8. Basin Interactions and Predictability

Noel Keenlyside, Yu Kosaka, Nicolas Vigaud, Andrew Robertson, Yiguo Wang, Dietmar Dommenget, Jing-Jia Luo, and Daniela Matei

8.1 Introduction

The general public is familiar with weather forecasts and their utility, and the field of weather forecasting is well established. Even the theoretical limit of the weather forecasting – two weeks – is known. In contrast, familiarity with climate prediction is low outside of the research field, the theoretical basis is not fully established, and we do not know the extent to which climate can be predicted. Variations in climate, however, can have large societal and economic consequences, as they can lead to droughts and floods, and spells of extreme hot and cold weather. Thus, improving our capabilities to predict climate is important and urgent, as it can enhance climate services and thereby contribute to the sustainable development of humans in this era of climate change.

Climate is predictable because of processes internal to the climate system and factors external to the climate system (Latif and Keenlyside, 2011). The El Niño Southern Oscillation (ENSO) is the most well-known and most predictable example of climate variability (Philander, 1990; Latif and Keenlyside, 2009; Tang et al., 2018). ENSO originates primarily from two-way interaction between ocean and atmosphere in the tropical Pacific that give rise to a preferred timescale of 2 – 7 years. The first successful predictions of ENSO were based on intermediate complexity models in the mid-1980's Cane et al., 1986; see Chapter 3). Great progress was made in understanding and modelling ENSO (Neelin et al., 1998; Yu and Mechoso, 2001) in the 1990's. This progress was facilitated by the step-wise enhancement in the observational network (Chapter 1; McPhaden et al., 1998) and rapid increase in computer power. Current coupled general circulation models (CGCMs) are able to skilfully predict ENSO events 6 to 12 months in advance (Latif et al., 1998). Now multiple centres around the world perform operational seasonal forecasts (Kirtman et al., 2014). There is a model based consensus that the predictability limit for ENSO might be around one year (Newman and Sardeshmukh, 2017), although some stronger events might be predicted up to two years in advance (Luo et al., 2008b).

Research during the last decade is showing that ENSO is not the sole source of climate predictability, and that other climate phenomenon in other regions and on other timescales are predictable. There is currently great interest in extending climate predictions to the shorter sub-seasonal timescale (Vitart and Robertson, 2018), with the World Climate Research Programme (WCRP) and the World Weather Research Programme (WWRP) launching the Sub-seasonal to Seasonal Prediction Project (S2S) in November 2013 (Robertson et al., 2014). The Madden-Julian Oscillation (MJO) dominates intra-seasonal variability in the tropics and could form the basis for sub-seasonal climate prediction in both the tropics and extra-tropics (Zhang, 2005, Vitart, 2017). On inter-annual time-scales, there are phenomena in the tropical Atlantic and Indian Ocean that are to partly independent of ENSO. Relevant here are the Atlantic Niño and the Indian Ocean Dipole (IOD) phenomena that are both linked to strong anomalies in regional climate, as described in Chapters 1 and 5. On longer decadal timescales, Atlantic multi-decadal variability (AMV) and Pacific decadal variability (PDV) are linked to large-scale fluctuations in climate and weather extremes. There is a growing consensus that AMV and many of its impacts can be predicted up to a decade in advance (Yeager and Robson, 2017). In contrast, PDV is hardly predictable a few years in advance (Doblas-Reyes et al., 2013a).

The interaction between phenomena in different regions and across timescales could also make climate more predictable. In particular, there is a scale-interaction between the MJO and ENSO, such that MJO variability can trigger ENSO events that further enhance MJO activity (Levine et al., 2016). This type of non-linear interaction can extend ENSO predictability. Recent studies have also shown that both Atlantic Niño and IOD can interact with ENSO variability, modifying its dynamics and predictability (See review by Cai et al., 2019). Lastly, recent studies indicate that AMV impacts on the Pacific provide a basis for multi-year predictability in the Indo-Pacific region, if this connection is properly represented in climate prediction models (Ruprich-Robert et al., 2016; Chikamoto et al., 2015). The interaction among such phenomena, however, is complex and can vary in time, and is not fully understood.

The previous chapters have discussed the mechanisms for climate variability in the different regions, interactions between these regions, and the impacts on continental climate. The principal goal of this chapter is to synthesize understanding of the potential of inter-basin interactions to enhance climate prediction. Special attention is given to the predictability of the key phenomena that can provide a basis for climate prediction beyond ENSO.

8.2 Intra-Seasonal Predictability

Sub-seasonal to seasonal climate prediction aims to close the gap between weather forecasts and seasonal predictions, focusing on predicting climate from 2 weeks to 2 months (Vitart et al., 2016). On these timescales prediction of climate is both an initial value problem – as in weather forecasting – and a boundary value problem, as in seasonal forecasting (Vitart and Robertson, 2018). In the first case, sources of predictability come from intra-seasonal variability in atmospheric phenomena, such as the MJO (Madden and Julian, 1972) and sudden stratospheric warmings (Baldwin et al., 2003). In the second case, atmospheric predictability comes from the influence of the slowly varying components of the climate system on the statistics of high-frequency chaotic atmospheric variability (Palmer, 1993). Tropical and extra-tropical sea surface temperature (SST), Arctic sea ice, soil moisture, and snow cover can all give rise to sub-seasonal predictability (e.g., Weisheimer et al., 2011, Orsolini et al., 2016).

8.2.1 The Madden Julian Oscillation

The MJO is the most important sources of sub-seasonal predictability, because it dominates intra-seasonal variability; its dynamics give rise to a preferred 30-90 day timescale, and its impacts are global (Zhang, 2005). An MJO lifecycle diagram of outgoing longwave radiation (OLR) at the top of the atmosphere and surface winds illustrates the predictable dynamics (Figure 8.1). MJO events develop over the Indian Ocean as atmospheric deep convection becomes organized at planetary scales and propagates eastward with a speed of around 5 m s^{-1}, reaching the western Pacific after about 2–3 weeks (Hendon and Salby, 1994). The atmospheric convection is associated with a zonally overturning circulation with low-level easterlies to the east of the deep convection and westerlies to the west, and reverse upper level circulation (Hsu et al., 2004). After reaching the dateline, MJO events continue to propagate eastward much more rapidly (30-35 m s^{-1}) as dry atmospheric disturbances, until they reach the Indian Ocean where they may trigger the next event (Zhang, 2005). This cycle underlies the predictability of the MJO.

The impacts of the MJO extend across the globe and have major consequences for society and economy. MJO effects can explain up to 35 % of the intra-seasonal rainfall variance in boreal summer over the western North Pacific, and up to 25% over the South Pacific in austral summer (Pariyar et al., 2019). The MJO impacts the Australian monsoon and Indian Summer monsoon (Wheeler and Hendon, 2004), and it is linked to most of the extended breaks in the Indian Summer monsoon (Joseph et al., 2009), and also affects rainfall over south eastern Asia (Zhang et al., 2009). It alters precipitation over equatorial Brazil (De Souza and Ambrizzi, 2006), and can increase daily precipitation by more than 30% and double the frequency of extreme rainfall events over central-east South America (Grimm, 2019). It also affects rainfall variability over western and eastern Africa (Niang et al., 2017, Mutai and Ward, 2000).

The MJO modulates the occurrence of tropical cyclone activity over the Indian and Pacific Oceans, and over Atlantic (Maloney and Hartmann, 2000; Liebmann et al., 1994). The large-scale heating anomalies associated with MJO, as it propagates over the Indian Ocean and into the Western North Pacific (Figure 8.1), also drive poleward propagating atmospheric Rossby waves that affect extra-tropical weather (Matthews and Meredith, 2004; Zhou and Miller, 2005). For example, when the MJO convection is active over the Indian Ocean (western Pacific) there is a tendency for occurrence of the positive (negative) North Atlantic Oscillation phase; this gives rise to predictability well beyond the weather prediction limit (Cassou, 2008). The MJO has also been linked to extreme temperature events around the globe (Lee and Grotjahn, 2019; Matsueda and Takaya, 2015).

Despite the prominence of the MJO, understanding of the phenomena remains incomplete (Zhang et al., 2013; DeMott et al., 2015). Although no existing theory is completely satisfactory, there is agreement that the MJO is primarily an intrinsic mode of atmospheric variability, and that interaction with the ocean can modulate its characteristics. Key aspects of the three main classes of theories are as follows. Observations show that low-level wind convergence (Figure 8.1) causes the build-up of moisture to the east of the organized deep convection that preconditions the eastward displacement of deep convection by around 10 days (Hendon and Salby, 1994). Based on this, a class of theories posits that the MJO results from coupling between atmospheric circulation and convection, involving frictionally driven low-level convergence (Maloney and Hartmann, 1998, Majda and Stechmann, 2009). However, warm SST and low-level convergence are also observed east of the MJO deep convection (Woolnough et al., 2000). Thus, another class of theories indicates that the warm SSTs contribute in driving the low-level convergence, through destabilizing the lower atmosphere (Flatau et al., 1997, Marshall et al., 2016, Tseng et al., 2015). In addition, the westerly winds to the west of the deep convection (Figure 8.1) drive enhanced evaporation and thereby are an important supply of moisture for the MJO. Therefore, still another class of theories considers the energy supply from ocean mixed layer by wind induced evaporation as key to the MJO amplitude and timescale (Maloney and Sobel, 2004, Sobel et al., 2010). Further research is required to determine whether these various theories can be unified and/or modified.

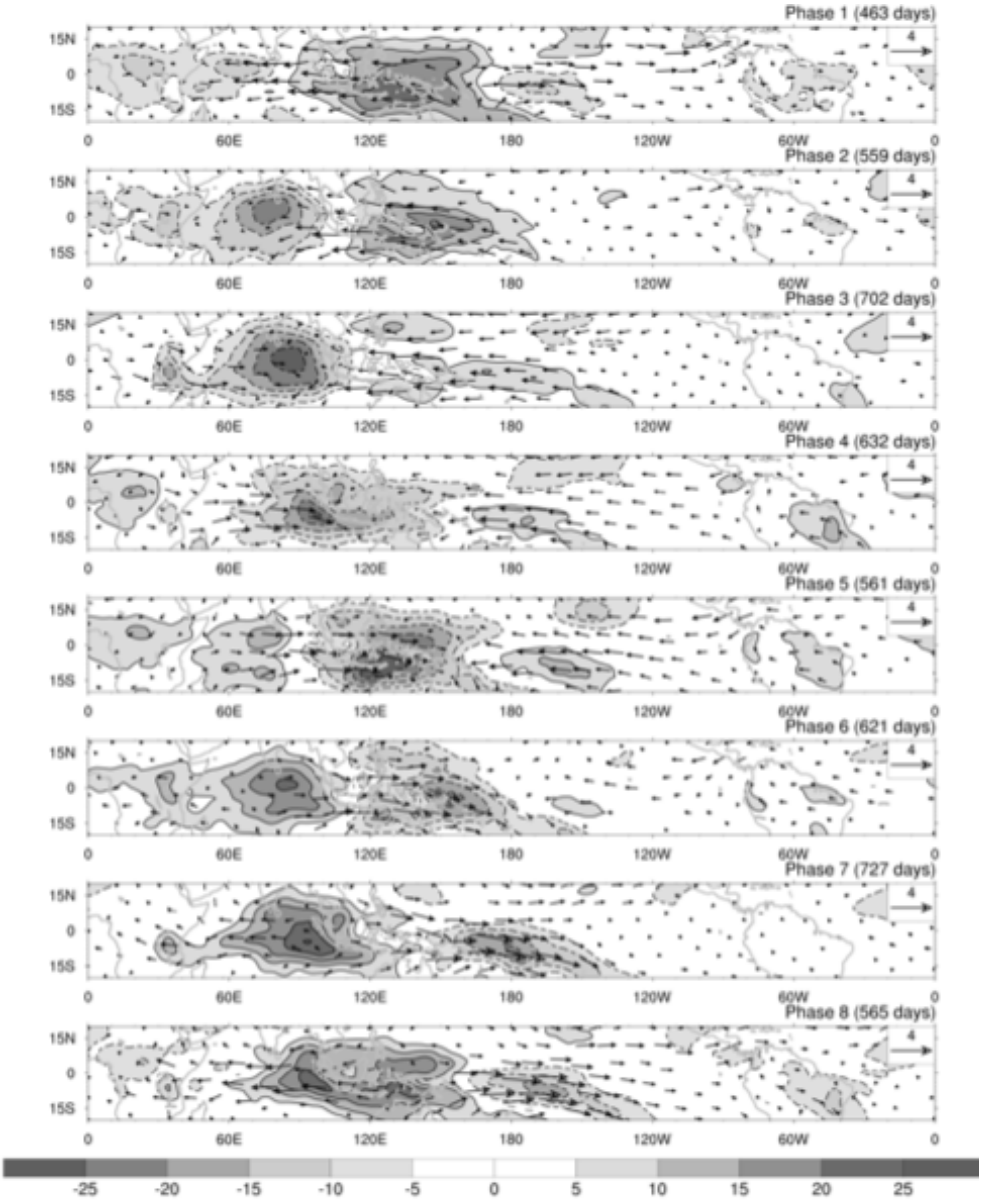

Figure 8.1: The MJO lifecycle in terms of eight phases from its development of over the Indian Ocean (top), strengthening and eastward propagation over the maritime continent (middle), until it crosses the dateline to rapidly propagate around the rest of equator (bottom). OLR anomalies in Wm^{-2} are shaded; negative values indicate atmospheric deep convection. Vectors show 10m wind anomalies. The eight phases are computed by composite analysis of the multi-variate MJO index from Wheeler and Hendon (2004), and using NOAA OLR data and ERA-interim winds. **(Figure created by Sunil Pariyar.)**

8.2.2 Numerical simulation and prediction of the MJO

The majority of numerical models fail to simulate the basic characteristics of the MJO (DeMott et al., 2015, Jiang et al., 2015; Ahn et al., 2017). In particular, models underestimate variance in the 30-90 day timescale and tend to simulate too much variability on longer timescales. They also generally fail to simulate eastward propagation of MJO like disturbances or obtain eastward propagations that are too fast. In addition, models that poorly simulate the MJO tend not simulate the low-level convergence that occurs to the east of deep atmospheric convection.

Despite these model deficiencies, the skill in predicting the MJO has improved dramatically such that its evolution can be now predicted up to four weeks in advance (Lee et al., 2016, Neena et al., 2014, Vitart, 2017). In particular, re-forecasts from ten operational prediction systems in the S2S database show that the European Centre for Medium Range Weather Forecast (ECMWF) system can reasonably predict the MJO evolution at around 34-days lead, while five other systems are skilful out to about 20-days lead (Figure 8.2) (Vitart and Robertson, 2018; Vitart, 2017). This is a dramatic improvement compared to systems from two decades before that had skill of less than 2 weeks (e.g., Hendon et al., 2000), well below that of empirical based forecasts that achieve skill out to about 20 days (Waliser et al., 1999). It is also a marked improvement compared to a set of ~10 year older systems from the Intraseasonal Variability Hindcast Experiment (ISVHE) that were skilful in predicting the MJO 15-20 days in advance during austral summer (Neena et al., 2014). Further improvement is expected, as perfect model studies indicate the MJO can be skilfully forecast 40-45 days in advance (Neena et al., 2014, Rashid et al., 2011, Xiang et al., 2015).

Skill in predicting the MJO may depend on the season, phase and amplitude of the MJO. In particular, skill tends to be higher in austral summer, when the MJO is most active; however the difference in skill among seasons varies among models, and the currently most skilful model has even higher skill scores in boreal summer (Vitart, 2017, Rashid et al., 2011). Perfect predictability analysis indicates that forecasts with a stronger initial MJO signal are more skilful (by ~10 days) than those started from weaker events (Neena et al., 2014), but differences are less clear when predicting observed variability (Rashid et al., 2011, Xiang et al., 2015). There is evidence of skill dependence on the initial and target MJO phase (Rashid et al., 2011, Xiang et al., 2015, Neena et al., 2014), and also on ENSO phase (Lee et al., 2016). Further work is however required to understand the dependence of MJO skill on such factors.

A better understanding of the causes of differences in skill among forecast systems can be useful to improve MJO forecast skill (Figure 8.2). The main factors that contribute to skilful climate prediction are advanced models and accurate observations, together with appropriate techniques to initialize ensemble forecasts. In the case of MJO prediction, the primary source of poor skill currently appears to be related to model errors in simulating the MJO. Predictions systematically underestimate the MJO amplitude by up to 50% within the first 10 days, and show large discrepancies in terms of eastward propagation speed (Vitart, 2017). Analysis of re-forecasts performed routinely between 2002-2012 with the ECMWF system showed that the skill in predicting the MJO improved at about 1 day per year of model development (Vitart, 2014), such that the ECMWF system is now far superior to other operational systems. The skill improvement of this system was mainly attributed to improvements in MJO simulation associated with the parameterisation of atmospheric convection. This finding is further supported by prediction case-studies of selected MJO events (Klingaman et al., 2015, Klingaman and Woolnough, 2014). Improving the representation of ocean-atmosphere interaction may also enhance skill (Marshall et al., 2016). Apart from model improvement, MJO skill is enhanced by increasing ensemble size through better sampling of unpredictable variability (Neena et al., 2014, Vitart, 2017). Better initialisation approaches could also lead to better skill, but this aspects has been hardly investigated and simple nudging techniques can give good results (Xiang et al., 2015).

