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Initialized Earth system prediction from subseasonal to decadal timescales

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Abstract (200 words max)

Initialized Earth system predictions are made by starting a climate model in a specific observed state, and running the model forward in time for up to ten years. Time slices from subseasonal to seasonal (S2S), seasonal to interannual (S2I), and seasonal to decadal (S2D) are analyzed by different communities for various applications. The premise is that there are processes in the climate system that, if captured in models and realistically initialized, will play out over weeks to years to provide skill, measured as agreement between predictions and observations. Skillful predictions can provide information on future weather and climate features useful for water resource management, infrastructure planning and risk management, estimating coastal impacts, and transportation planning. In this Review, we examine how such predictions are made, how observations are used to validate the models, how we are expanding our understanding of the processes and mechanisms we are trying to predict, and how the underlying and possibly predictable phenomena work. There are encouraging early signs that skillful predictions can be made at the different timescales of interest. Significant challenges remain, including how best to initialize models with observations, reducing model error, and predicting impactful climate system features beyond temperature and precipitation.

1. Introduction

Predictions about possible future states of the weather or climate have always been a central element of meteorology and climatology. Early on it was clear that information about what the weather would be like tomorrow or the day after could be tremendously important for multiple applications, from military to domestic, from alerts about upcoming weather hazards to simple information about how to plan outdoor events. Weather predictions bring many tangible benefits to society, and therefore such predictions have been done for many decades and are supported by governments and institutions around the world.

The tools with which such forecasts are made have become more sophisticated, particularly with the rise of numerical models of the atmosphere that could be run on computers developed after WWII, and with corresponding improved observations of atmospheric variables like temperature and rainfall. To go along with that evolution, our understanding of processes and mechanisms that influence weather prediction has improved along with the models and observations. Today, society almost takes for granted useful weather predictions up to a week in advance that are brought to bear on many aspects of daily life and commerce.

More recently the need for longer term predictions of climate conditions (the statistics of a series of weather events) has arisen for the coming weeks, months, seasons, and years. Such predictions of average conditions of, for example, future temperature, precipitation, and winds started with statistical models and have evolved, with the emergence of global climate models, to include multiple variables including ocean conditions such as surface temperature. For example, ehe requirements of stakeholders for climate information on longer timescales can include hydroclimate conditions months to seasons to years in advance for water resource management and agriculture, and temperature and wind conditions on those timescales for infrastructure planning.

The current framework for predictions of phenomena on various timescales (Merryfield et al., 2020) is illustrated in Fig. 1a with a focus specifically on "initialized predictions" that are made by starting a numerical model of the climate system at a particular point in time, with the observed state of the climate system at that time, and integrating the model forward for days, weeks, months, seasons, or years out to a decade. Phenomena at different points in that time spectrum are categorized by processes and mechanisms in the climate system that produce such phenomena (Fig. 1a), are usually separated by timescale, and are studied by different segments of the climate science community. There is intense interest in near-term predictions of "modes" of variability in the coupled physical climate system, as foreknowledge of their behavior may enhance prediction of societally relevant quantities, such as rainfall patterns and air temperature over large parts of the world.

Prediction on the subseasonal to seasonal (S2S) timescale (~ 2 weeks to 2 months; Vitart and Robertson, 2018; Pegion et al., 2019) has been focused on phenomena such as the Madden-Julian Oscillation (MJO) that affects weather from about two weeks to two months in advance over large areas of the tropics and other regions of the globe, and sudden stratospheric warmings (SSW) that influence weather over parts of Europe and North America on those same timescales. For the seasonal-to-interannual (S2I) timescale (2 to 12 months, Kirtman et al., 2014), a major effort has been made to predict the state of El Nino/Southern Oscillation (ENSO), a phenomenon that involves swings in the sea surface temperatures in the tropical Pacific that can affect regional-global climate, and the extratropical North Atlantic Oscillation (NAO) that affects Europe and North America (Scaife et al., 2014). Stratospheric variability associated with the Quasi-biennial Oscillation (QBO) is another S2I phenomenon that involves year-to-year reversals of the winds in the tropical lower stratosphere and can provide predictability via teleconnections to the surface climate (Baldwin et al. 2001; Marshall and Scaife 2009; Scaife et al 2014b). For the seasonal to decadal (S2D) timescale (about 3 months to ten years; Meehl et al., 2009, 2013), the longer time periods usually involve slowly evolving processes in the oceans that produce long-lived sea surface temperature anomalies. Ocean regimes such as Pacific Decadal Variability (PDV) and Atlantic Multidecadal Variability (AMV) can contribute to variations of not only regional weather and climate across the continents but also global mean surface temperature (GMST).

As noted above, these research efforts involve somewhat different communities, though all rely on similar initialization and verification methodologies (see Tables 1 and S1,2, 3). This constitutes a "seamless prediction" approach where one modeling framework can be used to address prediction across all of these timescales (Palmer et al., 2008).

It must be remembered that predictions of climate phenomena at different timescales all use the same basic methodology. As a model is initialized with observations and run forward in time, the S2S community would analyze the first 1 to 2 months of such predictions, the S2I community would analyze timescales from the first season to about a year, and the S2D community would focus on the interannual to ten-year time frame, where for the later years external forcing provides skill as the effects of the initial state decrease (Fig. 1b). In practice, however, there are currently differences in how the predictions are performed in these different communities with regards to, for example, initialization frequency. S2S models are currently initialized anywhere from daily to once per week, and run for 32 to 60 days, whereas the S2I systems start on run out to several months ahead. To be truly seamless, S2S and S2I could merge by simply having more frequent initialization with S2I, or longer leads with S2S, as is now done in some cases. S2D initialized simulations are run less frequently, and are usually initialized every year with a start date before November 15 (Boer et al., 2016).

