Warm-Arctic Cold-Siberian Anomaly. *J Climate*, **25,** 2561-2568, https://doi.org/10.1175/jcli-d-11-00449.1.

Jia, Y., P. Chang, I. Szunyogh, R. Saravanan, and J. T. Bacmeister, 2019: A Modeling Strategy for the Investigation of the Effect of Mesoscale SST Variability on Atmospheric Dynamics. *Geophys Res Lett*, **46,** 3982-3989, https://doi.org/10.1029/2019gl081960.

Johnson, N. C., D. C. Collins, S. B. Feldstein, M. L. L'Heureux, and E. E. Riddle, 2014: Skillful Wintertime North American Temperature Forecasts out to 4 Weeks Based on the State of ENSO and the MJO*. *Weather Forecast*, **29,** 23-38, https://doi.org/10.1175/waf-d-13-00102.1.

Kalnay, E. and A. Dalcher, 1987: Forecasting forecast skill. Mon. Weather Rev. 115, 349-356, https://doi.org/10.1175/1520-0493(1987)115<0349:FFS>2.0.CO;2.

Karpechko, A. Y., 2018: Predictability of Sudden Stratospheric Warmings in the ECMWF Extended-Range Forecast System. *Mon Weather Rev*, **146,** 1063-1075, https://doi.org/10.1175/mwr-d-17-0317.1.

Kim, H.-M., P. J. Webster, and J. A. Curry, 2012: Seasonal prediction skill of ECMWF System 4 and NCEP CFSv2 retrospective forecast for the Northern Hemisphere Winter. *Clim Dynam*, **39,** 2957-2973, https://doi.org/10.1007/s00382-012-1364-6.

Kornhuber, K., V. Petoukhov, S. Petri, S. Rahmstorf, and D. Coumou, 2017: Evidence for wave resonance as a key mechanism for generating high-amplitude quasi-stationary waves in boreal summer. *Clim Dynam*, **49,** 1961-1979, https://doi.org/10.1007/s00382-016-3399-6.

Koster, R. D., and M. J. Suarez, 2001: Soil Moisture Memory in Climate Models. *J Hydrometeorol*, **2,** 558-570, https://doi.org/10.1175/1525-7541(2001)002<0558:Smmicm>2.0.Co;2.

Koster, R. D., S. P. Mahanama, T. J. Yamada, G. Balsamo, A. A. Berg, M. Boisserie, P. A. Dirmeyer, F. J. Doblas-Reyes, G. Drewitt, C. T. Gordon, Z. Guo, J. Jeong, W. Lee, Z. Li, L. Luo, S. Malyshev, W. J. Merryfield, S. I. Seneviratne, T. Stanelle, B. J. van den Hurk, F. Vitart, and E.F. Wood, 2011: The Second Phase of the Global Land–Atmosphere Coupling Experiment: Soil

Moisture Contributions to Subseasonal Forecast Skill. *J Hydrometeor.,* **12**, 805–822, https://doi.org/10.1175/2011JHM1365.1.

Koster, R. D., Y. Chang, and S. D. Schubert, 2014: A Mechanism for Land–Atmosphere Feedback Involving Planetary Wave Structures. *J Climate*, **27,** 9290-9301, https://doi.org/10.1175/jcli-d-14-00315.1.

Koster, R. D., Y. Chang, H. Wang, and S. D. Schubert, 2016: Impacts of Local Soil Moisture Anomalies on the Atmospheric Circulation and on Remote Surface Meteorological Fields during Boreal Summer: A Comprehensive Analysis over North America. *J Climate,* **29**, 7345–7364, https://doi.org/10.1175/JCLI-D-16-0192.1.

Leroy, A., and M. C. Wheeler, 2008: Statistical Prediction of Weekly Tropical Cyclone Activity in the Southern Hemisphere. *Mon Weather Rev*, **136,** 3637-3654, https://doi.org/10.1175/2008mwr2426.1.

Li, H., and R. L. Sriver, 2018: Tropical Cyclone Activity in the High-Resolution Community Earth System Model and the Impact of Ocean Coupling. *J Adv Model Earth Sy*, **10,** 165-186, https://doi.org/10.1002/2017ms001199.