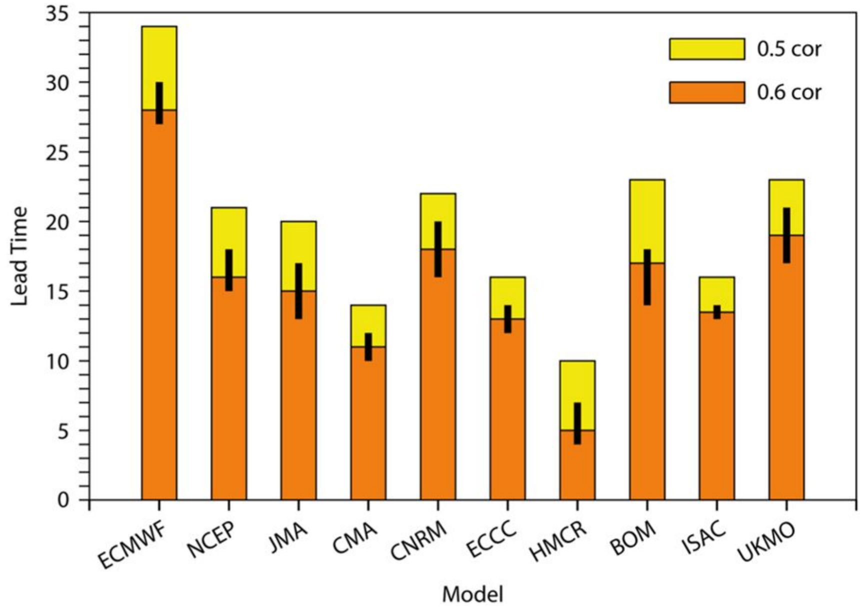

Figure 8.2: Current skill in forecasting the MJO from 10 operational prediction systems. The forecast lead time (days) when the MJO bivariate correlation drops to 0.6 (orange bars) and to 0.5 (yellow bars) is shown. The skill is computed over the common 1999-2010 re-forecast period, as available from the S2S database (Vitart et al., 2016). The 10% confidence interval for the bivariate correlation of 0.6 is shown by black vertical bar, as computed by a 10,000 re-sampling bootstrap. (From Figure 1 in Vitart and Robertson, 2018).

Not only is there now skill in predicting the MJO, but it is now possible to skilfully predict some of its important climatic impacts several weeks in advance, including tropical cyclone activity and extra-tropical weather. The MJO impact on tropical cyclones discussed above is likely most predictable over the Southern Hemisphere in austral summer, as the MJO is strongest and most predictable in this season. We highlight two published examples of successful sub-seasonal tropical cyclone forecasts. First, on the January 13th, 2019 the ECMWF system forecast 20-30% increased chance of landfalling tropical cyclones on Queensland, Australia from 26th January to 4th of February (i.e., around 3 weeks later); tropical cyclone Yasi made landfall on northern Queensland on February 3rd, causing an estimated AU$3.5 billion in damage (Vitart and Robertson, 2018). Secondly, operational forecasts systems predicted that Vanuatu was at increased risk of a tropical cyclone hit 2-3 weeks in advance of tropical cyclone Pam devastating Vanuatu on March 13th 2015 (Vitart, 2017).

Improved MJO driven teleconnections to the Northern Hemisphere have resulted in increased skill in predicting winter and summer weather over Eurasia. For example, several operational systems predicted high probability for extreme temperatures over Russia from three weeks before the summer 2010 Russian heat wave (Vitart and Robertson, 2018). Also, many systems capture the observed teleconnection to the Northern Hemisphere in boreal winter; however, they tend to overestimate the signals in the Pacific sector, and underestimate the connection to the North Atlantic – European sector (Vitart, 2017; Vitart et al., 2016); this teleconnection has been shown to increase skill scores in predicting the North Atlantic Oscillation on intra-seasonal timescales (Lin et al., 2010).

The development of multi-model probabilistic sub-seasonal forecasts is justified, as multi-model approaches can increase forecast reliability through sampling model uncertainties (e.g., Palmer et al., 2004). This has been investigated using the WWRP/WCRP Sub-seasonal to seasonal prediction project (S2S) data base and the extended logistic regression (ELR) approach (Vigaud et al., 2017a, Vigaud et al., 2018). ELR is a more robust means of computing probabilistic information from small ensembles than directly counting the number of members exceeding a given threshold. It allows for straightforward calibration and combination of probabilistic forecasts from multiple models, through averaging of the resulting forecast probabilities from individual models. This approach was applied to sub-monthly forecasts of rainfall from three ensemble prediction systems for the period 1999-2010: ECMWF, National Centers for Environmental Prediction (NCEP) and the China Meteorological Administration (CMA); in particular forecasts of tercile category were assessed for January-March and July-September over North America (Vigaud et al., 2017a), and September to April for East Africa and Western Asia (Vigaud et al., 2018). Separately calibrating each model produces reliable probabilistic for week-1, but not for weeks 2-4. However, the multi-model probabilistic forecasts have some reliability out to week 4 (Figure 8.3), through removing negative skill scores present in individual models.

(a) Single model system **(b) Multi-model system**

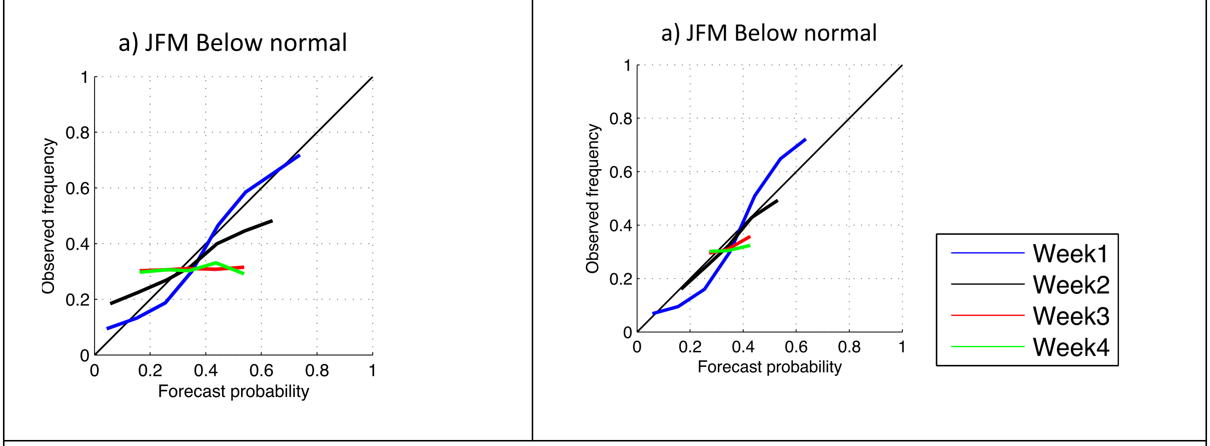

Figure 8.3: Reliability diagrams for week 1 to 4 forecast of the below-normal rainfall category in JFM over continental North America for (a) single model system and (b) multi-model system. The ECMWF system is shown in (a) while the multi-model in (b) includes the ECMWF, NCEP, and CMA systems. In both cases ELR is used to calibrate the forecasts. The reliability diagram compares the forecast probabilities to the observed frequency of the event. A reliable forecast system follows the diagonal line. (From Figures 3 and 4 in Vigaud et al., 2017a).

The skill in such sub-seasonal rainfall predictions is related to skill in forecasting the MJO as well as ENSO. Figure 8.4 illustrates an example of the probabilistic prediction skill for week 2+3 rainfall (15-28 days ahead) averaged over the tropical Atlantic region (15°S-15°N, 0-70°W), for forecasts initialized during various phases of ENSO and MJO in austral summer (Dec-Feb). Contrasting mean ranked probability skill score (RPSS) values suggest that skill is significantly enhanced for starts during La Niña. The asymmetry between ENSO phases might suggest nonlinearities in skill relationships to ENSO, but only a small 11-year 1999–2010 sample of years was used here that contained no strong El Niño events. However, the apparent non-linearity could be partly explained by El Niño induced droughts over North East Brazil translating into less skill while predicting low rainfall amounts compared to La Niña (Vigaud et al., 2017b).

Maximum skill is found during MJO phase 7, when convection is enhanced over the Western Pacific. MJO-induced latent heating anomalies in the warm pool could remotely increase convection over the tropical Atlantic through an equatorial wave mechanism similar to the boreal summer season, when these are known to increase convection over the neighbouring North American and West African monsoon regions (Lavender and Matthews, 2009; Matthews, 2004), and which could thus also lead to more skillful predictions over the tropical Atlantic in winter.

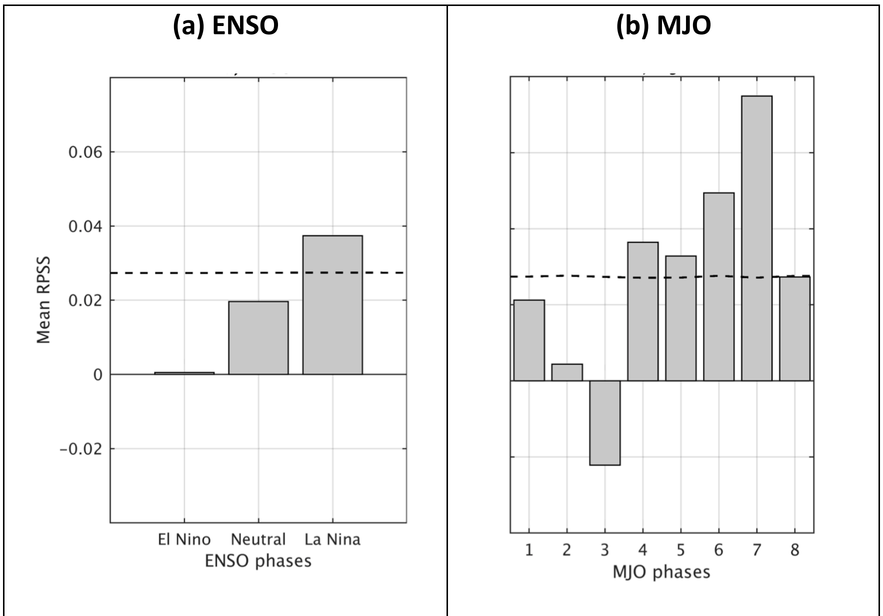

Figure 8.4: Mean multimodel Week 3–4 Ranked Probability Skill Score (RPSS) averaged over 15S-15N and 0-70W for forecasts initialized during observed phases of Niño3.4 index (a) and MJO phases (b) measured by the RMM1 and RMM2 indices of Wheeler and Hendon (2004). Dashed lines correspond to the 10% level of significance using Monte Carlo simulations. ENSO phases are defined ad: neutral when the absolute value of Niño3.4 is smaller than 0.5, and El Niño and La Niña for Niño3.4 greater than 0.5 and lower than −0.5 respectively. The forecasts used are described in (Vigaud et al., 2018). (Figure created by author.)

8.2.3 Interactions between MJO and ENSO

We next discuss the potential of sub-seasonal forecasts for enhancing seasonal forecasts of ENSO. Although ENSO predictions are skilful up to a year in advance, there is a spring predictability barrier that causes a notably drop in prediction skill as forecasts cross boreal spring (Duan and Wei, 2013, Webster, 1995) (Sec. 8.3.1). Key factors causing the spring predictability barrier are the greater influence of atmospheric noise and weaker coupled ocean-atmosphere interaction during boreal spring (ibid).

In particular, westerly wind bursts on sub-monthly timescales that are often related to the MJO can determine whether an El Niño event will develop into a strong event or will even develop at all. A prime example of this are the evolution of conditions in the Pacific during 2014 and 2015 (Levine and McPhaden, 2016; Hu and Fedorov, 2016). Operational systems forecasts made during the early part of 2014 predicted the occurrence of a major El Niño event on the basis of the build-up of ocean heat content in the equatorial Pacific. However, no El Niño event developed because instead of westerly wind bursts there was a strong easterly wind burst that terminated the development of the event. In contrast, in 2015 there was a series of westerly wind bursts linked to MJO activity that influenced the rapid development of one of the strongest events of the last few decades. The strong 1997/98 El Niño event is another example of an event influenced by the MJO and one that was poorly predicted (McPhaden, 1999).

Improved sub-seasonal forecasts of the MJO in boreal spring could enhance prediction of El Niño events because of following factors. Firstly MJO variability together with equatorial upper ocean heat content can explain more 60% of the peak SST anomalies at 2-3 seasons lead (McPhaden et al., 2006). Secondly, the relation between MJO and ENSO is strongest during boreal spring, as this is when MJO is most symmetric about the equator and most sensitive to SST at the warm pool edge (Hendon et al., 2007). Thirdly, the feedback involving the MJO, westerly wind bursts, and SST that occur at the western edge of the warm pool in the Pacific can further enhance predictability (Lengaigne et al., 2004, Levine et al., 2016; Marshall et al., 2016). These relations appear less important for La Niña events and may explain the greater strength of El Niño events (Levine et al., 2016). Further research on these topics is required to realise any potential gains in ENSO prediction skill from sub-seasonal climate prediction.

8.3 Seasonal predictability in the tropics

The ability to predict climate on seasonal timescales arises from the interaction of the atmosphere with the slower varying components of the climate system. As for sub-seasonal prediction, seasonal prediction is an initial value and boundary value problem. However, now the initial state of the slower varying components of the climate system becomes more important, rather than that of the atmosphere. These slower varying components include the ocean, sea ice, and land-surface conditions. Accounting for external forcing on the climate system is also necessary during this era of rapid global warming (Doblas-Reyes et al., 2006). There are several recent reviews of seasonal prediction (Doblas-Reyes et al., 2013b; Luo et al., 2015; Kirtman et al., 2014; Barnston et al., 2017; Becker et al., 2014), and thus here we only provide a brief overview of the status of seasonal prediction. We instead focus more on the potential of inter-basin interactions to enhance seasonal prediction.

8.3.1 Seasonal prediction of the Tropical Pacific

On seasonal timescales ENSO is the primary source of predictability. Ocean-atmosphere interaction is of critical importance for ENSO (Timmermann et al., 2018), and in general for climate predictability in the tropics (Chang et al., 2006b) (Chapters 1-5). In this respect SST is a key variable, as it is used to characterize patterns of climate variability that can drive large-scale atmospheric teleconnections, influencing climate over the globe (Chapter 2). Therefore, we illustrate the current level of seasonal prediction skill in terms of the anomaly correlation skill in predicting SST at six- and twelve-months lead; using other metrics would not change the key points summarized below. We present the average skill of the North American Multimodel Ensemble (NMME), considering forecasts started February, May, August and November of each of year from 1985-2010 (Kirtman et al., 2014). The NNME brings together multiple state-of-the-art models in order to increase forecast reliability, through accounting for model uncertainties (Palmer et al., 2004).

Before summarizing SST prediction skill, we discuss the skill in predicting societally more relevant quantities. Considering all four seasons, six-month lead prediction of surface temperature is skilful over the tropical oceans and partly over equatorial Africa and South America (Figure 8.5a); while three-month lead prediction of rainfall is essentially only skilful over the tropical Pacific (Figure 8.5b). Such low skill in seasonal prediction of rainfall and surface temperature over continental regions is well known (Weisheimer and Palmer, 2014). There is, however, skill in predicting rainfall over tropical land regions in specific seasons. In particular, there is a high level of predictability during the rainy season over northeast Brazil (boreal spring; Folland et al., 2001; Coelho et al., 2006), West Africa (boreal summer; Suárez-Moreno and Rodríguez-Fonseca, 2015; Philippon et al., 2010), and East Africa (June - September; Gleixner et al., 2017) at more than one season lead. There is also skill in predicting changes in some climatic extremes; for example, seasonal predictions of Atlantic hurricane numbers show relatively high skill, because key environmental factors can be predicted (Camargo et al., 2007).