The timescales and phenomena mentioned above are in the domain of initialized predictions. For climate change beyond S2D, uninitialized climate model simulations (usually referred to as climate change projections) are performed to determine mainly the effects of changes in external forcings, such as human-produced greenhouse gases, on the climate system. Such simulations have been run since the early days of climate modeling in the 1990s (Meehl et al. 2007) and typically start in the 1800s, then run forward with observed time-varying forcings such as changes in greenhouse gases, human-produced aerosols, volcanic eruptions, and solar variability. Typically many ensemble members are averaged together to determine the effects of these external forcings on the simulated climate. Any unpredictable internal variability is thus averaged out to focus on the externally forced response. The marked difference in initialized prediction is that the internally-generated, naturally-occurring climate variability is not considered noise but is a key aspect of the predictions of time-evolving climate (along with the response to changes in external forcing).

Though research on seasonal prediction using various methodologies, including initialized prediction, has been taking place for several decades (e.g. Barnett et al., 1988), the first paper on initialized decadal-scale climate predictions using a global coupled climate model was published in 2007 (Smith et al, 2007). This initiated a rapid acceleration of research into this new field of climate science to the point where operational systems are now being run (Kushnir et al., 2019). Efforts by individual modeling groups have become standardized with coordinated sets of decadal hindcasts and predictions made available to the research community as part of the Coupled Model Intercomparison Project phase 5 (CMIP5) (Meehl et al 2009, 2013) and currently CMIP6 (Boer et al 2016). The emergence of a number of modeling groups attacking the initialized Earth system prediction problem on S2D timescales with multiple methodologies has produced trial-and-error efforts to see what works and what does not with regards to, for example, initialization, model bias adjustment, and ensemble size (Boer et al 2016; Yeager et al 2018). Meanwhile, the S2S community has coordinated initialized predictions on that timescale through efforts like the S2S Prediction Project and Database (Vitart 2017) and the Subseasonal Experiment (SubX, Pegion et al. 2019). Similarly, the S2I community has their own coordinated efforts for making predictions on that timescale through programs such as the North American Multi-Model Ensemble (NMME) (Kirtman et al. 2014) and the Copernicus Climate Change Service (C3S).

In this review we will address initialized predictions for each of these timescales and associated phenomena, review current methodologies for initialized predictions, discuss the importance of establishing credibility of predictions by assessing skill, and address challenges and future directions.

2. Making Predictions

Before discussing the sources of predictability, we begin by describing the process of initialized prediction, and also focus on the methodological aspects involving validation with observations and measures of prediction skill (the level of agreement between an initialized prediction and the observed state it is meant to predict).

2. 1. Process of initialised prediction

Table 1 provides a brief summary of current activities in the three communities with regards to initialized prediction. Many more details of those efforts are expanded in Tables S1, S2 and S3. These tables illustrate that there are currently many differences among modeling centers with regard to how models are used to make predictions. One difference between the subseasonal and longer time scale prediction systems is the origin of the model. Many S2S prediction systems originate from the numerical weather prediction (NWP) community and utilize data assimilation and advanced methods of ensemble generation. Most of the S2I prediction systems, and all but one S2D prediction system, are based on climate or Earth system models that have been previously used for climate projections and have participated in Coupled Model Intercomparison Project (CMIP)-type simulations. Of the predictions systems described here, S2S prediction models tend to have the highest horizontal resolution in their atmospheric component (Tables S1, S2, S3), with nearly half of the models routinely run with horizontal resolutions of ~ 0.25^{o} to 0.5^{o}, and only one model with resolution coarser than ~ 1^{o}. Seasonal prediction models are fairly evenly distributed between models with ~ 0.5^{o}, 1^{o}, and 2^{o} horizontal resolution. The majority of decadal prediction models have a horizontal resolution of 1^{o}, with only one model with finer resolution of 0.5^{o} x 0.8^{o}. Similar resolutions are used in the ocean models across the different timescales.

The issue of how best to initialize a climate model with observations is a fundamental research question. Modeling groups have applied a variety of approaches such as using a hindcast spin-up in an ocean forced by observed atmospheric conditions (e.g. Yeager et al., 2018), nudging the ocean model to some observed ocean state (e.g. Smith et al., 2013), or using full ocean data assimilation (e.g. MacLachlan et al., 2014).

All of the S2S and S2I prediction models initialize the atmosphere, but only eight out of 14 S2D prediction models do so. Similarly, land is initialized in all S2I systems and in all but one S2S system, but only in six S2D prediction systems. Coupling between the atmosphere, ocean, and sea-ice is crucial for S2D prediction, but not so much for shorter timescales (Fig. 1a). As a result, the role of ocean coupling and initialization in S2S systems is considered less important, and hence 5 out of 18 S2S prediction models are not using a model coupled for the ocean and are not initializing the ocean (Table S1). On the other hand all S2D prediction models initialize the ocean, while the atmosphere is initialized in eight and land is initialized only in fiveof the 14 S2D prediction models (Table S3). S2I prediction falls in the time window where predictability comes from all Earth system components (Fig. 1b), and hence care is typically taken to initialize the ocean and land. Another large difference between the shorter and longer term prediction models is in how the initial variables are initialized: all S2S and S2I prediction models use full fields (e.g. temperature, wind, pressure), whereas about half of the S2D prediction models use anomaly initialization, meaning that an initial condition is constructed by adding observed (or reanalysis) anomalies to the model's climatology (e.g. Polkova et al., 2019, Smith et al 2013b).