Lim, E.-P., H. H. Hendon, G. Boschat, D. Hudson, D. W. J. Thompson, A. J. Dowdy, and J. M. Arblaster, 2019: Australian hot and dry extremes induced by weakenings of the stratospheric polar vortex. *Nat Geosci*, **12,** 896-901, https://doi.org/10.1038/s41561-019-0456-x.

Lin, H., G. Brunet, and R. Mo, 2010: Impact of the Madden–Julian Oscillation on Wintertime Precipitation in Canada. *Mon Weather Rev*, **138,** 3822-3839, https://doi.org/10.1175/2010mwr3363.1.

Lovejoy, S., 2018: Spectra, intermittency, and extremes of weather, macroweather and climate. *Sci Rep*, **8,** 12697, https://doi.org/10.1038/s41598-018-30829-4.

Luo, J.-J., S. K. Behera, Y. Masumoto, and T. Yamagata, 2011: Impact of Global Ocean Surface Warming on Seasonal-to-Interannual Climate Prediction. *J Climate*, **24,** 1626-1646, https://doi.org/10.1175/2010jcli3645.1.

Madden, R. A., and P. R. Julian, 1994: Observations of the 40–50-Day Tropical Oscillation—A Review. *Mon Weather Rev*, **122,** 814-837, https://doi.org/10.1175/1520-0493(1994)122<0814:Ootdto>2.0.Co;2.

Malloy, K. M., and B. P. Kirtman, 2019: Predictability of mid-summer Great Plains low-level jet and associated precipitation. *Weather Forecast*, https://doi.org/10.1175/waf-d-19-0103.1.

Mariotti, A., and Coauthors, 2019: Bridging the Weather-to-Climate Prediction Gap. *Eos*, **100**, https://doi.org/10.1029/2019eo115819.

Marshall, A. G., H. H. Hendon, S.-W. Son, and Y. Lim, 2016: Impact of the quasi-biennial oscillation on predictability of the Madden–Julian oscillation. *Clim Dynam*, **49,** 1365-1377, https://doi.org/10.1007/s00382-016-3392-0.

Mason, S. J., L. Goddard, N. E. Graham, E. Yulaeva, L. Sun, and P. A. Arkin, 1999: The IRI Seasonal Climate Prediction System and the 1997/98 El Niño Event. *Bulletin of the American Meteorological Society*, **80,** 1853-1873, https://doi.org/10.1175/1520-0477(1999)080<1853:Tiscps>2.0.Co;2.

Matthews, A. J., 2008: Primary and successive events in the Madden–Julian Oscillation. *Q J Roy Meteor Soc*, **134,** 439-453, https://doi.org/10.1002/qj.224.

Matthews, A. J., B. J. Hoskins, and M. Masutani, 2004: The global response to tropical heating in the Madden–Julian oscillation during the northern winter. *Q J Roy Meteor Soc*, **130,** 1991-2011, https://doi.org/10.1256/qj.02.123.

McCormick, M. P., and R. E. Veiga, 1992: SAGE II measurements of early Pinatubo aerosols. *Geophys Res Lett*, **19,** 155-158, https://doi.org/10.1029/91gl02790.

Molteni, F., and T. N. Palmer, 1991: A Real-Time Scheme for the Prediction of Forecast Skill. *Mon Weather Rev*, **119,** 1088-1097, https://doi.org/10.1175/1520-0493(1991)119<1088:Artsft>2.0.Co;2.

Moore, R. W., O. Martius, and T. Spengler, 2010: The Modulation of the Subtropical and Extratropical Atmosphere in the Pacific Basin in Response to the Madden–Julian Oscillation. *Mon Weather Rev*, **138,** 2761-2779, https://doi.org/10.1175/2010mwr3194.1.

Mori, M., M. Watanabe, H. Shiogama, J. Inoue, and M. Kimoto, 2014: Robust Arctic sea-ice influence on the frequent Eurasian cold winters in past decades. *Nat Geosci*, **7,** 869-873, https://doi.org/10.1038/ngeo2277.

Moron, V., A. W. Robertson, and M. Ghil, 2012: Impact of the modulated annual cycle and intraseasonal oscillation on daily-to-interannual rainfall variability across monsoonal India. *Clim Dynam*, **38,** 2409-2435, https://doi.org/10.1007/s00382-011-1253-4.

Moron, V., A. W. Robertson, J.-H. Qian, and M. Ghil, 2015: Weather types across the Maritime Continent: from the diurnal cycle to interannual variations. *Frontiers in Environmental Science*, **2**, https://doi.org/10.3389/fenvs.2014.00065.