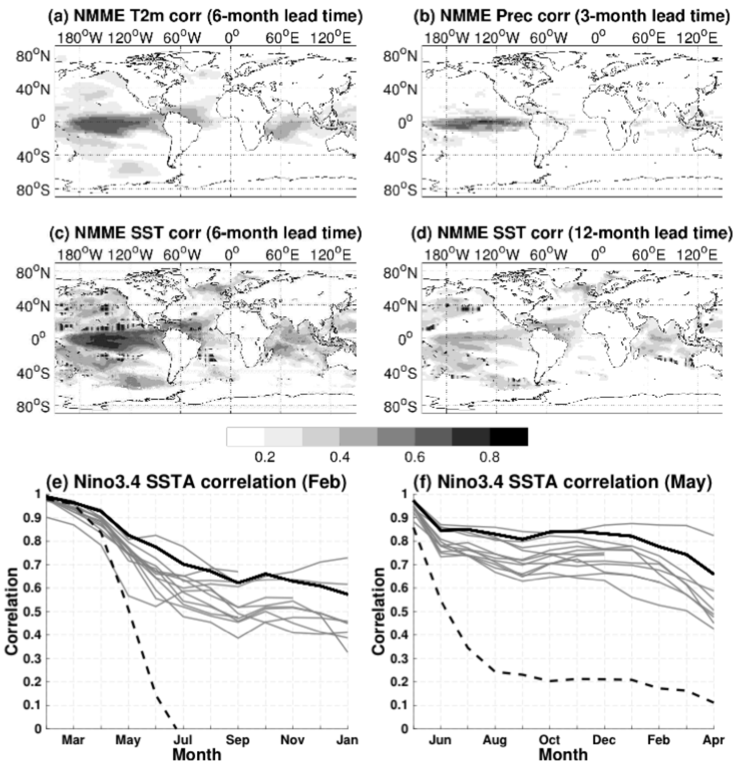

Figure 8.5: Current seasonal prediction skill of state-of-the-art system: anomaly correlation skill in predicting (a) 2-m temperature at 6-months lead, (b) precipitation at 3-months lead, (c, d) SST at 6- and 12-months lead. Skill is computed as the average over four start dates and 13 models from the North American Multimodel Ensemble (Kirtman et al., 2014) for the period 1985-2010. Only

correlations significantly different from zero at the 95% level are shaded; stippled shaded areas indicate regions were persistence skill beats model skill. (e, f) Skill of the multi-model mean (thick black), individual models (thin grey lines), and persistence (dashed lines) in predicting SST averaged over the Nino3.4 (5°N-5°S, 170°W-120°W) region for predictions started February 1st and May 1st. Figure is based on the model output used in Wang et al. (2019). (Figure created by author)

SST prediction skill at six-month lead is greatest over the central and eastern equatorial Pacific, where anomaly correlations exceed 0.6 over most of the region and are above 0.7 in large regions (Figure 8.5c). This skill is derived from the ability of models to predict ENSO. Prediction skill drops to around 0.4 over the equatorial Pacific by 12 months lead (Figure 8.5d). The greatest drop in ENSO prediction skill occurs as the cross boreal spring is crossed – the spring predictability barrier. In particular, predictions of the Nino3.4 SST index (a common ENSO index) started February 1st of all 13 models exhibit a sharp drop in skill around April, while all models maintain high level of skill for predictions started May 1st (Figure 8.5e,f). A lower signal to noise in boreal spring is a key cause of the spring barrier (Sec. 8.2.3). The drop-in skill is particularly obvious in the persistence statistical forecasts commonly used as a bench mark. Dynamical forecasts are less effected by the spring predictability barrier than statistical forecasts, likely because of more efficient use of ocean data (McPhaden, 2003).

Factors limiting climate prediction include model error, inaccuracies in initial conditions, and intrinsic sensitivity to initial conditions associated with non-linearities in the climate system. There is evidence that our ability to predict ENSO is now mainly limited by the third factor, and thus the theoretical predictability limit for ENSO may be around 12 months (Newman and Sardeshmukh, 2017). Climate models can now simulate key ENSO characteristics reasonably well (Bellenger et al., 2014). There is a well-established observational network in the tropical Pacific has been designed to support seasonal prediction (Chapter 1; Smith et al., 2019). Furthermore, prediction systems using data assimilation approaches and simpler analogue approaches achieve similar levels of skill, indicating that data-model inconsistencies are not limiting ENSO prediction (Ding et al., 2018). Lastly, the skill of state-of-the-art prediction systems is close to the theoretical limit of skill of linear inverse models, which represent the climate as a stochastic forced linear-dynamical system (Newman and Sardeshmukh, 2017).

However, there are also strong reasons to expect that ENSO predictability extends beyond a year. Model exhibit significant errors in the tropical Pacific, and most of the important processes and feedbacks for ENSO are biased (Bellenger et al. 2014, Vijayeta and Dommenget 2018). Furthermore, there are several studies that indicate that strong ENSO events may predicted up to two years in advance (Chen et al., 2004, Luo et al., 2008b). To date, analysis of ENSO predictability has largely focused on the dynamics in the tropical Pacific, involving the coupling between upper ocean heat content, SST, and the overlying atmospheric circulation (Figure 8.6). However, as we will discuss further below, the interaction among basins can extend ENSO predictability beyond a year.

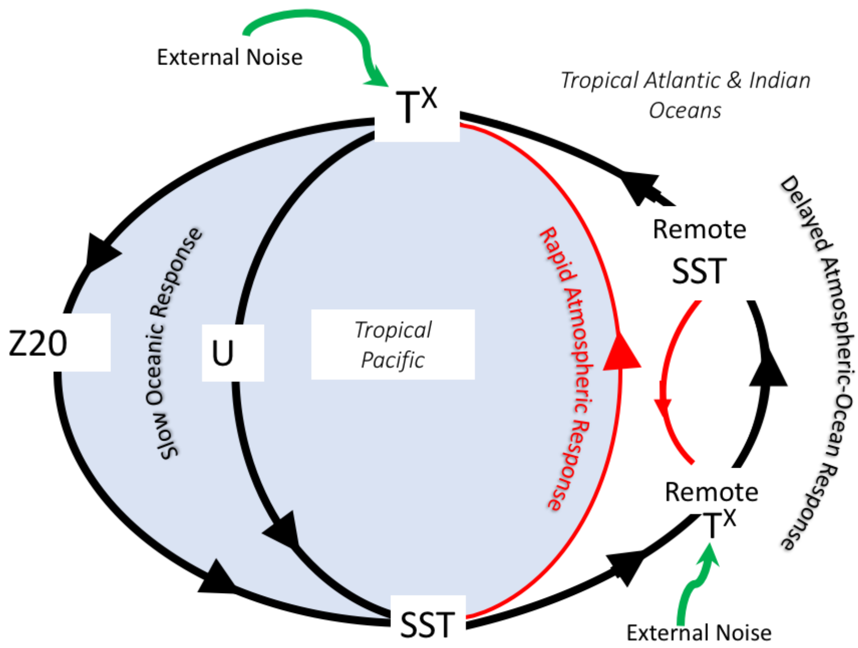

Figure 8.6: Schematic of feedback mechanisms and interactions underlying tropical climate variability. The primary driver of climate variability in the tropical Pacific including ENSO is ocean-atmosphere interaction within the basin involving slow ocean dynamics and rapid atmospheric response to SST anomalies. The impact of tropical Pacific climate variability extends to the tropical Atlantic and Indian Oceans, where it perturbs the ocean-atmosphere interaction within these basins. At the same time tropical Atlantic and Indian Ocean climate variability can impact ocean-atmosphere interaction in the tropical Pacific; thus, this constitutes a delayed feedback loop involving ocean-atmosphere interaction in remote basins that can alter the predictability of ENSO. External atmospheric noise can further perturb the coupled dynamics. Basin interactions involve atmospheric and oceanic teleconnections. Z20 refers to thermocline depth and U to surface currents. (Figure created by author.)

8.3.2 Seasonal predictability in the tropical Indian and Atlantic Oceans – ENSO impacts and local processes

Seasonal predictions also exhibit significant skill in the Indian and Atlantic Oceans, although skill is generally lower than in the Pacific (Figure 8.5 c,d). SST anomalies can be predicted over large parts of the Indian Ocean, with anomaly correlation skill exceeding 0.4 over the central and south western Indian Ocean at six-months lead and 0.3 over the same regions at 12-months lead. Over the tropical Atlantic, skill is primarily confined to the north tropical Atlantic, where anomaly correlation skill exceeds 0.5 at six-months lead and 0.4 at 12-months lead.

Thermodynamic interactions contribute relatively more to seasonal prediction skill in the tropical Indian and Atlantic Oceans than in the Pacific. In particular, there are pronounced long-term trends in SST that are related to global warming in both the tropical Indian and Atlantic Oceans (Nnamchi et al., 2016). For example, considering the reforecast period 1985-2010, around half of the correlation skill at six months lead and essentially all of the skill at 12 months lead in the north tropical Atlantic is attributed to the warming trend; in the Indian Ocean, however, the trend doesn't contribute to significant skill at seasonal timescales during this period (Wang et al., 2019).

Seasonal predictability in the tropical Indian and Atlantic Oceans also results from both local climate dynamics and remote forcing (Figure 8.6) and depends strongly on the season. Although a host of SST patterns of variability have been defined, the predictability of the tropical Indian Ocean is arguably best characterized by three SST patterns: the Indian Ocean Basin (IOB) mode; the Indian Ocean Dipole (IOD) mode; and a south-western Indian Ocean (SOWI) pattern (See Chapters 1 and 5). The IOD is a zonal asymmetric pattern of variability in SST, upper ocean heat content, and rainfall that occurs during September to November (Saji et al., 1999; Webster et al., 1999). IOD events generally co-occur with ENSO events, but can also occur independently (Meyers et al., 2007). Although the IOD pattern is observed, its statistical and physical interpretation have been questioned (Dommenget and Latif, 2002, Hannachi and Dommenget, 2009; Dommenget, 2011). The IOB is characterized by basin-wide SST warming (cooling) and increased (decreased) precipitation. It is primarily caused by ENSO induced radiative and turbulent surface heat fluxes, with SST anomalies peaking in late boreal winter and early spring after an ENSO event (Yang et al., 2007; Klein et al., 1999). The SWIO SST pattern is connected to a regional thermocline dome and largely driven by oceanic Rossby wave-induced subsurface temperature variations (Xie et al., 2002). ENSO atmospheric teleconnections are the dominant forcing for these Rossby waves and the SST pattern, which in turn significantly impacts the atmosphere.

Prediction skill in the Indian Ocean can be explained in terms of these SST patterns (Figure 8.5). In particular, skilful prediction of central Indian Ocean SST anomalies at six-months lead is connected to skill in predicting the IOB through skill in predicting ENSO and its thermodynamic impacts over the region (Zhu et al., 2015, Annamalai et al., 2003). Whereas skilful prediction of SWIO SST anomalies at six-months lead is connected to skill in predicting ENSO dynamical impacts and to accurate initialisation of upper ocean heat content over the Indian Ocean. IOD events can be generally predicted a season in advance, while some stronger events can be predicted at longer lead times (Luo et al., 2007; Luo et al., 2008a; Shi et al., 2012). Accurate initialisation of the upper ocean heat content in the Indian Ocean can contribute to enhance IOD prediction (Doi et al., 2017, Song et al., 2008). Although ENSO is the main source of IOD predictability, IOD events can be skilfully predicted in neutral ENSO years (Luo et al., 2008a).

Prediction skill in the tropical Atlantic can be related to the two most prominent patterns of tropical Atlantic SST interannual variability: the Atlantic meridional mode (AMM) and the Atlantic Niño (See Chapters 1 and 4; Chang et al., 2006b). The AMM represents asymmetric SST variations about the equator, associated with meridional shifts of the Intertropical Convergence Zone, and is most prominent in March to May (Sutton et al., 2000; Ruiz-Barradas et al., 2000; Servain et al., 1999). The wind evaporative SST (WES) feedback underlies the generation of the largely independent SST variations north and south of the equator (Xie and Philander; 1994, Ruiz-Barradas et al., 2003; Dommenget and Latif, 2000; Handoh et al., 2006). The Atlantic Niño (Niña) is a pattern of variability in SST, upper ocean heat content, winds, and rainfall that peaks in boreal summer and has similarities to El Niño (La Niña) (Chang et al., 2006b, Lübbecke et al., 2018) . A positive Bjerknes feedback and delayed negative feedback involving upper ocean heat content appear most relevant for Atlantic Niño variability, but they explain much less variance and have stronger seasonality than in the Pacific

(Zebiak, 1993, Keenlyside and Latif, 2007, Ding et al., 2010, Ruiz-Barradas et al., 2000); there also exist other mechanisms for this variability (Lübbecke et al., 2018).

As for the Indian Ocean, current skill in predicting tropical Atlantic SST results mainly from ENSO teleconnections. This is the case for predictions of north tropical Atlantic SST anomalies at six-months lead (Figure 8.5c; Chang et al., 2003). In particular, El Niño (La Niña) events cause the trade winds to weaken (strengthen) over the north tropical Atlantic in boreal winter, driving anomalous warm (cold) SST that peak in the subsequent spring (Alexander et al., 2002). While this is main source of predictability for the AMM, ocean dynamics in the Guinea Dome may enhance AMM predictability (Doi et al., 2010). The local AMM conditions can act to reinforce or cancel the remote ENSO forcing, and thus provide conditional predictability (Giannini et al., 2004; Barreiro et al., 2005).

The poor skill in predicting Atlantic Niño variability leads to low prediction skill in the south tropical Atlantic (Figure 8.5c). In particular, anomaly correlation skill for predicting the Atlantic Niño variability from February 1st drops rapidly to around 0.4 in May to July in the best models, hardly beating persistence skill (Richter et al., 2018). At best, models are only able to skilfully predict Atlantic Niño variability from May 1st (Prodhomme et al., 2016). Several factors may explain the low skill in this region: a dominant role of internal atmospheric dynamics (Richter et al., 2014, Crespo et al., 2019); the existence of multiple mechanisms of comparable importance to the Bjerknes feedbacks (Nnamchi et al., 2015; Richter et al., 2013; Foltz and McPhaden, 2010; Brandt et al., 2011), and large systematic model errors (Richter, 2015, Dippe et al., 2019) that affect the positive Bjerknes Feedback and simulated variability (Deppenmeier et al., 2016; Nnamchi et al., 2015; Jouanno et al., 2017). However, perhaps the most important factor is the inconsistent impact of ENSO on the equatorial Atlantic that results from the competing dynamic and thermodynamic affects (Chang et al., 2006a, Lübbecke and McPhaden, 2012).

8.3.3 Tropical Indian and Atlantic Ocean enhancing ENSO prediction

The tropical Atlantic and Indian Ocean do not respond passively to ENSO, but feedback on it modifying its dynamics and potentially enhancing its predictability (Figure 8.6; See Chapters 4 and 5, and Cai et al. 2019). As summarized above, El Niño events typically cause warming of the SWIO in late boreal summer, the development of an IOD event in boreal autumn (Figure 8.7c), and an IOB warming that persists into the following boreal spring (Xie et al., 2002; Du et al., 2009). The associated anomalous diabatic heating drives a westward shift in the Indo-Pacific Walker Circulation and a strengthening of the anti-cyclone over the North Western Pacific in boreal spring (Xie et al., 2002; Annamalai et al., 2010; Luo et al., 2010; Yang et al., 2007). This leads to an enhancement of the easterly winds over the western equatorial Pacific and a more rapid demise of the El Niño event (Kug and Kang, 2006; Dommenget et al., 2006). An oceanic pathway from the Indian Ocean is also able to promote the transition to La Niña following an IOD event (Zhou et al., 2015). The warming of the north tropical Atlantic in the boreal spring following an El Niño event likewise causes easterly wind anomalies over the central Pacific, further contributing to the demise of the event (Dommenget et al., 2006; Ham et al., 2013b). Thus, both the Indian Ocean and tropical Atlantic can act like capacitors storing energy and then releasing it (Xie et al., 2009; Wang et al., 2017).

Climate model experiments and conceptual studies indicate that this two-way interactions of the tropical Pacific with the other two tropical basins leads to ENSO variability with a more biennial character (Kug and Kang, 2006; Dommenget et al., 2006; Jansen et al., 2009). Furthermore, these feedbacks act in a similar manner to the oceanic feedbacks in the Pacific to produce a stronger delayed negative feedback; and there by enhance the predictability of ENSO (Dommenget and Yu, 2017). This is radically different to the traditional Pacific centric view of ENSO (Figure 8.6).

The tropical Atlantic and Indian Ocean can further enhance ENSO predictability through their own intrinsic behaviour (Figure 8.6). In particular, conditions resembling a negative IOD event tend to precede El Niño events by 5 seasons (Figure 8.7a). As described above, this SST pattern can drive westerly wind anomalies in the western Pacific in the following spring, favouring the development of an El Niño event (Kug and Kang, 2006). Consistently, accounting for IOD variability enables skilful statistical predictions of ENSO events 14 months in advance, through providing additional information during the critical boreal spring period (Izumo et al., 2010). Likewise, experiments with fully coupled climate models show that Indian Ocean conditions prior to the El Niño onset affect El Niño prediction (Luo et al., 2010; Zhou et al., 2019); in particular, constraining SST in the Indian Ocean to the observed climatology significantly deteriorated the predictions of the 1994, 1997/98 and 2006/7 events for forecasts initiated prior to the boreal spring. (Analogous experiments constraining Pacific Ocean SST to climatology show skill degradation in prediction of major IOD events that co-occur with El Niño, supporting the importance of two-way basin interactions). Other experiments support a significant impact of the Indian Ocean initial conditions for ENSO prediction, and further indicate the importance of oceanic teleconnections (Zhou et al., 2019). However, not all studies show that Indian Ocean variability can affect ENSO prediction (Jansen et al., 2009, Frauen and Dommenget, 2012).