Ensemble size is another aspect of prediction systems that varies tremendously between systems and affects predictive skill. This is illustrated for the S2S timescale in Fig. 2a using a 20 member ensemble of S2S hindcasts run with the Community Earth System Model, version 1 (CESM1, Richter et al. 2020). Using only 4 members from the same 20-member CESM1 ensemble yields an anomaly correlation coefficient (ACC, a measure or skill, the higher the ACC number, the greater the skill of the prediction) of global surface air temperature over land of ~ 0.29, whereas using 8 members increases that skill to ~ 0.33. Increasing the number of ensembles further to 16 raises that skill to 0.36. Above 16 ensemble members, the return on investment in larger ensembles diminishes. For individual seasonal prediction systems, ensemble sizes typically range between 10 and 50, although predictions from multiple systems may be combined to form larger ensembles that provide enhanced skill, not least due to ensemble size (e.g., Becker and van den Dool 2016). Similarly, seasonal predictions of the NAO rise slowly with ensemble size and 50 or so members are needed to capture the majority of the skill (Scaife et al., 2014). For S2D prediction, multi-year averaging of predictions with ensembles of at least 20 members have been most useful in predicting features like blocking and the NAO (Smith et al., 2019). For example, using 40 ensemble members, the largest ACC values are about 0.6 for an average of years 2 to 8 in the prediction of the NAO (Fig. 2b) (Athanasiadis et al., 2020). Further increases in NAO skill with ACC of 0.8 are possible with a very large multi-model ensemble (Smith et al 2020) thus demonstrating that large ensembles are needed as the modelled signal to noise ratio is too small.

As previously mentioned and confirmed by comparing Tables S1, S2, and S3, there are currently very few modeling centers that have been able to apply the concept of seamless prediction (i.e. using the same model and initialization technique to predict S2S, S2I and S2D phenomena) due to the numerous practical aspects (e.g. initialization method, initialization frequency, number of ensembles, etc.) that need to be solved before that goal can be reached. The most seamless system is operated by the UK Met Office which is providing S2S, S2I, and S2D forecasts operationally, using almost identical configurations of the model for all prediction systems. NCAR, although not an operational center, is also using the same model, CESM1 to generate S2S, S2I and S2D hindcasts (and predictions for research purposes) using the same modeling framework, although at this time initialization details vary among the three prediction systems.

2.2. Validation using observations

A key element of initialized prediction is having a good understanding of the climate phenomena we are trying to predict. This requires analyses of observations in comparison to the model simulations to provide insights into the processes and mechanisms involved with the phenomena that could provide skillful initialized predictions. On S2S and S2I timescales, the existing observational record provides a much better source of data to verify initialized hindcasts compared to the S2D timescales. In the past century or so-- the period of the instrumental record for sea-surface temperature (SST) and precipitation--there have been roughly 30 ENSO events and perhaps as many as 300 MJO cycles, in contrast to only 3 or so PDV and AMV transitions. And for many areas of the oceans, reliable observations are limited to the latter half of the 20th century (e.g., Deser et al. 2010), further limiting the number of phases of key modes of variability by which to compare S2D predictions. Of course for S2S and S2I phenomena, three-dimensional observed data in the atmosphere and ocean are desired for prediction verification, for understanding of processes and mechanisms, and for initialization of the predictions in the first place (Nie et al., 2019). Such sources of 3D gridded data are limited to the period of the satellite record (dating from the late-1970s) and to reanalyses that assimilate all available observations. Observations earlier in the 20^{th} century are more sparse and reanalyses more uncertain, which make consistent comparisons of prediction skill between the pre- and post-satellite era difficult.

Researchers in the field of initialized Earth system prediction on S2D timescales often cite the short observational record as a factor inhibiting our ability to study phenomena on that timescale. However comparable problems exist for S2I predictions. For example, ENSO can exhibit many different expressions (Capotondi et al., 2015) and undergo large decadal variations (Wittenberg, 2009), thus requiring a long observational record to capture such diversity and low-frequency modulations at sufficient sample size for robust analyses. Added to that, subsurface ocean observations are crucial to understanding slow variations in the climate system, and those observations have even shorter records. Therefore, if the observations are a moving target for verification, this adds to the difficulty of attempting to determine whether or not our physical understanding can help interpret the initialized predictions. Observations of critical atmospheric state variables, known to play a key role in both ENSO and PDV (e.g., surface winds), are similarly scarce. Nevertheless, zonal wind observations that have recently become available have greatly helped to shed some light on processes associated with interannual and decadal timescales of variability (e.g. Nieves et al., 2015; Capotondi et al., 2018).

The particular limitations of instrumental data length and coverage for verification of S2D predictions have pointed to paleoclimate reconstructions to provide a longer record of S2D climate fluctuations to assist the verification exercise. Such records have shown great potential to extend the record backward and provide additional realizations of decadal variability. A number of studies have shown the potential of such reconstructions from natural climate archives (e.g., trees, corals, speleothems) to improve our understanding of decadal climate fluctuations (e.g., Cobb et al. 2013; Emile-Geay et al. 2013; Linsley et al. 2015; Jimenez et al. 2018; Dassie et al. 2018; Buckley et al. 2019; Grothe et al. 2019; Abram et al. 2020) (Fig 3). Additionally, such records can provide insights into the physical mechanisms associated with that variability, such as westerly wind anomalies (Thompson et al., 2015), upwelling (Zaunbrecher et al., 2010; Druffel et al. 2014), and gyre circulation (Sanchez et al., 2016), as well as potential links among major modes of variability (e.g., ENSO and IOD, Abram et al. 2020). Recent advances in paleoclimate synthesis (e.g., Konecky et al., in revision; Neukom et al. 2019; McGregor et al.