Mundhenk, B. D., E. A. Barnes, E. D. Maloney, and C. F. Baggett, 2018: Skillful empirical subseasonal prediction of landfalling atmospheric river activity using the Madden–Julian oscillation and quasi-biennial oscillation. *npj Climate and Atmospheric Science*, **1**, https://doi.org/10.1038/s41612-017-0008-2.

Muñoz, Á. G., L. Goddard, A. W. Robertson, Y. Kushnir, and W. Baethgen, 2015: Cross–Time Scale Interactions and Rainfall Extreme Events in Southeastern South America for the Austral Summer. Part I: Potential Predictors. *J Climate*, **28,** 7894-7913, https://doi.org/10.1175/jcli-d-14-00693.1.

Muñoz, Á. G., L. Goddard, S. J. Mason, and A. W. Robertson, 2016: Cross–Time Scale Interactions and Rainfall Extreme Events in Southeastern South America for the Austral Summer. Part II: Predictive Skill. *J Climate*, **29,** 5915-5934, https://doi.org/10.1175/jcli-d-15-0699.1.

Nardi, K. M., C. F. Baggett, E. A. Barnes, E. D. Maloney, C. F. Baggett, D. S. Harnos, and L. M. Ciasto, 2019: Skillful all-season S2S prediction of U.S. precipitation using the MJO and QBO. Weather and Forecasting (submitted).

National Academies of Sciences, Engineering, and Medicine, 2016: Next Generation Earth System Prediction: Strategies for Subseasonal to Seasonal Forecasts. Washington, DC: The National Academies Press. https://doi.org/10.17226/21873.

National Academies of Sciences, Engineering, and Medicine. 2018. Thriving on Our Changing Planet: A Decadal Strategy for Earth Observation from Space. Washington, DC: The National Academies Press. https://doi.org/10.17226/24938.

Newman, M., and P. D. Sardeshmukh, 1998: The Impact of the Annual Cycle on the North Pacific/North American Response to Remote Low-Frequency Forcing. *J Atmos Sci*, **55,** 1336-1353, https://doi.org/10.1175/1520-0469(1998)055<1336:Tiotac>2.0.Co;2.

Newman, M., P. D. Sardeshmukh, C. R. Winkler, and J. S. Whitaker, 2003: A Study of Subseasonal Predictability. *Mon Weather Rev*, **131,** 1715-1732, https://doi.org/10.1175//2558.1.

Parker, T. J., G. J. Berry, and M. J. Reeder, 2014: The Structure and Evolution of Heat Waves in Southeastern Australia. *J Climate*, **27,** 5768-5785, https://doi.org/10.1175/jcli-d-13-00740.1.

Penland, C., and P. D. Sardeshmukh, 1995: The Optimal Growth of Tropical Sea Surface Temperature Anomalies. *J Climate*, **8,** 1999-2024, https://doi.org/10.1175/1520-0442(1995)008<1999:Togots>2.0.Co;2.

Petoukhov, V., and V. A. Semenov, 2010: A link between reduced Barents-Kara sea ice and cold winter extremes over northern continents. *Journal of Geophysical Research*, **115**, https://doi.org/10.1029/2009jd013568.

Plumb R. A., 2010. Planetary waves and the extratropical stratosphere. In “The Stratosphere: Dynamics, Transport, and Chemistry”, Geophysical Monograph Series, 190, https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1002/9781118666630.ch2.

Reale, O., K. M. Lau, and A. da Silva, 2011: Impact of Interactive Aerosol on the African Easterly Jet in the NASA GEOS-5 Global Forecasting System. *Weather Forecast*, **26,** 504-519, https://doi.org/10.1175/waf-d-10-05025.1.

Reale, O., K. M. Lau, A. da Silva, and T. Matsui, 2014: Impact of assimilated and interactive aerosol on tropical cyclogenesis. *Geophys Res Lett*, **41,** 3282-3288, https://doi.org/10.1002/2014GL059918.

Riddle, E. E., M. B. Stoner, N. C. Johnson, M. L. L'Heureux, D. C. Collins, and S. B. Feldstein, 2013: The impact of the MJO on clusters of wintertime circulation anomalies over the North American region. *Clim Dynam*, **40,** 1749-1766, https://doi.org/10.1007/s00382-012-1493-y.