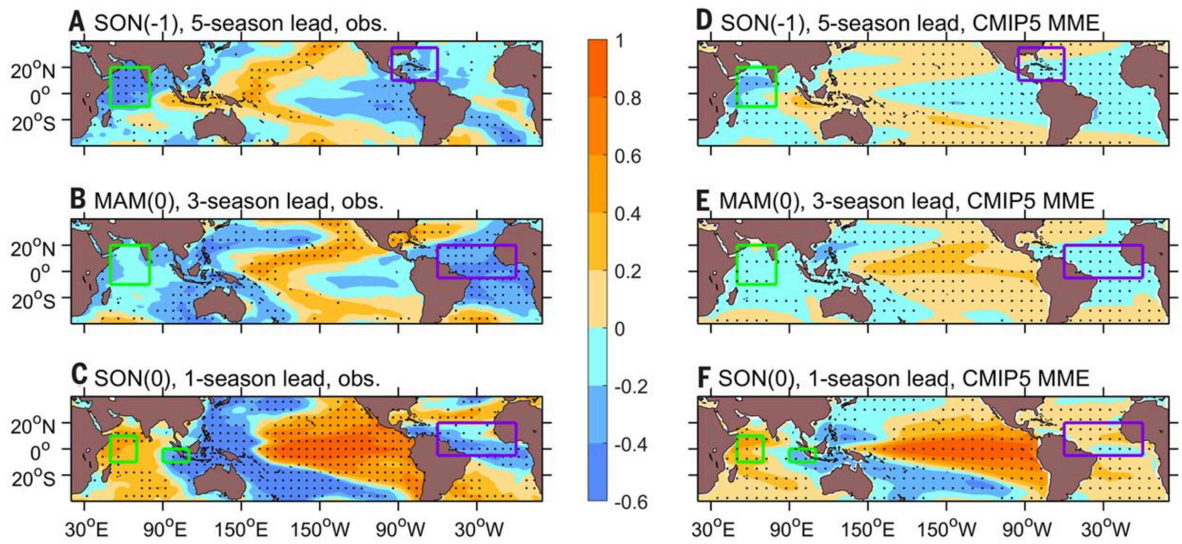

Figure 8.7: Lag correlation of November-January Nino3.4 SST with tropical SST in proceeding seasons from (left) observations and (right) an ensemble of (43 CMIP5) climate model simulations. Shown are correlations with (top) September-November five seasons prior, (middle) March-May three seasons prior, and (bottom) September-November one seasons prior. Observations are for the period 1980 to 2017; and stippling on the left panels indicates significant correlations at the 90% confidence level based on a Student's t test. Stippling on right panels indicates regions where 66% of models agree with the sign of the ensemble mean. (Adapted from Figure 4 in Cai et al. 2019)

Observations and model experiments indicate that Atlantic Niño variability has significantly impacted ENSO variations since the 1970's, through perturbing the Walker Circulation, with cold conditions in the Atlantic in boreal spring to summer preceding El Niño events by 2-3 seasons (Figure 8.7b, Chapter 4; Rodriguez-Fonseca et al., 2009; Ding et al., 2012). Being weakly influenced by ENSO (Sec. 8.3.2), Atlantic Niño variability is an important source of additional ENSO prediction skill. Statistical predictions, climate models with simplified representations of ENSO, and predictions with a complex climate model all indicate that accounting for Atlantic Niño variability can significantly increase ENSO prediction skill (Jansen et al., 2009; Frauen and Dommenget, 2012; Keenlyside et al., 2013). In particular, anomaly correlation skill in predicting October to December SST from February 1st is increased by around 0.2 when the climate model predictions include the observed evolution of equatorial Atlantic SST (Figure 8.8). The skill increase is largely because of the better predictions of the major 1982/83 and 1997/98 El Niño events, achieved through more realistic westerly wind anomalies over the central Pacific during boreal spring (Keenlyside et al., 2013).

In summary, there is growing evidence that inter-basin interactions can enhance ENSO prediction. However, these interactions are not well reproduced by climate models (Figure 8.7 d-f) (Luo et al. 2018). Another complication is that the impact of the Atlantic Niño on ENSO has varied and it was weak during middle of the 20th century (Martín-Rey et al., 2014); during these weak interaction periods equatorial Atlantic SST variations appear not to enhance ENSO prediction skill (Martín-Rey et al., 2015). Finally, promising results show that extended La Niña conditions can be predict 2-years in advance through accounting for both the Atlantic and Indian Ocean warming (Luo et al., 2017); nevertheless, more work is required to understand how inter-basin interactions might affect the predictability of the La Niña, as well as of different flavours of El Niño (Ham et al., 2013a; Yu et al., 2014).

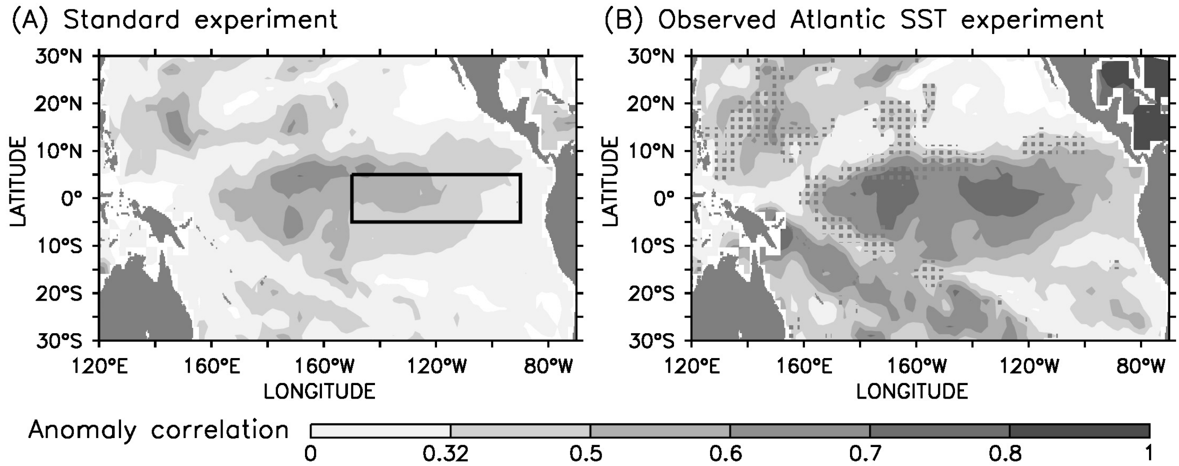

Fig 8.8: Anomaly correlation skill for October–December average SST for predictions starting on 1st February performed with (A) a fully coupled climate model and (B) the same model but with Atlantic SST restored to observations. The prediction period is 1980–2005; All predictions consist of nine-member ensemble members. Shaded positive values are significantly different from zero at 5% level according to a one-sided Student's t-test. Shaded non-stippled regions in (B) indicate where including observed Atlantic SST leads to a significant increase in skill at the 5% level, according to a one-sided t-test applied to Fisher-Z transformed values. (Adapted from Figure 1 in Keenlyside et al., 2013).

8.3.4 ENSO-Indian Ocean interaction as an origin of predictability in Asia

We now present an important example of inter-basin interactions enhancing climate predictability over land. El Niño is significantly correlated with climate anomalies in subsequent boreal summer in southern, southeastern and eastern Asia, despite equatorial Pacific SST anomalies having dissipated (Fig. 8.9; Huang et al., 2004). The El Niño impact is manifest through the Pacific-Japan pattern, with a surface anomalous anticyclone in the tropical Northwestern Pacific that extends to the northern Indian Ocean and an anomalous low-level cyclone in the midlatitude Northwestern Pacific (Fig. 8.9a; Nitta, 1987, Kosaka and Nakamura, 2006); The Pacific Japan pattern affects temperature (Wakabayashi and Kawamura, 2004, Hu et al., 2012), precipitation (Huang and Sun, 1992, Kosaka et al., 2011), and tropical cyclone activity (Choi et al., 2010, Wang et al., 2013) in Southeast and East Asia.

The lack of concurrent equatorial Pacific SST anomalies in summer indicates that the memory of preceding ENSO must persist elsewhere. One source of memory is the WES feedback that cause the persistence of SST and precipitation patterns over Northwestern Pacific and their extension into the northern Indian Ocean (Wang et al., 2000, Wang et al., 2003, Wang et al., 2005). The Indian Ocean capacitor effect is another source of memory. As described above, El Niño causes warming of the Indian Ocean that persists into the following boreal spring, and the teleconnections to this reinforce the anomalous anticyclone over the Northwestern Pacific (Xie et al., 2016). The interaction between these two sources of memory gives rise to an ocean-atmosphere coupled mode called the Indo-western Pacific Ocean capacitor. In fact, this capacitor mode is a dominant mode of variability in a coupled model simulation where ENSO is artificially suppressed (Kosaka et al., 2013).

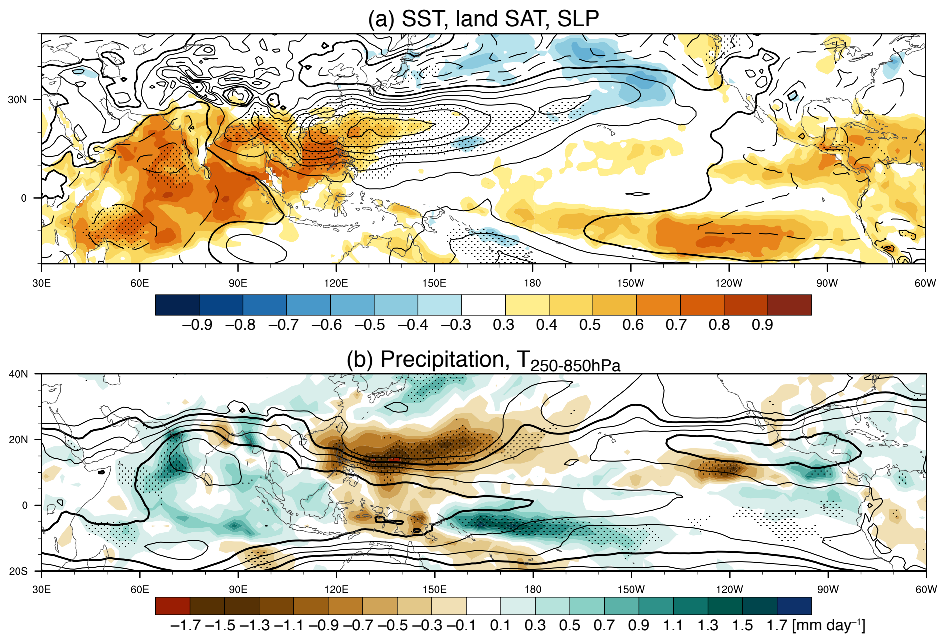

Figure 8.9: Correlations of (a) SST (shading) and (b) tropospheric temperature (averaged over 850-250 hPa, contours, interval is 0.1 starting from 0.3, with 0.4 and 0.7 contours thickened) and regressed anomalies of (a) SLP (contours, every 0.1 hPa) and (b) precipitation (shading) in June-July-August with respect to Niño3.4 SST in the preceding November-December-January. Stippling indicates confidence level > 95% for regressed anomalies under t-test. Based on JRA-55 (Kobayashi et al., 2015), CMAP (Xie and Arkin, 1997) and HadISST1.1 (Rayner et al., 2003) for 1979-2009. All data linearly detrended beforehand. (Figure created by author)

While the Indo-western Pacific Ocean capacitor mode can dominate without ENSO, ENSO is a leading driver of this capacitor mode in its decaying year. This provides seasonal predictability to South, Southeast and East Asian monsoon in summer (Kosaka et al., 2013, Takaya et al., 2017). Since ENSO is predictable after the spring prediction barrier, these mechanisms to relay the ENSO teleconnection and trigger the Indo-western Pacific Ocean capacitor mode can potentially provide predictability of the Asian summer monsoon five seasons in advance.

8.4 Multi-Year predictability

8.4.1 Decadal prediction

Multi-year, near-term or decadal prediction is in a pre-operational phase, being a relatively new field with the first publications around 10 years ago (Smith et al., 2007; Keenlyside et al., 2008). Climate prediction on these timescales is primarily a boundary value problem, with skill arising from dynamics internal to the climate system and from the response to external radiative forcing (Meehl et al., 2009; Latif and Keenlyside, 2011). Skill from the former decreases with lead time and relies on accurate initialisation of the slower varying components of the climate system; while skill of the latter is primarily linked to greenhouse gas emissions and under present conditions increases with lead time (Keenlyside and Ba, 2010; Hawkins and Sutton, 2009). AMV and PDV are considered the primary sources of predictability on multi-year to decadal timescales. These patterns of climate variability and their global impacts have been described in Chapter 1.

The near-term predictions performed for the Intergovernmental Panel on Climate Change (IPCC) assessment report five (AR5) has shown that SST variations over large parts of the global ocean can be predicted up to a decade in advance (Doblas-Reyes et al., 2013a). The current status in predicting SST five to nine years in advance is illustrated by results from the Community Earth System Model (CESM) decadal prediction large ensemble (Yeager et al., 2018). Skill is high in predicting SST over the entire Atlantic and Indian Oceans, and western and South Pacific; while skill is low over most of the tropical and North Pacific, and in the Southern Ocean (Figure 8.10 A). The skill over the Indian Ocean and Western Pacific mainly arises from external forcing (Figure 8.10 B; Guemas et al., 2012). The low skill over large regions of the Pacific is associated with limited skill in predicting PDV (Doblas-Reyes et al., 2013a). Despite this low skill, the major 1970's and 1990's shifts in PDV may be predicted several years in advance (Ding et al., 2013; Meehl and Teng, 2012). Chapter 9 further discusses predictability of PDV.

The skill in predicting Atlantic SST results mainly from external radiative forcing (Ting et al., 2009, Tokinaga and Xie, 2011; Booth et al., 2012). The subpolar North Atlantic is an exception: here skill is mainly due to the initializing the ocean (Figure 8.10B; Yeager and Robson, 2017). Although external forcing is the dominate source of skill in subtropical North Atlantic, teleconnections from the subpolar North Atlantic can enhance skill over this region (Smith et al., 2010). There are indications that initialization of upper ocean heat content in the subtropical South Atlantic is an important source of skill on decadal time scales (Figure 8.10 B). Other studies have shown that initialization can enhance skill in subsurface equatorial Atlantic (Corti et al., 2015).

Skill in predicting AMV translates to skill in predicting societally relevant quantities, including rainfall over the Sahel (Sheen et al., 2017; Yeager et al., 2018; Mohino et al., 2016) and the number of Atlantic hurricanes (Smith et al., 2010, Caron et al., 2017). Skill in predicting Sahel rainfall is degraded by inaccurate prediction of both PDV and impacts of global warming (Mohino et al., 2016). The skilful prediction of Atlantic hurricane numbers is linked to skill in predicting the relative warming of the north tropical Atlantic compared to the rest of the tropical oceans that also contributes to changes in wind shear over the hurricane main development region (Smith et al., 2010). Large and systematic model biases in the tropical Atlantic (Richter, 2015) may degrade predictions of Atlantic hurricane activity, as these biases cause simulated hurricane activity to be much weaker than observed (Hsu et al., 2018).

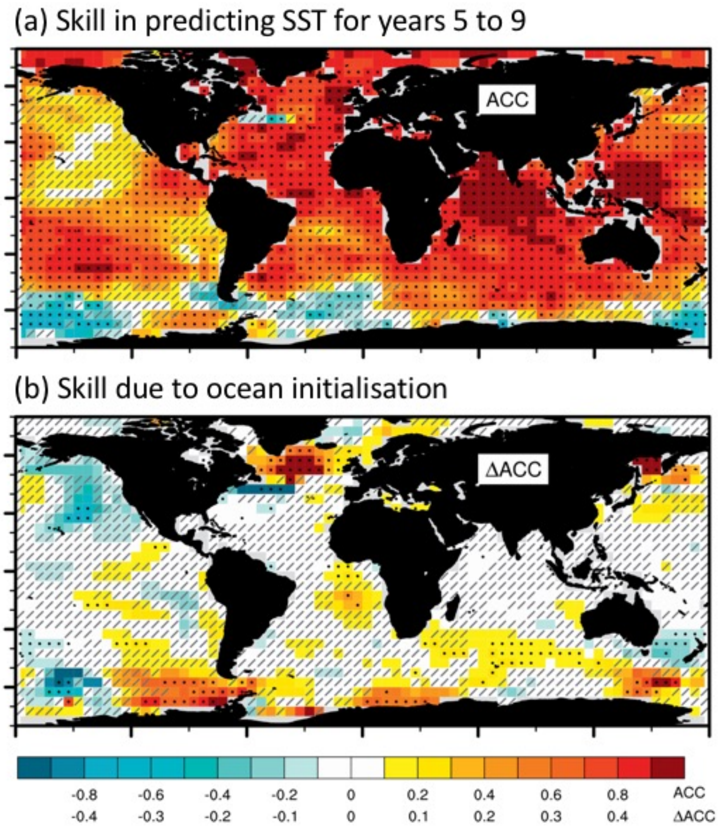

Figure 8.10 (A) Anomaly correlation skill in predicting SST for years 5 to 9 from the CESM Decadal Prediction Large Ensemble experiment that consist of 40 distinct member ensemble predictions started 1st of November every year from 1954 to 2008. **(B)** Anomaly correlation skill resulting from initialization of the ocean. Note the two-colour scales for (A) and (B). Boxes without a gray slash are significant at the 10% level; dots further indicate points whose p values pass a global (70°S–70°N) field significance test. (From Figure 2 in Yeager et al., 2018, © American Meteorological Society. Used with permission.)