2015; Tierney et al. 2015), full field paleoclimate reconstructions, and (paleo) data assimilation (DA) techniques (e.g., Hakim et al., 2016; Steiger et al. 2018) have also identified interactions among modes of low frequency variability and their impact over land (Steiger et al. 2019). Finally, development and expansion of proxy system models and toolboxes (PSMS, Evans et al. 2013; Dee et al. 2015; Dee et al. 2018)—models that describe the physical, chemical, and biological processes by which climate is incorporated into the "proxy" archive—have provided an essential framework for proxy-model comparisons (e.g., Thompson et al. 2011; Dee et al. 2015; Jones and Dee 2018; Konecky et al. 2019). Additionally, PSMs and the assimilation of paleo-data in the DA framework (e.g., Dee et al. 2016) have provided a rigorous assessment of the uncertainties that may contribute to the disagreement among paleoclimate reconstructions and models in the magnitude and evolution of decadal climate variability (e.g., Thompson et al. 2013; Conroy et al. 2017; Dee et al. 2017; Loope et al., 2019 in revision). All of these advances in paleoclimate research not only help with the verification of climate model simulations of phenomena of interest, particularly on the S2D timescale, but also inform the credibility of initialized predictions.

One challenge in identifying modes of internal climate variability in observational data for verifying S2D predictions is that it is difficult to objectively separate forced (natural + anthropogenic) and internal decadal-to-multidecadal climate variability, and there is an ongoing debate in the literature over best practices for attempting such signal separation (Mann and Emanuel 2006; Mann et al., 2014;2016; Steinman et al, 2015; Frankcombe et al, 2015;2018; Cheung et al., 2017).

2.3. Prediction skill

To account for model drifts and biases, the skill of initialized predictions is typically evaluated in terms of anomalies that are departures from some measure of mean climate. The calculation of anomalies and correction of model biases are addressed together, typically by calculating and removing the model climatology. For S2S predictions, the common methodology is to calculate a lead time dependent model climatology from a set of hindcasts from which to compute anomalies, but such a procedure is complicated due to the inhomogeneous nature of current subseasonal prediction systems (Pegion et al., 2019; Tippett 2018; Becker et al., 2014). For S2I predictions, this is accomplished by averaging over all years of the hindcast for a particular start time and lead or target time (Tippett 2018; Becker et al., 2014), thereby assuming stationarity of biases and drifts in the predictions.

For S2D predictions, there are multiple approaches for computing anomalies, and the problem of model drift from the observed state is at least as acute at this timescale (Fig. 4). One is to compute the model climatology of drifts from hindcasts over a prediction period of interest (e.g. average of lead years 3 to 7), and subtract that climatology from each 3 to 7 year prediction (Doblas-Reyes et al., 2013). A second method is to compute a mean time-evolving drift from a set of hindcasts, subtract that mean drift from a prediction, and compute anomalies as differences from the drift-adjusted prediction and time period (e.g. the previous 15 year average) immediately prior to the prediction (Meehl et al 2016). The former should work well for short timescale predictions where externally-forced trends are less of a factor, but may be problematic for longer timescales. The latter could work better to reduce the effects of an externally-forced trend, but raises the issue of how big a role the recent observed period should play in prediction verification. A third method that is useful when long-term trends in the hindcasts differ from observations is to correct biases in the trends in addition to those in the mean model climatology over the hindcast period (Kharin et al., 2012).

All three communities, S2S, S2I, and S2D, are dealing with similar issues regarding model resolution, hindcast period, model components, ensemble size, and initialization techniques. Models may also underestimate the magnitude of predictable signals relative to unpredictable internal variability, especially on seasonal and longer timescales in the extra-tropical north Atlantic sector. This leads to the counterintuitive implication that models are better at predicting the real climate variability than they are at predicting themselves and has been called the 'signal to noise paradox' (Scaife and Smith 2018). Consequently, to make the most skillful forecasts, it is necessary to take the mean of a very large ensemble to extract the predictable signal and then adjust its variance (Smith et al., 2019). Because the magnitude of predictable signals are too small, skill measures that are sensitive to this, including error measures and probabilistic measures, underestimate the potential skill. Furthermore, so-called "perfect model" techniques that assess a model's ability to predict a different realization of itself, can both overestimate and underestimate predictability. In both cases, they do not provide a reasonable estimate of the upper bounds of predictability, and may seriously underestimate the actual predictability of the climate system (e.g. Kumar 2009, Scaife and Smith, 2018; Boer et al., 2019). This signal to noise paradox occurs when the signal to noise ratio is larger in observations than models. It is not caused by initialization since it is also seen in uninitialized climate simulations of the historical period (Sévellec and Drijfhout, 2019; Zhang and Kirtman 2019), and potentially in modelled responses to volcanoes and solar variations (Scaife and Smith 2018). Although this highlights an important model deficiency, it is encouraging because it also implies an optimistic potential to use climate models to predict the observed system and is being actively studied to better understand the implications for understanding and analyzing initialized predictions (e.g. Weisheimer et al., 2019).