Robertson, A. W., V. Moron, N. Vigaud, N. Acharya, A. M. Greene, and D. S. Pai, 2019: Multi-scale variability and predictability of Indian summer monsoon rainfall. MAUSAM, 70, 277-292.

Scaife, A. A., and Coauthors, 2016: Seasonal winter forecasts and the stratosphere. *Atmospheric Science Letters*, **17,** 51-56, https://doi.org/10.1002/asl.598.

Schubert, S., H. Wang, and M. Suarez, 2011: Warm Season Subseasonal Variability and Climate Extremes in the Northern Hemisphere: The Role of Stationary Rossby Waves. *J Climate*, **24,** 4773-4792, https://doi.org/10.1175/jcli-d-10-05035.1.

Sigmond, M., J. F. Scinocca, V. V. Kharin, and T. G. Shepherd, 2013: Enhanced seasonal forecast skill following stratospheric sudden warmings. *Nat Geosci*, **6,** 98-102, https://doi.org/10.1038/ngeo1698.

Smirnov, D., M. Newman, M. A. Alexander, Y.-O. Kwon, and C. Frankignoul, 2015: Investigating the Local Atmospheric Response to a Realistic Shift in the Oyashio Sea Surface Temperature Front. *J Climate*, **28,** 1126-1147, https://doi.org/10.1175/jcli-d-14-00285.1.

Smith, K. L., and P. J. Kushner, 2012: Linear interference and the initiation of extratropical stratosphere-troposphere interactions. *Journal of Geophysical Research: Atmospheres*, **117,** https://doi.org/10.1029/2012jd017587.

Song, L., and R. Wu, 2019: Impacts of MJO Convection over the Maritime Continent on Eastern China Cold Temperatures. *J Climate*, **32,** 3429-3449, https://doi.org/10.1175/jcli-d-18-0545.1.

Strazzo, S., D. C. Collins, A. Schepen, Q. J. Wang, E. Becker, and L. Jia, 2019: Application of a Hybrid Statistical–Dynamical System to Seasonal Prediction of North American Temperature and Precipitation. *Mon Weather Rev*, **147,** 607-625, https://doi.org/10.1175/mwr-d-18-0156.1.

Stroeve, J., L. C. Hamilton, C. M. Bitz, and E. Blanchard-Wrigglesworth, 2014: Predicting September sea ice: Ensemble skill of the SEARCH Sea Ice Outlook 2008-2013. *Geophys Res Lett*, **41,** 2411-2418, https://doi.org/10.1002/2014gl059388.

Swain, D. L., D. Singh, D. E. Horton, J. S. Mankin, T. C. Ballard, and N. S. Diffenbaugh, 2017: Remote Linkages to Anomalous Winter Atmospheric Ridging Over the Northeastern Pacific. *Journal of Geophysical Research: Atmospheres*, **122,** 12,194-12,209, https://doi.org/10.1002/2017jd026575.

Taraphdar, S., F. Zhang, L. R. Leung, X. Chen, and O. M. Pauluis, 2018: MJO Affects the Monsoon Onset Timing Over the Indian Region. *Geophys Res Lett*, **45,** 10011-10018, https://doi.org/10.1029/2018gl078804.

Teng, H., and G. Branstator, 2017: Causes of Extreme Ridges That Induce California Droughts. *J Climate*, **30,** 1477-1492, https://doi.org/10.1175/jcli-d-16-0524.1.

Thompson, D. B., and P. E. Roundy, 2013: The Relationship between the Madden–Julian Oscillation and U.S. Violent Tornado Outbreaks in the Spring. *Mon Weather Rev*, **141,** 2087-2095, https://doi.org/10.1175/mwr-d-12-00173.1.

Ting, M., and P. D. Sardeshmukh, 1993: Factors Determining the Extratropical Response to Equatorial Diabatic Heating Anomalies. *J Atmos Sci*, **50,** 907-918, https://doi.org/10.1175/1520-0469(1993)050<0907:Fdtert>2.0.Co;2.

Tippett, M. K., A. G. Barnston, and S. Li, 2012: Performance of Recent Multimodel ENSO Forecasts. *Journal of Applied Meteorology and Climatology*, **51,** 637-654, https://doi.org/10.1175/jamc-d-11-093.1.