8.4.2 Interbasin interactions as a source of Pacific decadal predictability

There is great interest in improving prediction of PDV, because of its global impacts that include decadal modulation of global-mean surface temperature (Dai et al., 2015). In particular, PDV led to the so-called “hiatus” in surface global warming from the late 1990s to the early 2010s (See Chapter 9; Kosaka and Xie, 2013; England et al., 2014). PDV may partly arise from the Atlantic through forcing of inter-basin interactions (McGregor et al., 2014; Li et al., 2015; Chikamoto et al., 2016; Kucharski et al., 2016; Sun et al., 2017) and the Indian Ocean (Luo et al., 2012; Mochizuki et al., 2016). This finding is brought about by pacemaker experiments with ocean-atmosphere coupled models where SST anomalies are forced to follow their observed evolutions in a specific domain.

Thermodynamically, SST warming in a tropical ocean basin tends lead to warming of the entire tropical ocean surface through tropospheric warming that reduces surface heat release. Indeed, El Niño increases Atlantic and Indian Ocean SST especially in the decay seasons. However, Atlantic and Indian Ocean pacemaker experiments in the aforementioned studies show enhancements of inter-basin SST contrasts with the tropical eastern Pacific that must involve dynamical inter-basin coupling. Influence of both the Atlantic and Indian Ocean on the tropical Pacific is brought about by Walker Circulation changes associated with the Matsuno-Gill response (Chapter 2; Li et al., 2015; Luo et al., 2012). The associated strengthening of surface easterlies in the equatorial western Pacific induced by either Atlantic or Indian Ocean warming is amplified, through the Bjerknes feedback and induces SST cooling the equatorial Pacific, contributing to PDV (Figure 8.11a). Other elements of PDV, especially in the extra-tropical North Pacific may be inherently less predictable (Newman et al. 2016)

Interaction between the tropical Pacific and Atlantic also gives rises to a trans-basin pattern of variability that is predictable on multi-year timescales (Chikamoto et al., 2015). This trans-basin variability is characterized by a dipole pattern in sea level pressure between the tropical Atlantic and Pacific, that is linked to a cross-basin SST gradient and a large-scale rainfall pattern (Figure 8.11). The trans-basin mode can be skilfully predicted up to three years in advance, through accurate initialisation of the ocean state. This leads to skill in predicting climate, droughts and wildfires over the southwestern USA on multi-year timescales (Chikamoto et al., 2017). Trans-basin mode impacts also extend to other regions such as Australia (Choudhury et al., 2017).

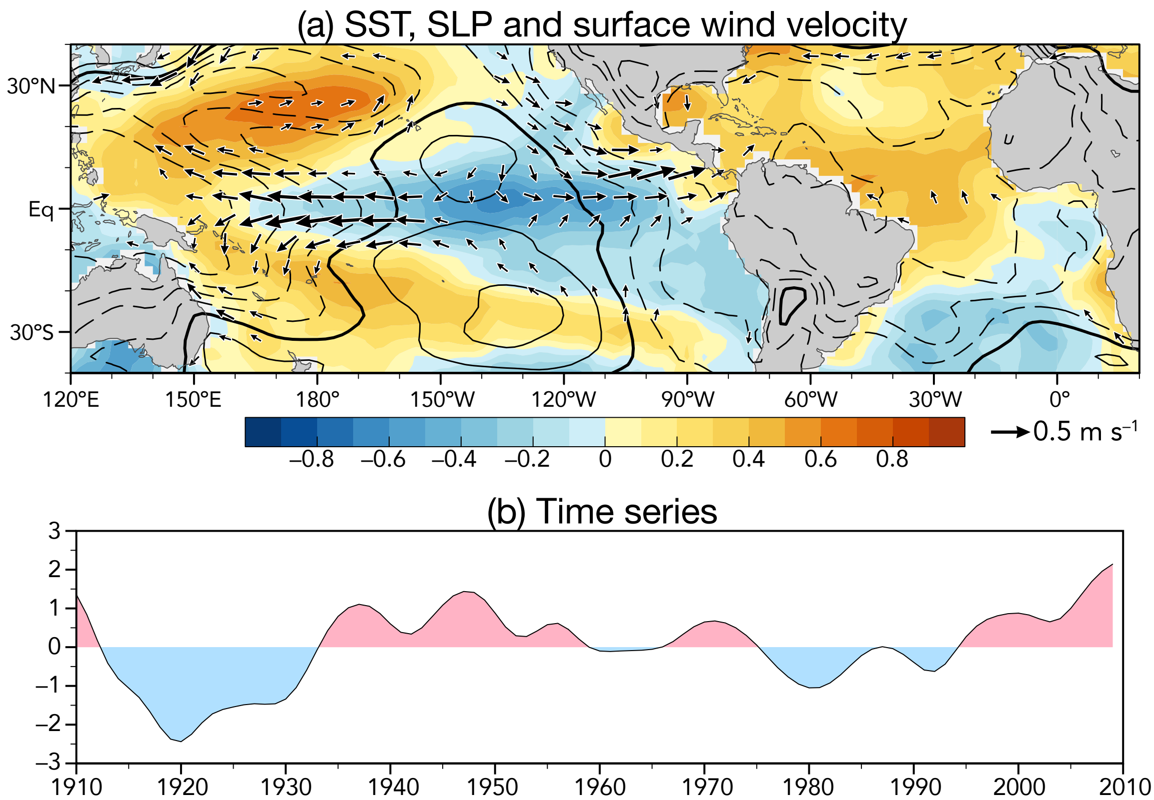

Figure 8.11: (a) Correlations of SST (shading), SLP (contours) and regressed surface wind velocity anomalies (arrows) with respect to the leading principal component of standardized SLP over 30ºS-30ºN shown in (b). Based on 10-year low-pass filtered annual-mean data of NOAA 20th century reanalysis version 2c (Compo et al., 2011) and linearly detrended Extended Reconstructed SST version 5 (Huang et al., 2017). Figure 1 in Yosaka et al., 2018)

8.5 Summary and outlook

Climate services based on predictions of climate from weeks to several years into the future are being demanded by society, as well as public and private sector stakeholders. Predictions on these timescales are of immediate and practical interest and can be more easily integrated in decision making than long-term climate projections (Vaughan and Dessai, 2014; Street, 2015). We have documented the current status in predicting climate from sub-seasonal to multi-year timescales focusing on the tropics. Intra-seasonal forecasts have achieved skill in predicting climatic impacts, including tropical cyclones and extra-tropical weather, primarily through the improving MJO prediction (Vitart and Robertson, 2018). Seasonal prediction skill is mainly linked to ENSO and its teleconnection patterns, but skill is improving in predicting patterns of climate variability in the Indian and Atlantic Oceans. Although seasonal prediction skill is generally low over continents, there is useful skill in predicting temperature, rainfall and climatic extremes in some regions and seasons (Doblas-Reyes et al., 2013b). On multi-year timescales there is skill in predicting AMV and SST over the Indian Ocean and Western Pacific, but relatively little skill in predicting PDV. Skill on multi-year timescales also extends to climate over some continental regions and climatic extremes, like rainfall over West Africa and Atlantic hurricane number (Kushnir et al., 2019).

The better representation of interactions among tropical basins and among climatic phenomena provides exciting possibilities to enhance climate prediction. The ENSO spring predictability barrier may be partly ameliorated through the improving skill in predicting the MJO and in capturing the scale-interaction between the MJO and ENSO. Inter-basin interactions can also help ameliorate the spring predictability barrier, as variability in both tropical Atlantic and Indian Oceans influences the winds over the Western Pacific during boreal spring; furthermore, the interaction among basins can lead to more predictable dynamics across the tropics as schematically shown in Figure 8.6. Inter-basin interactions may also improve skill in predicting PDV (Chikamoto et al., 2015).

There are many challenges to overcome in order to fully realise prediction skill from these interactions. Firstly, there are key uncertainties in our understanding. For example, the strength of inter-basin interactions is not stationary, and it is necessary to understand how low-frequency climate variability, long-term climate change, and internal-climate variability cause changes in these interactions. Likewise, it is important to understand how internal climate dynamics, changes in the background state, or subtle differences among events contribute to variations in teleconnections (Lee et al., 2008; Vitart, 2017). Secondly, model systematic errors impact the simulation of climate variability within the atmosphere and the individual basins, as well the interaction among them. The cold bias in the north tropical Atlantic weakens the teleconnections to the Indo-Pacific (McGregor et al., 2018) and the warm bias in the south eastern Atlantic degrades the prediction of equatorial Atlantic variability (Dippe et al., 2019); while the poor representation of the ITCZ in the Pacific (Mechoso et al., 1995) can also impact global teleconnections. Although long-term model improvement is required, alternate approaches to reduce model biases can enhance the simulation and prediction of climate in the short-term (Shen et al., 2016, Vecchi et al., 2014).

Enhancement of the observational network, increasing computing power, improved capabilities to model and assimilate observational data have led to a steady improvement in numerical weather forecasting (Bauer et al., 2015). For the same reasons, we may expect the continued improvement in climate prediction.

Acknowledgments

Sunil Pariyar and Francois Counillon kindly provided figures. NK, YK, and DM gratefully acknowledge the support of the JPI-Climate/Belmont Forum project InterDec. NK was supported by the ERC STERCP project (Grant Agreement no. 648982). YW was supported by the Trond Mohn Foundation under the project number BFS2018TMT01. NK is thankful for encouragement from his father.

References

Ahn, M.-S., Kim, D., Sperber, K. R., Kang, I.-S., Maloney, E., Waliser, D., Hendon, H., on behalf of, W. M. J. O. T. F. (2017). MJO simulation in CMIP5 climate models: MJO skill metrics and process-oriented diagnosis. *Climate Dynamics,* 49(11), 4023-4045.

Alexander, M. A., Blade, I., Newman, M., Lanzante, J. R., Lau, N. C., Scott, J. D. (2002). The atmospheric bridge: The influence of ENSO teleconnections on air-sea interaction over the global oceans. *Journal of Climate,* 15(16), 2205-2231.

Annamalai, H., Kida, S., Hafner, J. (2010). Potential Impact of the Tropical Indian Ocean–Indonesian Seas on El Niño Characteristics. *Journal of Climate,* 23(14), 3933-3952.

Annamalai, H., Murtugudde, R., Potemra, J., Xie, S. P., Liu, P., Wang, B. (2003). Coupled dynamics over the Indian Ocean: spring initiation of the Zonal Mode. *Deep Sea Research Part II: Topical Studies in Oceanography,* 50(12), 2305-2330.

Baldwin, M. P., Stephenson, D. B., Thompson, D. W. J., Dunkerton, T. J., Charlton, A. J. and O'Neill, A. (2003). Stratospheric memory and extended-range weather forecasts. *Science,* 301, 636–640.

Barnston, A. G., Tippett, M. K., Ranganathan, M., L'Heureux, M. L. (2019). Deterministic skill of ENSO predictions from the North American Multimodel Ensemble. *Climate Dynamics*. *53*(12), 7215-7234.

Barreiro, M., Chang, P., Ji, L., Saravanan, R., Giannini, A. (2005). Dynamical elements of predicting boreal spring tropical Atlantic sea-surface temperatures. *Dynamics of Atmospheres and Oceans,* 39(1), 61-85.

Bauer, P., Thorpe, A., Brunet, G. (2015). The quiet revolution of numerical weather prediction. *Nature,* 525(7567), 47-55.

Becker, E., den Dool, H. v., Zhang, Q. (2014). Predictability and Forecast Skill in NMME. *Journal of Climate,* 27(15), 5891-5906.

Bellenger, H., Guilyardi, E., Leloup, J., Lengaigne, M., Vialard, J. (2014). ENSO representation in climate models: from CMIP3 to CMIP5. *Climate Dynamics,* 42(7-8), 1999-2018.

Booth, B. B. B., Dunstone, N. J., Halloran, P. R., Andrews, T., Bellouin, N. (2012). Aerosols implicated as a prime driver of twentieth-century North Atlantic climate variability. *Nature,* 484(7393), 228-232.

Brandt, P., Funk, A., Hormann, V., Dengler, M., Greatbatch, R. J., Toole, J. M. (2011). Interannual atmospheric variability forced by the deep equatorial Atlantic Ocean. *Nature, 473*(7348), 497-500.

Cai, W., Wu, L., Lengaigne, M., Li, T., McGregor, S., Kug, J.-S., Yu, J.-Y., Stuecker, M. F., Santoso, A., Li, X., Ham, Y.-G., Chikamoto, Y., Ng, B., McPhaden, M. J., Du, Y., Dommenget, D., Jia, F., Kajtar, J. B., Keenlyside, N., Lin, X., Luo, J.-J., Martín-Rey, M., Ruprich-Robert, Y., Wang, G., Xie, S.-P., Yang, Y., Kang, S. M., Choi, J.-Y., Gan, B., Kim, G.-I., Kim, C.-E., Kim, S., Kim, J.-H., Chang, P. (2019). Pantropical climate interactions. *Science,* 363(6430), eaav4236.

Camargo, S. J., Barnston, A. G., Klotzbach, P. J., Landsea, C. W. (2007). Seasonal tropical cyclone forecasts. *WMO Bulletin,* 56(4), 297.

Caron, L.-P., Hermanson, L., Dobbin, A., Imbers, J., Lledó, L., Vecchi, G. A. (2017). How Skillful are the Multiannual Forecasts of Atlantic Hurricane Activity? *Bulletin of the American Meteorological Society,* 99(2), 403-413.

Cassou, C. (2008). Intraseasonal interaction between the Madden-Julian Oscillation and the North Atlantic Oscillation. *Nature,* 455(7212), 523-527.

Chang, P., Fang, Y., Saravanan, R., Ji, L., Seidel, H. (2006a). The cause of the fragile relationship between the Pacific El Nino and the Atlantic Nino. *Nature,* 443(7109), 324-328.

Chang, P., Saravanan, R., Ji, L. (2003). Tropical Atlantic seasonal predictability: The roles of El Niño remote influence and thermodynamic air-sea feedback. *Geophysical Research Letters.* 30(10), 1501.

Chang, P., Yamagata, T., Schopf, P., Behera, S. K., Carton, J., Kessler, W. S., Meyers, G., Qu, T., Schott, F., Shetye, S., Xie, S. P. (2006b) Climate Fluctuations of Tropical Coupled Systems-The Role of Ocean Dynamics. *Journal of Climate,* 19(20), 5122-5174.

Chen, D., Cane, M. A., Kaplan, A., Zebiak, S. E., Huang, D. (2004). Predictability of El Nino over the past 148 years. *Nature,* 428(6984), 733-736.

Chikamoto, Y., Mochizuki, T., Timmermann, A., Kimoto, M., Watanabe, M. (2016). Potential tropical Atlantic impacts on Pacific decadal climate trends. *Geophysical Research Letters,* 43(13), 7143-7151.

Chikamoto, Y., Timmermann, A., Luo, J.-J., Mochizuki, T., Kimoto, M., Watanabe, M., Ishii, M., Xie, S.-P., Jin, F.-F. (2015). Skilful multi-year predictions of tropical trans-basin climate variability', *Nature Communications,* 6, 6869.

Chikamoto, Y., Timmermann, A., Widlansky, M. J., Balmaseda, M. A., Stott, L. (2017). Multi-year predictability of climate, drought, and wildfire in southwestern North America. *Scientific Reports,* 7(1), 6568.

Choi, K.-S., Wu, C.-C., Cha, E.-J. (2010). Change of tropical cyclone activity by Pacific-Japan teleconnection pattern in the western North Pacific. *Journal of Geophysical Research: Atmospheres,* 115. D19114.

Choudhury, D., Sen Gupta, A., Sharma, A., Taschetto, A. S., Mehrotra, R., Sivakumar, B. (2017). Impacts of the tropical trans-basin variability on Australian rainfall. *Climate Dynamics,* 49(5). 1617-1629.

Coelho, C. A. S., Stephenson, D. B., Balmaseda, M., Doblas-Reyes, F. J., van Oldenborgh, G. J. (2006). Toward an Integrated Seasonal Forecasting System for South America. *Journal of Climate,* 19(15), 3704-3721.

Compo, G. P., Whitaker, J. S., Sardeshmukh, P. D., Matsui, N., Allan, R. J., Yin, X., Gleason, B. E., Vose, R. S., Rutledge, G., Bessemoulin, P., Brönnimann, S., Brunet, M., Crouthamel, R. I., Grant, A. N., Groisman, P. Y., Jones, P. D., Kruk, M. C., Kruger, A. C., Marshall, G. J., Maugeri, M., Mok, H. Y., Nordli, Ø., Ross, T. F., Trigo, R. M., Wang, X. L., Woodruff, S. D., Worley, S. J. (2011). The Twentieth Century Reanalysis Project. *Quarterly Journal of the Royal Meteorological Society,* 137(654), 1-28.