One issue that remains to be resolved for S2D is whether there are indeed well-defined timescales of variability that are distinct from the background of climatic noise, i.e. modes of large-scale variability that display a statistically significant spectral peak in the decadal-to-multidecadal range. Such signals offer the best prospect for long-term predictability. An analysis of the CMIP5 control simulations found patterns and timescales of decadal variability in the Pacific associated with a type of PDV called the Interdecadal Pacific Oscillation (IPO) to resemble observations but with lower amplitude (Henley et al., 2017). A subsequent analysis of three generations of climate models (CMIP3, CMIP5 and CMIP6) shows progressive improvement over time of climate models' simulations of PDV (Fasullo et al., 2020). Another study did not find convincing evidence across state-of-the-art coupled models for distinct oscillatory signals, other than on the interannual (3-7 year) El Nino/Southern Oscillation timescale (Mann et al 2020). However, low frequency phenomena on decadal timescales are usually characterized by a window of variability in the 10 to 30 year band and not by distinct oscillations.

Strong low-frequency variability in paleoclimate "proxy" records, which is not captured by most climate models, suggests that either models do indeed underestimate low-frequency modes of variability, that proxy observations are characterized by non-climate memory or red noise, or some combination thereof (Ault et al., 2013Laepple and Huybers 2014a; Parsons and Loope 2017; Loope et al. in review; Loope et al. accepted). Even if there is no distinct low-frequency (oscillating) phenomenon, predictability on decadal timescales could also come from memory and slowly varying components of the Earth system, and initialization would be expected to contribute to skill in such cases.

Clearly a major challenge for initialized prediction on any timescale is the mean drift of the model away from its initialized state to its preferred systematic error state (Fig. 4). All the efforts at bias adjustment and drift correction arise from the fundamental characteristic of model error. Thus, significant improvements in initialized prediction could be realized by reducing model error. This is easier said than done since model improvements rely on increases in understanding of the climate system and increases in computer power to run higher resolution models.

3. S2S initialized predictions

Subseasonal predictability is largely an initial value problem, in which primarily atmosphere, ocean, land and sea-ice contriute to prediction skill on the subseasonal time scale through their memory of the initial state.(Fig. 1a,b, NASEM 2017; NRC 2010). Therefore, initialization of atmosphere and land, including generation of ensemble spread, are treated carefully in the S2S models. Ocean initialization and ocean coupling can also play a significant role at subseasonal timescale especially in the tropical regions, although it is difficult to represent these processes accurately and ocean initialization and coupling to the ocean model is sometimes less of a priority at these timescales. Modes of variability such as the MJO that exhibit a quasi-oscillatory behavior are additional sources of subseasonal predictability (Robertson and Vitart, 2018; Pegion et al., 2019), as is the stratosphere that affects surface climate via stratosphere-troposphere coupling and teleconnections (Butler et al., 2019). Though NWP targets deterministic predictions of the time evolution of individual storm systems on timescales of days and utilizes the highest practicable model resolution to accurately simulate such storm systems, some S2S models can afford high enough resolution to predict the genesis and evolution of tropical cyclones (e.g., Fudeyasu et al. 2008), while some S2I models permit predicting tropical cyclone track density (Vecchi et al. 2014).

a. Modes of variability

The MJO, a planetary-scale convectively coupled phenomenon varying within a 30 to 60-day period, is recognized as one of the leading sources of subseasonal predictability (Kim et al., 2018). The strong interaction between the tropics and extratropics on subseasonal timescales provides a source of global subseasonal prediction skill (see Stan et al., 2017 for detailed review). The recent international Subseasonal-to-Seasonal Project (S2S) and Subseasonal Experiment (SubX) forecast models can predict the MJO skillfully up to 4 weeks (Vitart 2017; Kim et al., 2019; Lim et al., 2018). However, challenges remain (e.g., the Maritime Continent "barrier") to MJO prediction, and mean-state versus MJO trade-off issues (Kim et al., 2018). As the MJO propagates eastward from the Indian Ocean to the western Pacific, the MJO-associated diabatic heating induces atmospheric Rossby-wave propagation into the extratropics, thus modulating the weather therein and providing predictability sources for extreme events such as storm tracks (Zheng et al., 2019), atmospheric rivers (DeFlorio et al., 2019), and tornados (Baggett et al., 2018). Skill has been shown in predicting the MJO in a multi-model framework consisting of six SubX models for week three predictions averaged over days 15-21 (Pegion et al., 2019; Fig. 5). Most of these models are able to reproduce the eastward propagation of outgoing longwave radiation (OLR) anomalies (associated with convection anomalies), however some cannot reproduce the propagation across the Maritime Continent (eastward of 120^{o}E), noted above as the “barrier” problem.

S2S variability and related extremes in large regions of Europe and North America are largely influenced by the NAO. Studies using the NCEP Climate Forecast System version 2 (CFSv2) and the Met Office Global Seasonal forecast System 5 (GloSea5) suggests that the NAO exhibits predictability out to months ahead (Riddle et al. 2013; Scaife et al. 2014). All of the SubX models demonstrated significant NAO skill at week 3 (Pegion et al. 2019). The NAO is dependent on the state of ENSO (Broennimann et al. 2007), which serves as a lower boundary condition in subseasonal forecasts. It is also affected by sea-ice and the stratosphere (described below).

b. Initial state

The land surface, specifically soil moisture, is a source of predictability on S2S timescales for temperature and precipitation because it varies more slowly than the atmosphere (NAS 2010; NASEM 2017). The storage of moisture in the soil impacts the atmospheric energy budget through changes in evaporation (NAS 2010; NASEM 2017). In particular, the subseasonal timescale has been identified for variations in soil moisture that have their largest contribution to predictability (Dirmeyer et al., 2018). This predictability is most pronounced during boreal spring and summer because variability is less dominated by mid-latitude synoptic systems than during winter (NAS 2010; NASEM 2017). The contribution of soil moisture anomalies to subseasonal predictability varies regionally, with the largest contribution in regions of strong land-atmosphere interactions (e.g. Koster et al., 2004). Since the land-surface (e.g. soil moisture) is an important source of S2S predictability, it is initialized in most current operational subseasonal prediction systems and all research subseasonal systems (Tables S1, S2). The proper initialization of soil moisture anomalies has been shown to provide improved skill for subseasonal predictions of temperature and precipitation, though model errors impact the full realization of this skill (Koster et al., 2010; Koster et al., 2011; Seo et al., 2018; Diremeyer et al., 2018).