Tripathi, O. P., and Coauthors, 2015: The predictability of the extratropical stratosphere on monthly time-scales and its impact on the skill of tropospheric forecasts. *Q J Roy Meteor Soc*, **141,** 987-1003, https://doi.org/10.1002/qj.2432.

Tseng, K. C., E. A. Barnes, and E. D. Maloney, 2018: Prediction of the Midlatitude Response to Strong Madden-Julian Oscillation Events on S2S Time Scales. *Geophys Res Lett*, **45,** 463-470, https://doi.org/10.1002/2017gl075734.

Unger, D. A., H. van den Dool, E. O'Lenic, and D. Collins, 2009: Ensemble Regression. *Mon Weather Rev*, **137,** 2365-2379, https://doi.org/10.1175/2008mwr2605.1.

Vautard, R., and Coauthors, 2007: Summertime European heat and drought waves induced by wintertime Mediterranean rainfall deficit. *Geophys Res Lett*, **34**, https://doi.org/10.1029/2006gl028001.

Ventrice, M. J., C. D. Thorncroft, and P. E. Roundy, 2011: The Madden–Julian Oscillation's Influence on African Easterly Waves and Downstream Tropical Cyclogenesis. *Mon Weather Rev*, **139,** 2704-2722, https://doi.org/10.1175/mwr-d-10-05028.1.

Vigaud, N., and A. W. Robertson, 2017: Convection regimes and tropical-midlatitude interactions over the Intra-American Seas from May to November. *International Journal of Climatology*, **37,** 987-1000, https://doi.org/10.1002/joc.5051.

Vigaud, N., A. W. Robertson, and M. K. Tippett, 2017a: Multimodel Ensembling of Subseasonal Precipitation Forecasts over North America. *Mon Weather Rev*, **145,** 3913-3928, https://doi.org/10.1175/mwr-d-17-0092.1.

Vigaud, N., A. W. Robertson, M. K. Tippett, and N. Acharya, 2017b: Subseasonal Predictability of Boreal Summer Monsoon Rainfall from Ensemble Forecasts. *Frontiers in Environmental Science*, **5**, https://doi.org/10.3389/fenvs.2017.00067.

Vigaud, N., and A. Giannini, 2018: West African convection regimes and their predictability from submonthly forecasts. *Clim Dynam*, **52,** 7029-7048, https://doi.org/10.1007/s00382-018-4563-y.

——, 2018a: Predictability of Recurrent Weather Regimes over North America during Winter from Submonthly Reforecasts. *Mon Weather Rev*, **146,** 2559-2577, https://doi.org/10.1175/mwr-d-18-0058.1.

Vigaud, N., M. K. Tippett, and A. W. Robertson, 2018b: Probabilistic Skill of Subseasonal Precipitation Forecasts for the East Africa–West Asia Sector during September–May. *Weather Forecast*, **33,** 1513-1532, https://doi.org/10.1175/waf-d-18-0074.1.

Vigaud, N., M. K. Tippett, J. Yuan, A. W. Robertson, and N. Acharya, 2019: Probabilistic Skill of Subseasonal Surface Temperature Forecasts over North America. *Weather Forecast*, **34,** 1789-1806, https://doi.org/10.1175/waf-d-19-0117.1.

Vitart, F., 2017: Madden-Julian Oscillation prediction and teleconnections in the S2S database. *Q J Roy Meteor Soc*, **143,** 2210-2220, https://doi.org/10.1002/qj.3079.

Vitart, F., and Coauthors, 2017: The Subseasonal to Seasonal (S2S) Prediction Project Database. *Bulletin of the American Meteorological Society*, **98,** 163-173, https://doi.org/10.1175/bams-d-16-0017.1.

Wang, B., and Coauthors, 2009: Advance and prospectus of seasonal prediction: assessment of the APCC/CliPAS 14-model ensemble retrospective seasonal prediction (1980–2004). *Clim Dynam*, **33,** 93-117, https://doi.org/10.1007/s00382-008-0460-0.

Wang, H., S. Schubert, R. Koster, Y.-G. Ham, and M. Suarez, 2014: On the Role of SST Forcing in the 2011 and 2012 Extreme U.S. Heat and Drought: A Study in Contrasts. *J Hydrometeorol*, **15,** 1255-1273, https://doi.org/10.1175/jhm-d-13-069.1.