Corti, S., Palmer, T., Balmaseda, M., Weisheimer, A., Drijfhout, S., Dunstone, N., Hazeleger, W., Kröger, J., Pohlmann, H., Smith, D., Storch, J.-S. v., Wouters, B. (2015). Impact of Initial Conditions versus

External Forcing in Decadal Climate Predictions: A Sensitivity Experiment. *Journal of Climate,* 28(11), 4454-4470.

Crespo, L. R., Keenlyside, N., Koseki, S. (2019). The role of sea surface temperature in the atmospheric seasonal cycle of the equatorial Atlantic. *Climate Dynamics,* 52(9), 5927-5946.

Dai, A., Fyfe, J. C., Xie, S.-P., Dai, X. (2015). Decadal modulation of global surface temperature by internal climate variability. *Nature Climate Change,* 5, 555.

De Souza, E. B., Ambrizzi, T. (2006). Modulation of the intraseasonal rainfall over tropical Brazil by the Madden–Julian oscillation. *International Journal of Climatology,* 26(13), 1759-1776.

DeMott, C. A., Klingaman, N. P., Woolnough, S. J. (2015). Atmosphere-ocean coupled processes in the Madden-Julian oscillation. *Reviews of Geophysics,* 53(4), 1099-1154.

Deppenmeier, A.-L., Haarsma, R. J., Hazeleger, W. (2016). The Bjerknes feedback in the tropical Atlantic in CMIP5 models', *Climate Dynamics,* 47(7), 2691-2707.

Ding, H., Greatbatch, R. J., Latif, M., Park, W., Gerdes, R. (2013). Hindcast of the 1976/77 and 1998/99 Climate Shifts in the Pacific. *Journal of Climate,* 26(19), 7650-7661.

Ding, H., Keenlyside, N., Latif, M. (2012). Impact of the Equatorial Atlantic on the El Niño Southern Oscillation. *Climate Dynamics,* 38(9), 1965-1972.

Ding, H., Keenlyside, N. S., Latif, M. (2010). Equatorial Atlantic interannual variability: Role of heat content. *Journal of Geophysical Research,* 115(C9), C09020.

Ding, H., Newman, M., Alexander, M. A., Wittenberg, A. T. (2018). Skillful Climate Forecasts of the Tropical Indo-Pacific Ocean Using Model-Analogs. *Journal of Climate,* 31(14), 5437-5459.

Dippe, T., Greatbatch, R. J., Ding, H. (2019). Seasonal prediction of equatorial Atlantic sea surface temperature using simple initialization and bias correction techniques. *Atmospheric Science Letters,* 20(5), e898.

Doblas-Reyes, F. J., Andreu-Burillo, I., Chikamoto, Y., Garcia-Serrano, J., Guemas, V., Kimoto, M., Mochizuki, T., Rodrigues, L. R. L., van Oldenborgh, G. J. (2013a). Initialized near-term regional climate change prediction. *Nature Communications,* 4, 1715.

Doblas-Reyes, F. J., García-Serrano, J., Lienert, F., Biescas, A. P., Rodrigues, L. R. L. (2013b). Seasonal climate predictability and forecasting: status and prospects. *Wiley Interdisciplinary Reviews: Climate Change,* 4(4), 245-268.

Doblas-Reyes, F. J., Hagedorn, R., Palmer, T. N., Morcrette, J. J. (2006). Impact of increasing greenhouse gas concentrations in seasonal ensemble forecasts. *Geophysical Research Letters,* 33(7), L07708.

Doi, T., Storto, A., Behera, S. K., Navarra, A., Yamagata, T. (2017). Improved Prediction of the Indian Ocean Dipole Mode by Use of Subsurface Ocean Observations. *Journal of Climate,* 30(19), 7953-7970.

Doi, T., Tozuka, T., Yamagata, T. (2010). The Atlantic Meridional Mode and Its Coupled Variability with the Guinea Dome. *Journal of Climate,* 23(2), 455-475.

Dommenget, D. (2011). An objective analysis of the observed spatial structure of the tropical Indian Ocean SST variability. Climate Dynamics, 36(11), 2129-2145.

Dommenget, D., Latif, M. (2000). Interannual to Decadal Variability in the Tropical Atlantic', *Journal of Climate,* 13(4), 777-792.

Dommenget, D., Latif, M. (2002). A Cautionary Note on the Interpretation of EOFs. *Journal of Climate,* 15(2), 216-225.

Dommenget, D., Semenov, V., Latif, M. (2006). Impacts of the tropical Indian and Atlantic Oceans on ENSO. *Geophysical Research Letters,* 33, L11701.

Dommenget, D., Yu, Y. (2017). The effects of remote SST forcings on ENSO dynamics, variability and diversity. *Climate Dynamics,* 49(7), 2605-2624.

Du, Y., Xie, S.-P., Huang, G., Hu, K. (2009) .Role of Air–Sea Interaction in the Long Persistence of El Niño–Induced North Indian Ocean Warming. *Journal of Climate,* 22(8), 2023-2038.

Duan, W., Wei, C. (2013) .The 'spring predictability barrier' for ENSO predictions and its possible mechanism: results from a fully coupled model. *International Journal of Climatology,* 33(5), 1280-1292.

England, M. H., McGregor, S., Spence, P., Meehl, G. A., Timmermann, A., Cai, W., Gupta, A. S., McPhaden, M. J., Purich, A., Santoso, A. (2014). Recent intensification of wind-driven circulation in the Pacific and the ongoing warming hiatus. *Nature Climate Change,* 4(3), 222-227.

Flatau, M., Flatau, P. J., Phoebus, P., Niller, P. P. (1997). The feedback between equatorial convection and local radiative and evaporative processes: The implications for intraseasonal oscillations. *Journal of the Atmospheric Sciences,* 54(19). 2373-2386.

Folland, C. K., Colman, A. W., Rowell, D. P., Davey, M. K. (2001).Predictability of Northeast Brazil Rainfall and Real-Time Forecast Skill, 1987–98. *Journal of Climate,* 14(9), 1937-1958.

Foltz, G. R., McPhaden, M. J. (2010). Interaction between the Atlantic meridional and Niño modes. *Geophysical Research Letters,* 37(18), L18604.

Frauen, C., Dommenget, D. (2012). Influences of the tropical Indian and Atlantic Oceans on the predictability of ENSO. *Geophysical Research Letters,* 39(2), L02706.

Giannini, A., Saravanan, R., Chang, P. (2004). The preconditioning role of Tropical Atlantic Variability in the development of the ENSO teleconnection: implications for the prediction of Nordeste rainfall. *Climate Dynamics,* 22(8), 839-855.

Gleixner, S., Keenlyside, N. S., Demissie, T. D., Counillon, F., Wang, Y., Viste, E. (2017). Seasonal predictability of Kiremt rainfall in coupled general circulation models. *Environmental Research Letters,* 12(11), 114016.

Grimm, A. M. (2019). Madden–Julian Oscillation impacts on South American summer monsoon season: precipitation anomalies, extreme events, teleconnections, and role in the MJO cycle. *Climate Dynamics,* 53(1), 907-932.

Guemas, V., Corti, S., García-Serrano, J., Doblas-Reyes, F. J., Balmaseda, M., Magnusson, L. (2012). The Indian Ocean: The Region of Highest Skill Worldwide in Decadal Climate Prediction. *Journal of Climate,* 26(3), 726-739.

Ham, Y.-G., Kug, J.-S., Park, J.-Y. (2013a). Two distinct roles of Atlantic SSTs in ENSO variability: North Tropical Atlantic SST and Atlantic Niño. *Geophysical Research Letters,* 40(15), 4012-4017.

Ham, Y.-G., Kug, J. -S., Park, J.-Y., Jin, F.-F. (2013b). Sea surface temperature in the north tropical Atlantic as a trigger for El Niño/Southern Oscillation events. *Nature Geoscience,* 6(2), 112-116.

Handoh, I. C., Matthews, A. J., Bigg, G. R., Stevens, D. P. (2006). Interannual variability of the tropical Atlantic independent of and associated with ENSO: Part I. The North Tropical Atlantic. *International Journal of Climatology,* 26(14), 1937-1956.

Hannachi, A., Dommenget, D. (2009). Is the Indian Ocean SST variability a homogeneous diffusion process? *Climate Dynamics,* 33(4), 535-547.

Hawkins, E., Sutton, R. (2009). The Potential to Narrow Uncertainty in Regional Climate Predictions. *Bulletin of the American Meteorological Society,* 90(8), 1095-1107.

Hendon, H. H., Liebmann, B., Newman, M., Glick, J. D., Schemm, J. E. (2000). Medium-Range Forecast Errors Associated with Active Episodes of theMadden–Julian Oscillation. *Monthly Weather Review,* 128(1), 69-86.

Hendon, H. H., Salby, M. L. (1994). The Life-Cycle of the Madden-Julian Oscillation. *Journal of the Atmospheric Sciences,* 51(15), 2225-2237.

Hendon, H. H., Wheeler, M. C., Zhang, C. (2007). Seasonal Dependence of the MJO–ENSO Relationship. *Journal of Climate,* 20(3), 531-543.

Hsu, H. H., Weng, C. H., Wu, C. H. (2004). Contrasting characteristics between the northward and eastward propagation of the intraseasonal oscillation during the boreal summer. *Journal of Climate,* 17(4), 727-743.

Hsu, W.-C., Patricola, C. M., Chang, P. (2019). The impact of climate model sea surface temperature biases on tropical cyclone simulations. *Climate Dynamics*. 53(1), 173-192.

Hu, K., Huang, G., Qu, X., Huang, R. (2012). The impact of Indian Ocean variability on high temperature extremes across the southern Yangtze River valley in late summer. *Advances in Atmospheric Sciences,* 29(1), 91-100.

Hu, S., Fedorov, A. V. (2016). Exceptionally strong easterly wind burst stalling El Niño of 2014', *Proceedings of the National Academy of Sciences,* 113(8), 2005.

Huang, B., Thorne, P. W., Banzon, V. F., Boyer, T., Chepurin, G., Lawrimore, J. H., Menne, M. J., Smith, T. M., Vose, R. S., Zhang, H. -M. (2017). Extended Reconstructed Sea Surface Temperature, Version 5 (ERSSTv5): Upgrades, Validations, and Intercomparisons. *Journal of Climate,* 30(20), 8179-8205.

Huang, R., Chen, W., Yang, B., Zhang, R. (2004). Recent advances in studies of the interaction between the East Asian winter and summer monsoons and ENSO cycle. *Advances in Atmospheric Sciences,* 21(3), 407-424.

Huang, R., Sun, F. (1992). Impacts of the Tropical Western Pacific on the East Asian Summer Monsoon. *Journal of the Meteorological Society of Japan. Ser. II,* 70(1B),. 243-256.

Izumo, T., Vialard, J., Lengaigne, M., Montegut, C. D., Behera, S. K., Luo, J. J., Cravatte, S., Masson, S. and Yamagata, T. (2010).Influence of the state of the Indian Ocean Dipole on the following year's El Niño', *Nature Geoscience,* 3(3), 168-172.

Jansen, M. F., Dommenget, D. and Keenlyside, N. (2009).Tropical Atmosphere-Ocean Interactions in a Conceptual Framework', *Journal of Climate,* 22(3), 550-567.

Jiang, X., Waliser, D. E., Xavier, P. K., Petch, J., Klingaman, N. P., Woolnough, S. J., Guan, B., Bellon, G., Crueger, T., DeMott, C., Hannay, C., Lin, H., Hu, W., Kim, D., Lappen, C.-L., Lu, M.-M., Ma, H.-Y., Miyakawa, T., Ridout, J. A., Schubert, S. D., Scinocca, J., Seo, K.-H., Shindo, E., Song, X., Stan, C., Tseng, W.-L., Wang, W., Wu, T., Wu, X., Wyser, K., Zhang, G. J., Zhu, H. (2015). Vertical structure and physical processes of the Madden-Julian oscillation: Exploring key model physics in climate simulations. *Journal of Geophysical Research: Atmospheres,* 120(10), 4718-4748.

Joseph, S., Sahai, A. K., Goswami, B. N. (2009).Eastward propagating MJO during boreal summer and Indian monsoon droughts. *Climate Dynamics,* 32(7), 1139-1153.

Jouanno, J., Hernandez, O., Sanchez-Gomez, E. (2017). Equatorial Atlantic interannual variability and its relation to dynamic and thermodynamic processes. *Earth System Dynamics,* 8(4), 1061-1069.

Keenlyside, N. S., Ba, J. (2010). Prospects for decadal climate prediction. *Wiley Interdisciplinary Reviews: Climate Change,* 1(5), 627-635.

Keenlyside, N. S., Ding, H., Latif, M. (2013). Potential of equatorial Atlantic variability to enhance El Niño prediction. *Geophysical Research Letters,* 40(10), 2278-2283.

Keenlyside, N. S., Latif, M. (2007). Understanding equatorial Atlantic interannual variability'. *Journal of Climate,* 20(1), 131-142.

Keenlyside, N. S., Latif, M., Jungclaus, J., Kornblueh, L., Roeckner, E. (2008). Advancing decadal-scale climate prediction in the North Atlantic Sector. *Nature,* 453, 84–88.

Kirtman, B. P., Min, D., Infanti, J. M., Kinter, J. L., Paolino, D. A., Zhang, Q., van den Dool, H., Saha, S., Mendez, M. P., Becker, E., Peng, P., Tripp, P., Huang, J., DeWitt, D. G., Tippett, M. K., Barnston, A. G., Li, S., Rosati, A., Schubert, S. D., Rienecker, M., Suarez, M., Li, Z. E., Marshak, J., Lim, Y.-K., Tribbia, J., Pegion, K., Merryfield, W. J., Denis, B., Wood, E. F. (2014). The North American Multimodel Ensemble: Phase-1 Seasonal-to-Interannual Prediction; Phase-2 toward Developing Intraseasonal Prediction. *Bulletin of the American Meteorological Society,* 95(4), 585-601.

Klein, S. A., Soden, B. J., Lau, N.-C. (1999). Remote Sea Surface Temperature Variations during ENSO: Evidence for a Tropical Atmospheric Bridge. *Journal of Climate,* 12(4), 917-932.

Klingaman, N. P., Woolnough, S. J. (2014). Using a case-study approach to improve the Madden–Julian oscillation in the Hadley Centre model. *Quarterly Journal of the Royal Meteorological Society,* 140(685), 2491-2505.

Klingaman, N. P., Woolnough, S. J., Jiang, X., Waliser, D., Xavier, P. K., Petch, J., Caian, M., Hannay, C., Kim, D., Ma, H.-Y., Merryfield, W. J., Miyakawa, T., Pritchard, M., Ridout, J. A., Roehrig, R., Shindo, E., Vitart, F., Wang, H., Cavanaugh, N. R., Mapes, B. E., Shelly, A., Zhang, G. J. (2015). Vertical structure and physical processes of the Madden-Julian oscillation: Linking hindcast fidelity to simulated diabatic heating and moistening. *Journal of Geophysical Research: Atmospheres,* 120(10), 4690-4717.

Kobayashi, S., Ota, Y., Harada, Y., Ebita, A., Moriya, M., Onoda, H., Onogi, K., Kamahori, H., Kobayashi, C., Endo, H., Miyaoka, K., Takahashi, K. (2015). The JRA-55 Reanalysis: General Specifications and Basic Characteristics. *Journal of the Meteorological Society of Japan. Ser. II,* 93(1), 5-48.

Kosaka, Y. (2018). Slow warming and the ocean see-saw. *Nature Geoscience,* 11(1), 12-13.

Kosaka, Y., Nakamura, H. (2006). Structure and dynamics of the summertime Pacific–Japan teleconnection pattern. *Quarterly Journal of the Royal Meteorological Society,* 132(619), 2009-2030.

Kosaka, Y., Xie, S.-P. (2013). Recent global-warming hiatus tied to equatorial Pacific surface cooling', *Nature,* 501(7467), 403-407.

Kosaka, Y., Xie, S.-P. (2016). The tropical Pacific as a key pacemaker of the variable rates of global warming. *Nature Geoscience,* 9, 669-673.

Kosaka, Y., Xie, S.-P., Lau, N.-C., Vecchi, G. A. (2013). Origin of seasonal predictability for summer climate over the Northwestern Pacific. *Proceedings of the National Academy of Sciences,* 110(19), 7574- 7579.

Kosaka, Y., Xie, S.-P., Nakamura, H. (2011). Dynamics of Interannual Variability in Summer Precipitation over East Asia. *Journal of Climate,* 24(20), 5435-5453.

Kucharski, F., Ikram, F., Molteni, F., Farneti, R., Kang, I.-S., No, H.-H., King, M. P., Giuliani, G., Mogensen, K. (2016). Atlantic forcing of Pacific decadal variability. *Climate Dynamics,* 46(7), 2337-2351.

Kug, J.-S., Kang, I.-S. (2006). Interactive Feedback between ENSO and the Indian Ocean. *Journal of Climate,* 19(9), 1784-1801.

Kushnir, Y., Scaife, A. A., Arritt, R., Balsamo, G., Boer, G., Doblas-Reyes, F., Hawkins, E., Kimoto, M., Kolli, R. K., Kumar, A., Matei, D., Matthes, K., Müller, W. A., O'Kane, T., Perlwitz, J., Power, S., Raphael, M., Shimpo, A., Smith, D., Tuma, M., Wu, B. (2019). Towards operational predictions of the near-term climate. *Nature Climate Change,* 9(2), 94-101.