Ocean-sea ice-atmosphere coupled models are now routinely used for operational S2S initialized predictions, as the coupling of the atmosphere to the ocean and sea-ice are thought to become important for lead times longer than two weeks. Sub-seasonal prediction of sea-ice has many potential applications, especially in the Arctic region. Yet, this potential has not yet been widely investigated. There is a growing demand for reliable predictions of Arctic sea-ice up to months ahead, due to the increased human activities in the region as sea ice retreats. Currently, the best subseasonal models show skillful forecasts of more than 1.5 months ahead (Zampieri et al., 2018). Yet, many current operational forecast models lack skill even on timescales of a week, hence, there is more work to be done to improve the S2S forecast skill of Arctic sea-ice variables.

Sea-ice conditions (such as the location of the sea-ice edge) can have significant feedbacks with the atmosphere and hence impact the forecast of the coupled system in initialized predictions (Jung et al., 2016). Studies show that the largest midlatitude forecast skill improvements are due to improved Arctic predictions in regions over eastern Europe, northern Asia, and North America (Jung et al., 2014). There are studies that show a link between sea-ice reduction in the Arctic and anomalous anticyclonic circulation over eastern Europe and Russia that can influence predictability in the region on subseasonal to seasonal timescales (e.g., Semmler et al., 2012; Yang and Christensen, 2012, Jung et al., 2014). The potential for skillful initialized predictions of Arctic sea-ice on S2S timescales has improved significantly in the last decade, yet there is still a lot more to be explored and improved. We still need to understand what are the key processes driving sub-seasonal variations of sea-ice and improve the representation of these processes in the S2S models. Improved coupled data assimilation of the ocean, sea-ice and the atmospheric coupled system can help improve initial conditions for coupled forecasts and concomitantly the forecast skill of features that are sensitive to the initial state (Subramanian et al., 2019; Penny et al., 2019).

c**. Stratosphere**

The largest recognized influence of the stratosphere on the troposphere comes from extreme states of the stratospheric polar vortex, particularly sudden stratospheric warmings (SSWs). SSWs are followed by tropospheric circulation anomalies that can last up to 60 days and resemble the negative phase of the NAO (Baldwin and Dunkerton,2001; Baldwin et al.,2003 Butler et al., 2014). S2S forecasts initialized near the onset of SSW thus show increased skill for mid- to high-latitude surface climate (Sigmond et al., 2013) and seasonal predictability of the NAO is dependent on the presence of sudden stratospheric warmings in ensemble predictions (Scaife et al., 2016). TheQBO is the primary mode of variability in the tropical lower stratosphere, and can influence the troposphere on S2S timescales by influencing the strength of the stratospheric polar vortex (Holton and Tan 1980; Anstey and Shepherd 2014), affecting the subtropical jet and storm tracks (Garfinkely and Hartman 2010; Wang et al., 2018), and also affecting the strength of the MJO (Yoo and Son 2016 Son et al., 2017). The MJO has been shown to influence the NAO via the stratospheric polar vortex on a subseasonal timescale (Barnes et al. 2019).

4. S2I initialized predictions

For the most part, S2I initialized predictions are relatively mature compared to either S2S or S2D predictions. This is evidenced by the number of national operational meteorological services that maintain state-of-the-art initialized S2I prediction systems (Kirtman et al., 2014; Tompkins et al., 2017; and example websites https://www.copernicus.eu/en; https://www.apcc21.org/main.do?lang=en). From the perspective of operational predictions, the examples noted here primarily rely on a multi-model approach (e.g., the NMME; https://www.cpc.ncep.noaa.gov/products/NMME/). This is largely based on pragmatic considerations where model diversity is used to quantify forecast uncertainty and improved forecast reliability (Kirtman et al., 2014). Nevertheless, research into other techniques for resolving forecast uncertainty and improving reliability such as perturbed physics ensembles (REF) or stochastic physics (Berner et al., 2008) remain active. Primary sources and mechanisms of S2I predictability consist of slowly evolving boundary conditions of SST, land-surface conditions (moisture, snow cover), sea-ice variations, and stratospheric state. Additional predictability might be gained from atmospheric composition which is typically not well represented in S2I models. Successful initialized Earth system predictions, consequently, require models or tools that are able to predict the evolution of these slowly evolving boundary conditions, their interactions with the atmosphere and with each other.

a. ENSO

Unquestionably, the largest source of S2I predictability is associated with the canonical ENSO that maximizes SST anomalies in the eastern Pacific. This canonical ENSO is an intrinsically coupled ocean-atmosphere phenomenon that develops, grows, decays and even can reverse phase through complex feedbacks among atmospheric winds, SSTs and thermocline variations (Kirtman et al. 2013). ENSO provides skill in rainfall across the tropics (Scaife et al., 2018) and in surface climate across the globe (Hu et al., 2020). Observational, theory and modeling studies have clearly demonstrated that the predictability of the canonical ENSO is largely derived from sub-surface ocean processes. Specifically, in the deep tropical Pacific the atmosphere winds and SST are largely in equilibrium and the sub-surface temperature or thermocline variations are in dis-equilibrium, and capturing this dis-equilibrium in the initial state in earth system models is the primary mechanism for predictability.