Watson, P. A. G., A. Weisheimer, J. R. Knight, and T. N. Palmer, 2016: The role of the tropical West Pacific in the extreme Northern Hemisphere winter of 2013/2014. *Journal of Geophysical Research: Atmospheres*, **121,** 1698-1714, https://doi.org/10.1002/2015jd024048.

Waugh, D. W., A. H. Sobel, and L. M. Polvani, 2017: What Is the Polar Vortex and How Does It Influence Weather? *Bulletin of the American Meteorological Society*, **98,** 37-44, https://doi.org/10.1175/bams-d-15-00212.1.

Wheeler, M. C., H. H. Hendon, S. Cleland, H. Meinke, and A. Donald, 2009: Impacts of the Madden–Julian Oscillation on Australian Rainfall and Circulation. *J Climate*, **22,** 1482-1498, https://doi.org/10.1175/2008jcli2595.1.

White, C. J., and Coauthors, 2017: Potential applications of subseasonal-to-seasonal (S2S) predictions. *Meteorological Applications*, **24,** 315-325, https://doi.org/10.1002/met.1654.

WMO, 2018: WWRP/WCRP Sub-seasonal to Seasonal Prediction Project (S2S) Phase II Proposal. WWRP 2018 - 4 WCRP Report, No. 11/2018.

Zhang, C., and B. Zhang, 2018: QBO-MJO Connection. *Journal of Geophysical Research: Atmospheres*, **123,** 2957-2967, https://doi.org/10.1002/2017jd028171.

Zhang, J., and R. Zhang, 2015: On the evolution of Atlantic Meridional Overturning Circulation Fingerprint and implications for decadal predictability in the North Atlantic. *Geophys Res Lett*, **42,** 5419-5426, https://doi.org/10.1002/2015gl064596.

Zhang, X., C. Lu, and Z. Guan, 2012: Weakened cyclones, intensified anticyclones and recent extreme cold winter weather events in Eurasia. *Environmental Research Letters*, **7**, https://doi.org/10.1088/1748-9326/7/4/044044.

Zheng, Z., Z. Z. Hu, and M. L'Heureux, 2016: Predictable Components of ENSO Evolution in Real-time Multi-Model Predictions. *Sci Rep*, **6,** 35909, https://doi.org/10.1038/srep35909.

List of Figures

Figure 1: SSW events affect cyclone track frequency (panels a-c) and surface air temperature anomalies (panels d-f) for at least a month after they occur. Cyclone track frequency (cyclones per week) is calculated using Hodges (1994) tracking algorithm within 250 km of a given location for subsets of 1980-2015 January, February, or March days in the MERRA-2 data. (a) Cyclones that occurred within 30-days after a SSW event and (b) cyclones not within 30-days after a SSW event; (c) The difference between (a) and (b) with significance hatched at the 80% confidence interval. Panels (d)-(f) as in (a)-(c) but for daily 2-meter temperature anomalies (K), with significance in (f) hatched at the 95% interval. Significance tested with n=1000 bootstrap resampling without replacement.

Figure 2. The LIM empirical forecast model applied to identify MSLP winter forecasts of opportunity in the Pacific basin for up to six weeks lead time. The figure shows median hindcast skill (1999-2010) of wintertime Pacific basin MSLP weekly-averaged anomalies predicted by operational NCEP CFS and ECMWF IFS models and by the LIM model, for forecast leads ranging from 1 to 6 weeks. For each forecast system, two categories are shown: one where the LIM expects skill will lie in the upper 10% of all hindcasts (darker bars) and a second consisting of the remaining 90% of hindcasts (lighter bars). Whiskers denote uncertainty due to the small hindcast sample size (based on bootstrap confidence intervals). Skill is measured by the pattern correlation of the forecast MSLP anomaly with its verification in the region 20º-60ºN, 120ºE-120ºW. [Adapted from Albers and Newman (2019)].