Latif, M., Anderson, D., Barnett, T., Cane, M., Kleeman, R., Leetmaa, A., O'Brien, J., Rosati, A., Schneider, E. (1998). A review of the predictability and prediction of ENSO. *Journal of Geophysical Research-Oceans,* 103(C7), 14375-14393.

Latif, M., Keenlyside, N. S. (2009). El Niño/Southern Oscillation response to global warming', *Proceedings of the National Academy of Sciences,* 106(49), 20578-20583.

Latif, M., Keenlyside, N. S. (2011). A perspective on decadal climate variability and predictability. *Deep Sea Research Part II: Topical Studies in Oceanography,* 58, 1880-1894.

Lavender, S. L., Matthews, A. J. (2009). Response of the West African Monsoon to the Madden–Julian Oscillation', *Journal of Climate,* 22(15), 4097-4116.

Lee, J.-Y., Fu, X., Wang, B. (2016). Predictability and Prediction of the Madden-Julian Oscillation: A Review on Progress and Current Status. *The Global Monsoon System: Vol. Volume 9 World Scientific Series on Asia-Pacific Weather and Climate*: World Scientific, 147-159.

Lee, S.-K., Enfield, D. B., Wang, C. (2008).Why do some El Niños have no impact on tropical North Atlantic SST? *Geophysical Research Letters,* 35(16), L16705.

Lee, Y.-Y., Grotjahn, R. (2019). Evidence of Specific MJO Phase Occurrence with Summertime California Central Valley Extreme Hot Weather. *Advances in Atmospheric Sciences,* 36(6), 589-602.

Lengaigne, M., Guilyardi, E., Boulanger, J.-P., Menkes, C., Delecluse, P., Inness, P., Cole, J., Slingo, J. (2004). Triggering of El Niño by westerly wind events in a coupled general circulation model. *Climate Dynamics,* 23(6), 601-620.

Levine, A., Jin, F. F., McPhaden, M. J. (2016). Extreme Noise–Extreme El Niño: How State-Dependent Noise Forcing Creates El Niño–La Niña Asymmetry. *Journal of Climate,* 29(15), 5483-5499.

Levine, A. F. Z., McPhaden, M. J. (2016). How the July 2014 easterly wind burst gave the 2015–2016 El Niño a head start. *Geophysical Research Letters,* 43(12),.6503-6510.

Li, X., Xie, S.-P., Gille, S. T. Yoo, C. (2015). Atlantic-induced pan-tropical climate change over the past three decades. *Nature Climate Change,* 6, 275.

Liebmann, B., Hendon, H. H., Glick, J. D. (1994).The Relationship Between Tropical Cyclones of the Western Pacific and Indian Oceans and the Madden-Julian Oscillation. *Journal of the Meteorological Society of Japan. Ser. II,* 72(3), 401-412.

Lin, H., Brunet, G. and Fontecilla, J. S. (2010). Impact of the Madden-Julian Oscillation on the intraseasonal forecast skill of the North Atlantic Oscillation, *Geophysical Research Letters,* 37(19), L19803.

Lübbecke, J. F., McPhaden, M. J. (2012).On the inconsistent relationship between Pacific and Atlantic Niños. *Journal of Climate,* 25(12), 4294-4303.

Lübbecke, J. F., Rodríguez-Fonseca, B., Richter, I., Martín-Rey, M., Losada, T., Polo, I., Keenlyside, N. S. (2018). Equatorial Atlantic variability—Modes, mechanisms, and global teleconnections. *Wiley Interdisciplinary Reviews: Climate Change,* 9(4), e527.

Luo, J.-J., Behera, S., Masumoto, Y., Sakuma, H., Yamagata, T. (2008a). Successful prediction of the consecutive IOD in 2006 and 2007. *Geophysical Research Letters,* 35(14), L14S02.

Luo, J.-J., Liu, G., Hendon, H., Alves, O., Yamagata, T. (2017). Inter-basin sources for two-year predictability of the multi-year La Niña event in 2010–2012. *Scientific Reports,* 7(1), 2276.

Luo, J.-J., Masson, S., Behera, S., Yamagata, T. (2007). Experimental Forecasts of the Indian Ocean Dipole Using a Coupled OAGCM. *Journal of Climate,* 20(10), 2178-2190.

Luo, J.-J., Masson, S., Behera, S. K.. Yamagata, T. (2008b). Extended ENSO Predictions Using a Fully Coupled Ocean–Atmosphere Model. *Journal of Climate,* 21(1), 84-93.

Luo, J.-J., Sasaki, W., Masumoto, Y. (2012). Indian Ocean warming modulates Pacific climate change. *Proceedings of the National Academy of Sciences,* 109(46), 18701.

Luo, J.-J., Wang, G., Dommenget, D. (2018), May common model biases reduce CMIP5's ability to simulate the recent Pacific La Niña-like cooling?, *Climate Dynamics*, *50*(3), 1335-1351.

Luo, J.-J., Yuan, C., Sasaki, W., Behera, S. K., Masumoto, Y., Yamagata, T., Lee, J.-Y. and Masson, S. (2015). Current Status of Intraseasonal-Seasonal-to-Interannual Prediction of the Indo-Pacific Climate. *Indo-Pacific Climate Variability and Predictability: Vol. Volume 7 World Scientific Series on Asia-Pacific Weather and Climate*: WORLD SCIENTIFIC,. 63-107.

Luo, J. J., Zhang, R., Behera, S. K., Masumoto, Y., Jin, F. F., Lukas, R., Yamagata, T. (2010). Interaction between El Niño and extreme Indian ocean dipole. *Journal of Climate,* 23(3), 726-742.

Madden, R. A., Julian, P. R. (1972).Description of Global-Scale Circulation Cells in Tropics with a 40-50 Day Period, *Journal of the Atmospheric Sciences,* 29(6), 1109-1123.

Majda, A. J. and Stechmann, S. N. (2009).The skeleton of tropical intraseasonal oscillations, *Proceedings of the National Academy of Sciences,* 106(21), 8417.

Maloney, E. D. and Hartmann, D. L. (1998).Frictional moisture convergence in a composite life cycle of the Madden-Julian oscillation, *Journal of Climate,* 11(9), 2387-2403.

Maloney, E. D. and Hartmann, D. L. (2000). Modulation of hurricane activity in the Gulf of Mexico by the Madden-Julian oscillation, *Science,* 287(5460),. 2002-2004.

Maloney, E. D. and Sobel, A. H. (2004). Surface fluxes and ocean coupling in the tropical intraseasonal oscillation', *Journal of Climate,* 17(22), 4368-4386.

Marshall, A. G., Hendon, H. H. and Wang, G. (2016).On the role of anomalous ocean surface temperatures for promoting the record Madden-Julian Oscillation in March 2015, *Geophysical Research Letters,* 43(1), 472-481.

Martín-Rey, M., Rodríguez-Fonseca, B. and Polo, I. (2015). Atlantic opportunities for ENSO prediction, *Geophysical Research Letters,* 42(16), 6802-6810.

Martín-Rey, M., Rodríguez-Fonseca, B., Polo, I. and Kucharski, F. (2014).On the Atlantic–Pacific Niños connection: a multidecadal modulated mode, *Climate Dynamics,* 43(11), 3163-3178.

Matsueda, S. and Takaya, Y. (2015). The Global Influence of the Madden–Julian Oscillation on Extreme Temperature Events. *Journal of Climate,* 28(10), 4141-4151.

Matthews, A. J. (2004). Intraseasonal Variability over Tropical Africa during Northern Summer', *Journal of Climate,* 17(12), 2427-2440.

Matthews, A. J. and Meredith, M. P. (2004).Variability of Antarctic circumpolar transport and the Southern Annular Mode associated with the Madden-Julian Oscillation', *Geophysical Research Letters,* 31(24).

McGregor, S., Stuecker, M. F., Kajtar, J. B., England, M. H. and Collins, M. (2018).Model tropical Atlantic biases underpin diminished Pacific decadal variability, *Nature Climate Change,* 8(6), 493-498.

McGregor, S., Timmermann, A., Stuecker, M. F., England, M. H., Merrifield, M., Jin, F.-F., Chikamoto, Y. (2014). Recent Walker circulation strengthening and Pacific cooling amplified by Atlantic warming, *Nature Clim. Change,* 4(10), 888-892.

McPhaden, M. J. (1999). Genesis and evolution of the 1997-98 El Nino, *Science,* 283(5404),. 950-954.

McPhaden, M. J. (2003). Tropical Pacific Ocean heat content variations and ENSO persistence barriers, *Geophysical Research Letters,* 30(9), 1480.

McPhaden, M. J., Busallacchi, A. J., Cheney, R., Donguy, J.-R., Gage, K. S., Halpern, D., Ji, M., Julian, P., Meyers, G., Mitchum, G. T., Niiler, P. P., Picaut, J., Reynolds, R. W., Smith, N. and Takeuchi, K. (1998). The Tropical Ocean Global Atmosphere observing system: A decade of progress, *Journal of Geophysical Research,* 103(C7), 14,169–14,240.

McPhaden, M. J., Zhang, X., Hendon, H. H., Wheeler, M. C. (2006). Large scale dynamics and MJO forcing of ENSO variability. *Geophysical Research Letters,* 33(16), L16702.

Mechoso, C. R., Robertson, A. W., Barth, N., Davey, M. K., Delecluse, P., Gent, P. R., Ineson, S., Kirtman, B., Latif, M., Le Treut, L., Nagai, T. Neelin, J. D., Philander, S. G. H., Polcher, J., Schopf, P. S., Stockdale, T. Suarez, M. J., Terray, L., Thual, O., Tribbia, J. J. (1995). The seasonal cycle over the Tropical Pacific in General Circulation Models. *Monthly Weather Rev*iew, 123, 2825-2838.

Meehl, G. A., Goddard, L., Murphy, J., Stouffer, R. J., Boer, G., Danabasoglu, G., Dixon, K., Giorgetta, M. A., Greene, A. M., Hawkins, E., Hegerl, G., Karoly, D., Keenlyside, N., Kimoto, M., Kirtman, B., Navarra, A., Pulwarty, R., Smith, D., Stammer, D., Stockdale, T. (2009). Decadal Prediction Can It Be Skillful? *Bulletin of the American Meteorological Society,* 90(10), 1467-+.

Meehl, G. A., Teng, H. (2012). Case studies for initialized decadal hindcasts and predictions for the Pacific region. *Geophysical Research Letters,* 39(22), L22705.

Meyers, G., McIntosh, P., Pigot, L., Pook, M. (2007). The Years of El Niño, La Niña, and Interactions with the Tropical Indian Ocean. *Journal of Climate,* 20(13), 2872-2880.

Mochizuki, T., Kimoto, M., Watanabe, M., Chikamoto, Y., Ishii, M. (2016). Interbasin effects of the Indian Ocean on Pacific decadal climate change. *Geophysical Research Letters,* 43(13), 7168-7175.

Mohino, E., Keenlyside, N., Pohlmann, H. (2016). Decadal prediction of Sahel rainfall: where does the skill (or lack thereof) come from? *Climate Dynamics,* 47(11), 3593-3612.

Mutai, C. C., Ward, M. N. (2000). East African Rainfall and the Tropical Circulation/Convection on Intraseasonal to Interannual Timescales. *Journal of Climate,* 13(22), 3915-3939.

Neelin, J. D., Battisti, D. S., Hirst, A. C., Jin, F.-F., Wakata, Y., Yamagata, T., Zebiak, S. E. (1998). ENSO Theory, *Journal of Geophysical Research,* 103, 14,261–14,290.

Neena, J. M., Lee, J. Y., Waliser, D., Wang, B., Jiang, X. (2014). Predictability of the Madden–Julian Oscillation in the Intraseasonal Variability Hindcast Experiment (ISVHE). *Journal of Climate,* 27(12), 4531-4543.

Newman, M., Alexander, M.A., Ault, T.R. , Cobb, K.M., Deser, C., Di Lorenzo, E., Mantua, N.J., Miller, A.J., Minobe, S., Nakamura, H., Schneider, N., Vimont, D.J., Phillips, A.S., Scott, J.D., Smith, C.A. (2016). The Pacific Decadal Oscillation, Revisited. *J. Climate,* 29, 4399–4427

Newman, M., Sardeshmukh, P. D. (2017). Are we near the predictability limit of tropical Indo-Pacific sea surface temperatures? *Geophysical Research Letters,* 44(16), 8520-8529.

Niang, C., Mohino, E., Gaye, A. T., Omotosho, J. B. (2017). Impact of the Madden Julian Oscillation on the summer West African monsoon in AMIP simulations. *Climate Dynamics,* 48(7), 2297-2314.

Nitta, T. (1987). Convective Activities in the Tropical Western Pacific and Their Impact on the Northern Hemisphere Summer Circulation. *Journal of the Meteorological Society of Japan. Ser. II,* 65(3), 373-390.

Nnamchi, H. C., Li, J., Kucharski, F., Kang, I.-S., Keenlyside, N. S., Chang, P., Farneti, R. (2015). Thermodynamic controls of the Atlantic Nino, *Nature Communications,* 6:8895.

Nnamchi, H. C., Li, J., Kucharski, F., Kang, I.-S., Keenlyside, N. S., Chang, P., Farneti, R. (2016). An Equatorial–Extratropical Dipole Structure of the Atlantic Niño. *Journal of Climate,* 29(20), 7295-7311.

Orsolini, Y. J., Senan, R., Vitart, F., Balsamo, G., Weisheimer, A., Doblas-Reyes, F. J. (2016). Influence of the Eurasian snow on the negative North Atlantic Oscillation in subseasonal forecasts of the cold winter 2009/2010. *Climate Dynamics,* 47(3), 1325-1334.

Palmer, T. N. (1993). Extended-Range Atmospheric Prediction and the Lorenz Model. *Bulletin of the American Meteorological Society,* 74(1), 49-66.

Palmer, T. N., Alessandri, A., Andersen, U., Cantelaube, P., Davey, M., Delecluse, P., Deque, M., Diez, E., Doblas-Reyes, F. J., Feddersen, H., Graham, R., Gualdi, S., Gueremy, J. F., Hagedorn, R., Hoshen, M., Keenlyside, N., Latif, M., Lazar, A., Maisonnave, E., Marletto, V., Morse, A. P., Orfila, B., Rogel, P., Terres, J. M. and Thomson, M. C. (2004). Development of a European multimodel ensemble system for seasonal-to-interannual prediction (DEMETER), *Bulletin of the American Meteorological Society,* 85(6), 853-872.

Pariyar, S. K., Keenlyside, N., Bhatt, B. C., Omrani, N.-E. (2019). The dominant patterns of intra-seasonal rainfall variability in May-October and November-April over the Tropical Western Pacific. *Monthly Weather Review*. 147(8), 2941-2960.

Philander, S. G. H. (1990) *El Niño, La Niña, and the Southern Oscillation.* London: Academic Press, 293pp.

Philippon, N., Doblas-Reyes, F. J. and Ruti, P. M. (2010). Skill, reproducibility and potential predictability of the West African monsoon in coupled GCMs. *Climate Dynamics,* 35(1), 53-74.

Prodhomme, C., Batté, L., Massonnet, F., Davini, P., Bellprat, O., Guemas, V., Doblas-Reyes, F. J. (2016) Benefits of Increasing the Model Resolution for the Seasonal Forecast Quality in EC-Earth. *Journal of Climate,* 29(24), 9141-9162.

Rashid, H. A., Hendon, H. H., Wheeler, M. C., Alves, O. (2011). Prediction of the Madden-Julian oscillation with the POAMA dynamical prediction system. *Climate Dynamics,* 36(3-4), 649-661.

Rayner, N. A., Parker, D. E., Horton, E. B., Folland, C. K., Alexander, L. V., Rowell, D. P., Kent, E. C., Kaplan, A. (2003). Global analyses of sea surface temperature, sea ice, and night marine air temperature since the late nineteenth century. *Journal of Geophysical Research,* 108(D14), 4407.

Richter, I. (2015). Climate model biases in the eastern tropical oceans: causes, impacts and ways forward. *Wiley Interdisciplinary Reviews: Climate Change,* 6(3), 345-358.

Richter, I., Behera, S., Doi, T., Taguchi, B., Masumoto, Y., Xie, S.-P. (2014). What controls equatorial Atlantic winds in boreal spring. *Climate Dynamics,* 43(11), 3091-3104.

Richter, I., Behera, S. K., Masumoto, Y., Taguchi, B., Sasaki, H., Yamagata, T. (2013). Multiple causes of interannual sea surface temperature variability in the equatorial Atlantic Ocean, *Nature Geoscence,* 6(1), 43-47.

Richter, I., Doi, T., Behera, S. K., Keenlyside, N. (2018). On the link between mean state biases and prediction skill in the tropics: an atmospheric perspective. *Climate Dynamics,* 50(9), 3355-3374.

Robertson, A. W., Kumar, A., Peña, M., Vitart, F. (2014). Improving and Promoting Subseasonal to Seasonal Prediction. *Bulletin of the American Meteorological Society,* 96(3), ES49-ES53.