Overall, current state-of-the-art prediction systems are able to predict SSTs in the eastern Pacific up to 6-9 months in advance with modest skill. This is particularly true for forecasts initialized in June and verifying in the following boreal winter. Current prediction systems consistently struggle to predict through the boreal spring season (i.e., the so-called spring prediction barrier; Tippet et al., 2020). The rapid onset or initiation of canonical ENSO events also remains a challenge - this is largely a challenge because onset often requires triggers (e.g., westerly wind bursts, McPhadden, 1999) which are largely stochastic in nature. Nevertheless, there are modeling studies that suggest that including westerly wind bursts (or other triggers) as stochastic parameterizations can improve model simulations of ENSO (Tan et al., 2020) and forecast skill (Lopez and Kirtman, 2014).

Much of the discussion above has focused on canonical ENSO events that have their largest amplitude in the eastern Pacific. Recently, however, the diversity of ENSO events has come into focus (see Capotondi et al., 2015) with particular attention on events that tend to have their largest SST anomalies displaced from the eastern Pacific. ENSO diversity raises predictability issues in terms of mechanisms such as Pacific Meridional Modes (e.g., Vimont et al., 2014; Larson and Kirtman, 2013; Capotondi and Sardeshmukh, 2015; Amaya, 2019), forecast skill (e.g., Larson and Kirtman, 2014, Ren et al., 2016), teleconnections (Infanti and Kirtman, 2016), multi-year events (DiNezio et al., 2017), and interpretation in the paleo-record (Freund et al. 2019)--many of which remain unresolved.

b. Other modes of Ocean Surface Temperature variability

While not as dominant as ENSO, Tropical Atlantic SST anomalies are also predictable on S2I time-scales. The SST anomaly variability is broadly categorized into two spatial patterns. The first is often referred to as the "Atlantic Nino" and involves many of the feedback mechanisms noted for ENSO (e.g., Chang et al., 2006). The Atlantic Nino is shorter lived and weaker than ENSO and typically is estimated to be less predictable than ENSO. The second pattern of variability is usually referred to the Atlantic Meridional Mode (AMM) because it is characterized as a north-south dipole that straddles the equator with largest amplitudes displaced from the equator (Kushnir et al., 2006). Current estimates suggest that AMM is predictable one to two seasonas in advance and the mechanisms for predictability largely rest with near surface air-sea interactions (i.e., thermocline variability is of secondary importance). Systematic errors with current initialized Earth prediction systems continue to seriously limit our ability to predict tropical Atlantic S2I variability.

Much like the Atlantic, Indian Ocean SST anomaly variability is smaller and less predictable than the Pacific, but is important for regional teleconnections and impacts. Indian Ocean SST anomaly variability has three distinct patterns of interest: (i) the so-called Indian Ocean Dipole (IOD) that can be triggered by ENSO but can also emerge independently of ENSO (Saji et al. 1999; Huang and Kinter 2002); (ii) a basin wide pattern that is an ENSO teleconnection (e.g. Krishnamurthy and Kirtman, 2003); and (iii) meridional mode pattern similar to that in the Atlantic (Wu et al., 2008). The IOD also can affect processes on the S2S timescale (Shinoda and Han 2005), including the MJO.

With initialized Earth system prediction systems, the basin wide pattern has prediction skill comparable to ENSO largely due to its connection to ENSO, whereas the models struggle to beat persistence with respect to the IOD (Zhu et al., 2015) except in some large amplitude cases (e.g. Lu et al., 2017).

c. Land Surface Processes

Slowly varying S2I soil moisture anomalies influence Prediction skill of precipitation and temperature (Shukla, 1998; Paolino et al. 2011). Soil moisture affects surface turbulent heat fluxes which then translate into surface temperature and rainfall anomalies. Overall, current understanding is that the memory due to large soil moisture anomalies in the initial conditions last about 2-3 months (Dirmeyer, 2003), but there are also case-by-case examples where the predictability can be considerably longer, particularly for surface temperature. In a large sample of initialized Earth system prediction experiments, Infanti and Kirtman (2016) argue that forecast skill could be considerably improved by reducing model error in the land surface component along with air-land interactions.

d. Stratosphere

Improved surface prediction resulting from stratosphere-related processes has been demonstrated in several studies on the seasonal timescale. Marshall and Scaife (2010) have shown that a GCM with higher vertical resolution in the stratosphere captures SSWs earlier than the lower vertical resolution model, and has a positive influence on the simulations of European surface climate at seasonal timescales. The QBO has also been shown to lead to enhanced predictability on seasonal timescales (e.g. Boer and Hamilton (2008); Marshall and Scaife (2009)) including the predictability of the NAO (Scaife et al., 2014).

e. Atmospheric Composition

There are additional sources and mechanisms for seasonal to interannual predictability that are not particularly well modeled in S2I prediction. For example, slowly evolving greenhouse gases such as CO_2 and methane are known to be a source of forecast skill (e.g., Doblas-Reyes et al., 2006). However, an approximate time-history of CO_2, methane and CFCs is typically specified and not predicted thus limiting the potential to capture short-term variability or regional effects. Moreover, dust and aerosol concentrations on S2S and S2I time-scales are known to affect human health, but these changes in atmospheric composition are usually not included in our prediction systems.