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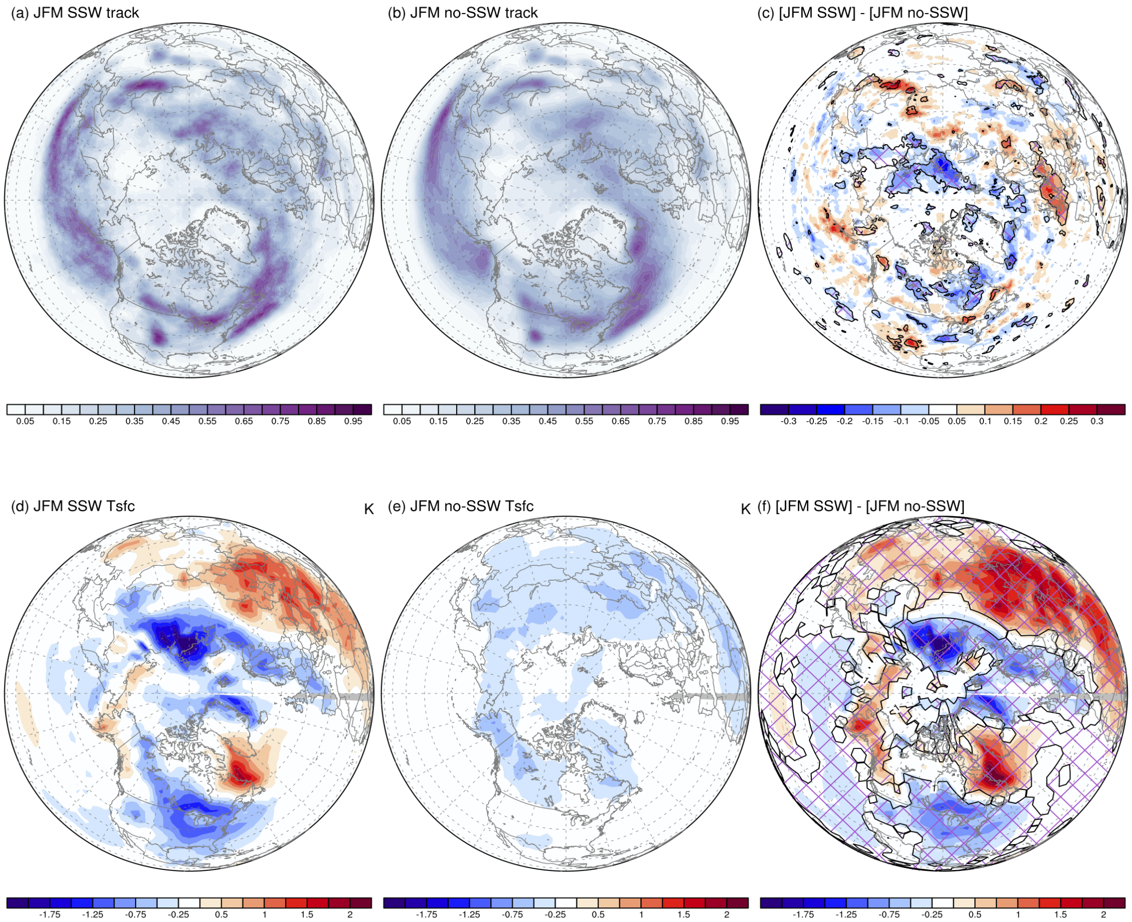
FIGURES



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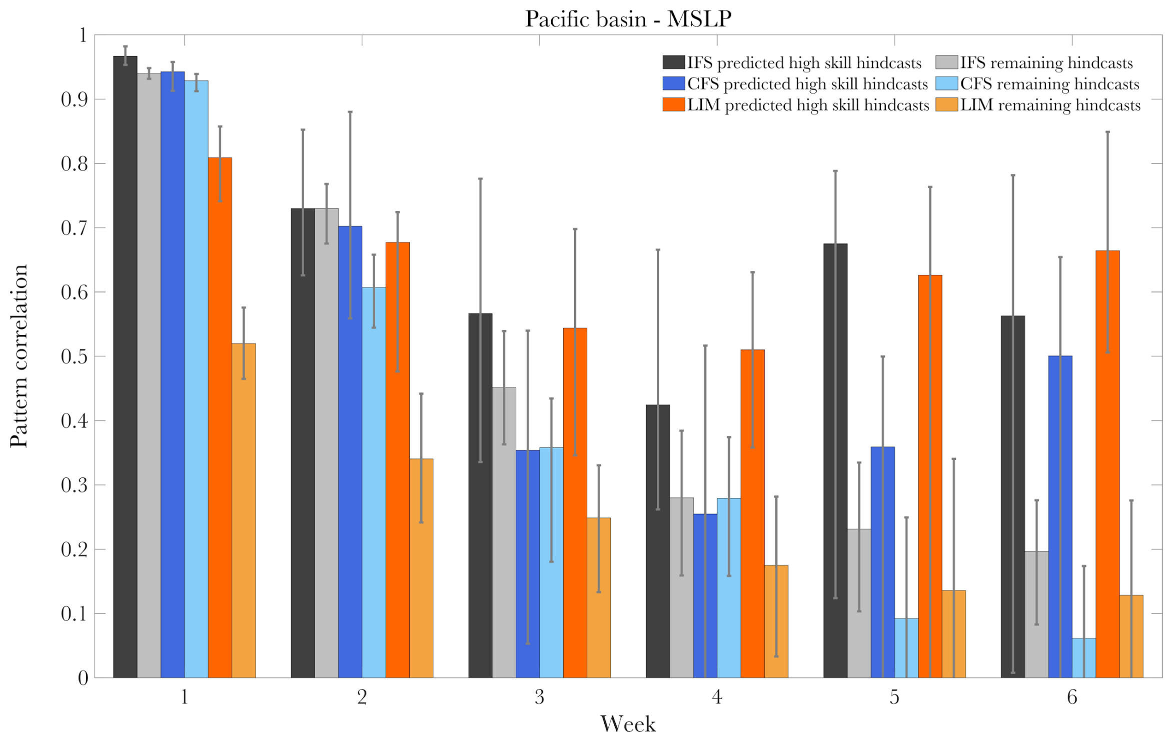