Rodriguez-Fonseca, B., Polo, I., Garcia-Serrano, J., Losada, T., Mohino, E., Mechoso, C. R., Kucharski, F. (2009). Are Atlantic Niños enhancing Pacific ENSO events in recent decades? *Geophysical Research Letters,* 36(20), L20705.

Ruiz-Barradas, A., Carton, J. A., Nigam, S. (2000). Structure of Interannual-to-Decadal Climate Variability in the Tropical Atlantic Sector. *Journal of Climate,* 13(18), 3285-3297.

Ruiz-Barradas, A., Carton, J. A., Nigam, S. (2003). Role of the Atmosphere in Climate Variability of the Tropical Atlantic. *Journal of Climate,* 16(12), 2052-2065.

Ruprich-Robert, Y., Msadek, R., Castruccio, F., Yeager, S., Delworth, T., Danabasoglu, G. (2016). Assessing the Climate Impacts of the Observed Atlantic Multidecadal Variability Using the GFDL CM2.1 and NCAR CESM1 Global Coupled Models. *Journal of Climate,* 30(8), 2785-2810.

Saji, N. H., Goswami, B. N., Vinayachandran, P. N., Yamagata, T. (1999). A dipole mode in the tropical Indian Ocean. *Nature,* 401(6751), 360-363.

Servain, J., Wainer, I., McCreary, J. P., Dessier, A. (1999). Relationship between the equatorial and meridional modes of climatic variability in the tropical Atlantic. *Geophysical Research Letters,* 26(4), 485-488.

Sheen, K. L., Smith, D. M., Dunstone, N. J., Eade, R., Rowell, D. P., Vellinga, M. (2017). Skilful prediction of Sahel summer rainfall on inter-annual and multi-year timescales. *Nature Communications,* 8, 14966.

Shen, M.-L., Keenlyside, N., Selten, F., Wiegerinck, W., Duane, G. S. (2016). Dynamically combining climate models to “supermodel” the tropical Pacific. *Geophysical Research Letters,* 43(1), 359-366.

Shi, L., Hendon, H. H., Alves, O., Luo, J.-J., Balmaseda, M., Anderson, D. (2012). How Predictable is the Indian Ocean Dipole? *Monthly Weather Review,* 140(12), 3867-3884.

Smith, D. M., Cusack, S., Colman, A. W., Folland, C. K., Harris, G. R., Murphy, J. M. (2007). Improved surface temperature prediction for the coming decade from a global climate model. *Science,* 317, 796-799.

Smith, D. M., Eade, R., Dunstone, N. J., Fereday, D., Murphy, J. M., Pohlmann, H., Scaife, A. A. (2010). Skilful multi-year predictions of Atlantic hurricane frequency. *Nature Geoscience,* 3(12), 846-849.

Smith, N., Kessler, W. S., Cravatte, S., Sprintall, J., Wijffels, S., Cronin, M. F., Sutton, A., Serra, Y. L., Dewitte, B., Strutton, P. G., Hill, K., Sen Gupta, A., Lin, X., Takahashi, K., Chen, D., Brunner, S. (2019). Tropical Pacific Observing System. *Frontiers in Marine Science,* 6, 31.

Sobel, A. H., Maloney, E. D., Bellon, G., Frierson, D. M. (2010). Surface Fluxes and Tropical Intraseasonal Variability: a Reassessment. *Journal of Advances in Modeling Earth Systems,* 2(1).

Song, Q., Vecchi, G. A., Rosati, A. J. (2008). Predictability of the Indian Ocean sea surface temperature anomalies in the GFDL coupled model. *Geophysical Research Letters,* 35(2).

Street, R., et al. (2015) *A European research and innovation roadmap for climate services*: European Commission.

Suárez-Moreno, R., Rodríguez-Fonseca, B. (2015). S4CAST v2.0: sea surface temperature based statistical seasonal forecast model. *Geoscience Model Development Discussiod,* 8(5), 3971-4018.

Sun, C., Kucharski, F., Li, J., Jin, F.-F., Kang, I.-S. Ding, R. (2017). Western tropical Pacific multidecadal variability forced by the Atlantic multidecadal oscillation. *Nature Communications,* 8, 15998.

Sutton, R. T., Jewson, S. P. Rowell, D. P. (2000). The Elements of Climate Variability in the Tropical Atlantic Region. *Journal of Climate,* 13(18), 3261-3284.

Takaya, Y., Yasuda, T., Fujii, Y., Matsumoto, S., Soga, T., Mori, H., Hirai, M., Ishikawa, I., Sato, H., Shimpo, A., Kamachi, M. and Ose, T. (2017). Japan Meteorological Agency/Meteorological Research Institute-Coupled Prediction System version 1 (JMA/MRI-CPS1) for operational seasonal forecasting', *Climate Dynamics,* 48(1), 313-333.

Tang, Y., Zhang, R.-H., Liu, T., Duan, W., Yang, D., Zheng, F., Ren, H., Lian, T., Gao, C., Chen, D. and Mu, M. (2018). Progress in ENSO prediction and predictability study', *National Science Review,* 5(6), 826-839.

Timmermann, A., An, S.-I., Kug, J.-S., Jin, F.-F., Cai, W., Capotondi, A., Cobb, K. M., Lengaigne, M., McPhaden, M. J., Stuecker, M. F., Stein, K., Wittenberg, A. T., Yun, K.-S., Bayr, T., Chen, H.-C., Chikamoto, Y., Dewitte, B., Dommenget, D., Grothe, P., Guilyardi, E., Ham, Y.-G., Hayashi, M., Ineson, S., Kang, D., Kim, S., Kim, W., Lee, J.-Y., Li, T., Luo, J.-J., McGregor, S., Planton, Y., Power, S., Rashid, H., Ren, H.-L., Santoso, A., Takahashi, K., Todd, A., Wang, G., Wang, G., Xie, R., Yang, W.-H., Yeh, S.-W., Yoon, J., Zeller, E., Zhang, X. (2018). El Niño–Southern Oscillation complexity. *Nature,* 559(7715), 535-545.

Ting, M. F., Kushnir, Y., Seager, R., Li, C. H. (2009). Forced and Internal Twentieth-Century SST Trends in the North Atlantic. *Journal of Climate,* 22(6), 1469-1481.

Tokinaga, H., Xie, S. P. (2011). Weakening of the equatorial Atlantic cold tongue over the past six decades. *Nature Geoscience,* 4(4), 222-226.

Tseng, W.-L., Tsuang, B.-J., Keenlyside, N. S., Hsu, H.-H., Tu, C.-Y. (2015). Resolving the upper-ocean warm layer improves the simulation of the Madden–Julian oscillation. *Climate Dynamics,* 44(5), 1487-1503.

Vaughan, C., Dessai, S. (2014). Climate services for society: origins, institutional arrangements, and design elements for an evaluation framework. *Wiley Interdisciplinary Reviews: Climate Change,* 5(5), 587-603.

Vecchi, G. A., Delworth, T., Gudgel, R., Kapnick, S., Rosati, A., Wittenberg, A. T., Zeng, F., Anderson, W., Balaji, V., Dixon, K., Jia, L., Kim, H. S., Krishnamurthy, L., Msadek, R., Stern, W. F., Underwood, S. D., Villarini, G., Yang, X. Zhang, S. (2014). On the Seasonal Forecasting of Regional Tropical Cyclone Activity. *Journal of Climate,* 27(21), 7994-8016.

Vigaud, N., Robertson, A. W., Tippett, M. K. (2017a). Multimodel Ensembling of Subseasonal Precipitation Forecasts over North America. *Monthly Weather Review,* 145(10), 3913-3928.

Vigaud, N., Robertson, A. W., Tippett, M. K., Acharya, N. (2017b). Subseasonal Predictability of Boreal Summer Monsoon Rainfall from Ensemble Forecasts. *Frontiers in Environmental Science,* 5, 67.

Vigaud, N., Tippett, M. K., Robertson, A. W. (2018). Probabilistic Skill of Subseasonal Precipitation Forecasts for the East Africa–West Asia Sector during September–May. *Weather and Forecasting,* 33(6), 1513-1532.

Vijayeta, A., Dommenget, D. (2018). An evaluation of ENSO dynamics in CMIP simulations in the framework of the recharge oscillator model, *Climate Dynamics*, *51*(5), 1753-1771.

Vitart, F. (2014). Evolution of ECMWF sub-seasonal forecast skill scores. *Quarterly Journal of the Royal Meteorological Society,* 140(683), 1889-1899.

Vitart, F. (2017). Madden—Julian Oscillation prediction and teleconnections in the S2S database. *Quarterly Journal of the Royal Meteorological Society,* 143(706), 2210-2220.

Vitart, F., Ardilouze, C., Bonet, A., Brookshaw, A., Chen, M., Codorean, C., Déqué, M., Ferranti, L., Fucile, E., Fuentes, M., Hendon, H., Hodgson, J., Kang, H. S., Kumar, A., Lin, H., Liu, G., Liu, X., Malguzzi, P., Mallas, I., Manoussakis, M., Mastrangelo, D., MacLachlan, C., McLean, P., Minami, A., Mladek, R., Nakazawa, T., Najm, S., Nie, Y., Rixen, M., Robertson, A. W., Ruti, P., Sun, C., Takaya, Y., Tolstykh, M., Venuti, F., Waliser, D., Woolnough, S., Wu, T., Won, D. J., Xiao, H., Zaripov, R., Zhang, L. (2016). The Subseasonal to Seasonal (S2S) Prediction Project Database. *Bulletin of the American Meteorological Society,* 98(1), 163-173.

Vitart, F., Robertson, A. W. (2018). The sub-seasonal to seasonal prediction project (S2S) and the prediction of extreme events. *npj Climate and Atmospheric Science,* 1(1), 3.

Wakabayashi, S., Kawamura, R. (2004). Extraction of Major Teleconnection Patterns Possibly Associated with the Anomalous Summer Climate in Japan. *Journal of the Meteorological Society of Japan. Ser. II*. 82(6), 1577-1588.

Waliser, D. E., Jones, C., Schemm, J.-K. E., Graham, N. E. (1999). A Statistical Extended-Range Tropical Forecast Model Based on the Slow Evolution of the Madden–Julian Oscillation. *Journal of Climate,* 12(7), 1918-1939.

Wang, B., Ding, Q., Fu, X., Kang, I.-S., Jin, K., Shukla, J., Doblas-Reyes, F. (2005). Fundamental challenge in simulation and prediction of summer monsoon rainfall. *Geophysical Research Letters,* 32(15).

Wang, B., Wu, R. Fu, X. (2000). Pacific–East Asian Teleconnection: How Does ENSO Affect East Asian Climate? *Journal of Climate,* 13(9), 1517-1536.

Wang, B., Wu, R., Li, T. (2003).Atmosphere–Warm Ocean Interaction and Its Impacts on Asian–Australian Monsoon Variation. *Journal of Climate,* 16(8), 1195-1211.

Wang, B., Xiang, B., Lee, J.-Y. (2013). Subtropical High predictability establishes a promising way for monsoon and tropical storm predictions. *Proceedings of the National Academy of Sciences,* 110(8), 2718.

Wang, L., Yu, J.-Y., Paek, H. (2017). Enhanced biennial variability in the Pacific due to Atlantic capacitor effect. *Nature Communications,* 8, 14887.

Wang, Y., Counillon, F., Keenlyside, N., Svendsen, L., Gleixner, S., Kimmritz, M., Dai, P., Gao, Y. (2019). Seasonal predictions initialised by assimilating sea surface temperature observations with the EnKF, *Climate Dynamics*. 53(9-10), 5777–5797.

Webster, P. J. (1995). The annual cycle and the predictability of the tropical coupled ocean-atmosphere system. *Meteorology and Atmospheric Physics,* 56(1), 33-55.

Webster, P. J., Moore, A. M., Loschnigg, J. P., Leben, R. R. (1999). Coupled ocean–atmosphere dynamics in the Indian Ocean during 1997–98. *Nature,* 401(6751), 356-360.

Weisheimer, A., Doblas-Reyes, F. J., Jung, T., Palmer, T. N. (2011). On the predictability of the extreme summer 2003 over Europe. *Geophysical Research Letters,* 38(5), L05704.

Weisheimer, A., Palmer, T. N. (2014). On the reliability of seasonal climate forecasts. *Journal of the Royal Society Interface,* 11(96), 20131162.

Wheeler, M. C., Hendon, H. H. (2004). An all-season real-time multivariate MJO index: Development of an index for monitoring and prediction. *Monthly Weather Review,* 132(8), 1917-1932.

Woolnough, S. J., Slingo, J. M.. Hoskins, B. J. (2000). The relationship between convection and sea surface temperature on intraseasonal timescales. *Journal of Climate,* 13(12), 2086-2104.

Xiang, B., Zhao, M., Jiang, X., Lin, S.-J., Li, T., Fu, X., Vecchi, G. (2015). The 3–4-Week MJO Prediction Skill in a GFDL Coupled Model. *Journal of Climate,* 28(13), 5351-5364.

Xie, P., Arkin, P. A. (1997). Global Precipitation: A 17-Year Monthly Analysis Based on Gauge Observations, Satellite Estimates, and Numerical Model Outputs. *Bulletin of the American Meteorological Society,* 78(11), 2539-2558.

Xie, S.-P., Annamalai, H., Schott, F. A., McCreary, J. P. (2002). Structure and Mechanisms of South Indian Ocean Climate Variability. *Journal of Climate,* 15(8), 864-878.

Xie, S.-P., Hu, K., Hafner, J., Tokinaga, H., Du, Y., Huang, G., Sampe, T. (2009). Indian Ocean Capacitor Effect on Indo–Western Pacific Climate during the Summer following El Niño. *Journal of Climate,* 22(3), 730-747.

Xie, S.-P., Kosaka, Y., Du, Y., Hu, K., Chowdary, J. S., Huang, G. (2016). Indo-western Pacific ocean capacitor and coherent climate anomalies in post-ENSO summer: A review. *Advances in Atmospheric Sciences,* 33(4), 411-432.

Xie, S.-P., Philander, S. G. H. (1994). A coupled ocean-atmosphere model of relevance to the ITCZ in the eastern Pacific. *Tellus A,* 46(4), 340-350.

Yang, J., Liu, Q., Xie, S.-P., Liu, Z., Wu, L. (2007). Impact of the Indian Ocean SST basin mode on the Asian summer monsoon. *Geophysical Research Letters,* 34(2), L02708.

Yeager, S. G., Danabasoglu, G., Rosenbloom, N. A., Strand, W., Bates, S. C., Meehl, G. A., Karspeck, A. R., Lindsay, K., Long, M. C., Teng, H., Lovenduski, N. S. (2018). Predicting Near-Term Changes in the Earth System: A Large Ensemble of Initialized Decadal Prediction Simulations Using the Community Earth System Model. *Bulletin of the American Meteorological Society,* 99(9), 1867-1886.

Yeager, S. G., Robson, J. I. (2017). Recent Progress in Understanding and Predicting Atlantic Decadal Climate Variability. *Current Climate Change Reports,* 3(2), 112-127.

Yu, J.-Y., Kao, P.-k., Paek, H., Hsu, H.-H., Hung, C.-W., Lu, M.-M., An, S.-I. (2014). Linking Emergence of the Central Pacific El Niño to the Atlantic Multidecadal Oscillation. *Journal of Climate,* 28(2), 651-662.

Yu, J. -Y., Mechoso, C. R. (2001). A coupled atmosphere-ocean GCM study of the ENSO cycle. *J. Climate*, **14**, 2329-2350

Zebiak, S. E. (1993). Air-Sea Interaction in the Equatorial Atlantic Region. *Journal of Climate,* 6(8), 1567-1568.

Zhang, C., Gottschalck, J., Maloney, E. D., Moncrieff, M. W., Vitart, F., Waliser, D. E., Wang, B., Wheeler, M. C. (2013). Cracking the MJO nut. *Geophysical Research Letters,* 40(6), 1223-1230.

Zhang, C. D. (2005). Madden-Julian oscillation. *Reviews of Geophysics,* 43(2), RG2003.

Zhang, L., Wang, B., Zeng, Q. (2009). Impact of the Madden–Julian Oscillation on Summer Rainfall in Southeast China. *Journal of Climate,* 22(2), 201-216.

Zhou, Q., Duan, W., Mu, M. Feng, R. (2015). Influence of positive and negative Indian Ocean Dipoles on ENSO via the Indonesian Throughflow: Results from sensitivity experiments. *Advances in Atmospheric Sciences,* 32(6), 783-793.

Zhou, Q., Mu, M., Duan, W. (2019). The Initial Condition Errors Occurring in the Indian Ocean Temperature That Cause "Spring Predictability Barrier" for El Niño in the Pacific Ocean. *Journal of Geophysical Research: Oceans,* 124(2), 1244-1261.

Zhou, S., Miller, A. J. (2005). The Interaction of the Madden–Julian Oscillation and the Arctic Oscillation. *Journal of Climate,* 18(1), 143-159.

Zhu, J., Huang, B., Kumar, A., Kinter Iii, J. L. (2015). Seasonality in Prediction Skill and Predictable Pattern of Tropical Indian Ocean SST. *Journal of Climate,* 28(20), 7962-7984.