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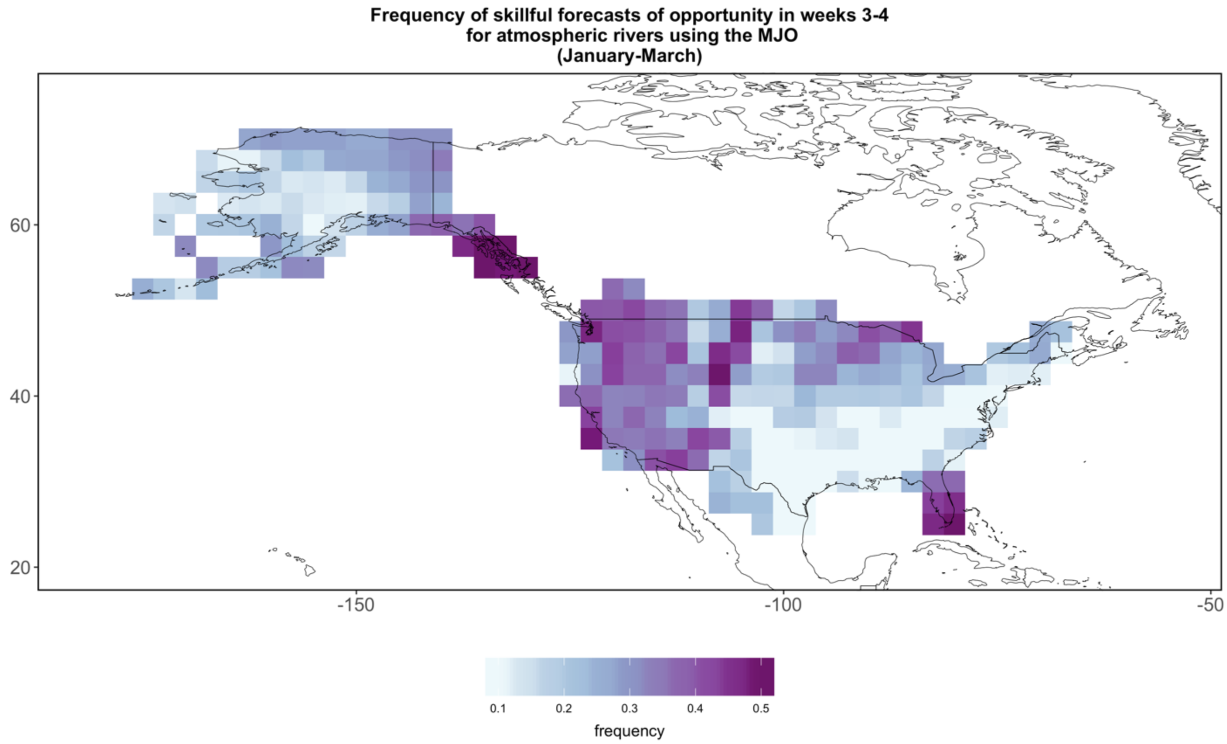

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