5. S2D initialized predictions

There is a high level of interest in, and expectations of, initialized Earth system predictions on timescales beyond S2S and S2I. For example, even with the limitations noted earlier, there is evidence of skill in predicting surface temperature on S2D timescales (Fig. 6), with less current skill in predicting precipitation and sea level pressure (e.g. Smith et al., 2019). Despite showing less skill than temperature predictions, decadal predictions of precipitation do show significant positive correlation with observed rainfall in some regions when using large multi-model ensembles (Smith et al., 2019), and initialization seems to contribute to this skill in the Sahel and parts of the Amazon. These skillful predictions of precipitation over land indicate potential benefit to communities from multi-year predictions. In particular, summer drought indicators in major European agricultural regions have been shown to be predictable on multi-year timescales (Solaraju-Murali et al., 2019).

Processes and mechanisms have been identified that could provide skill for fundamental quantities like SST in initialized predictions. Attention has been focused on AMV (Cassou et al., 2018, also referred to as the Atlantic Multidecadal Oscillation, AMO, Ting et al.,2009) and associated climate impacts (Knight et al., 2006; Zhang and Delworth 2006). Predictions of PDV (Cassou et al., 2018; Liu and DiLorenzo, 2018), which is often described in terms of the IPO (Power et al., 1999) over the Pacific basin, and the Pacific Decadal Oscillation (PDO Mantua et al., 1999; Newman et al., 2016) over the North Pacific, are also of great interest. Other modes of variability associated with decadal timescales include the Meridional Modes (Chiang and Vimont, 2004) and the North Pacific Gyre Oscillation (NPGO, DiLorenzo et al., 2008) in the North Pacific. Decadal variability in the Indian Ocean (Han et al 2014a) could affect interannual variability such as the IOD and warming events near the Australian west coast (Feng et al. 2015; Ummenhofer et al., 2017).

Some of the biggest challenges facing initialized prediction on the S2D timescale, which are not as big a factor in S2S and S2I predictions, arise because of the relatively short duration of the observational record as noted earlier and a limited understanding of the processes we try to predict in this relatively new field of climate science (Kirtman et al., 2013). Here we review the evidence for processes and mechanisms acting on the S2D timescale that could contribute to the skill of initialized predictions (Kushnir et al., 2019; Smith et al., 2019).

5.1 Global temperatures

The idealized “rising staircase” (Fig. 7a) of global mean surface temperature (GMST) trends represents actual epochs of larger or smaller amplitude positive GMST trends (Fig. 7b) in a world with steadily increasing positive radiative forcing from increasing GHGs (Kosaka and Xie, 2016). This means that the entire Earth system warms steadily, but the manifestation of that warming at the Earth’s surface on decadal timescales depends on how heat is redistributed in the climate system. If more heat remains near the ocean surface the GMST rate of warming will be larger, but if more heat is distributed into the deeper ocean, then the GMST trend will be reduced (Tung and Chen, 2018). It is recognized that the slowdown in the rate of GMST warming in the early 2000s likely was a combination of internal variability from the negative phase of the IPO in the Pacific (England et al., 2014; Fyfe et al., 2016; Xie and Kosaka 2017; Seager et al., 2019) and/or variations in the strength of the AMOC (Chen and Tung, 2014). These internal modes re-distributed heat into the subsurface ocean, although there is disagreement on whether the heat is primarily stored in the tropics (Nieves et al., 2015), or at high-latitudes (Tung and Chen, 2018). However, external forcing from a collection of moderate sized volcanic eruptions (Santer et al 2017) and from anthropogenic aerosols (Smith et al., 2016), may have also played a role in the slowdown, though this latter issue is not entirely settled (Oudar et al., 2018).

Initialized predictions have been shown to successfully predict the onset of the warming slowdown, linked to increased ocean heat uptake in the tropical Pacific and Atlantic oceans (Guemas et al., 2013; Meehl et al., 2014). Spatial patterns of predicted 20-year surface air temperature trends have been shown to depend on the initial state of the Pacific Ocean (Bordbar et al., 2019), with initialised model predictions exhibiting a large spread in projected multi-decadal global warming unless the initial state of the Pacific Ocean is known and well represented in the model. Apart from its link to the recent global warming slowdown, negative phase of the IPO has also been linked to regional climate changes at higher latitudes, including the more rapid rate of Arctic sea ice decrease in the early 2000s (Meehl et al., 2018) and Antarctic sea ice expansion during that same period (Meehl et al., 2016a; Purich et al. 2016).

Statistical methods (Mann et al., 2016) and initialized predictions (Meehl et al., 2016b; Thoma et al., 2015) foretold a transition of the IPO in the tropical Pacific from negative to positive in the 2014-2015 time frame, with a resumption of more rapid rates of global warming. Subsequently, there is observational evidence that rapid Antarctic sea ice retreat started around the time of the IPO transition to its positive phase (Meehl et al., 2019).

There is a chronic shortage of observed data in the ocean to document heat redistribution, though in models this redistribution has been shown to involve the subtropical cells in the Pacific, Antarctic Bottom Water formation, and the AMOC in the Atlantic (Meehl et al 2011; 2013) as well as changes in the zonal slope of the equatorial thermocline (England et al., 2014; Yin et al., 2018) associated with changes in tropical winds. However, deciphering decadal timescale variability in the observed climate system, and how to interpret such variability in the context of initialized predictions, is complicated by the presence of external forcings (such as aerosols) that can produce decadal variability in the Pacific (e.g. Smith et al., 2016; Kuntz and Schrag, 2017) or Atlantic (Booth et al., 2012; Watanabe and Tatebe, 2019) with similar patterns to presumptive internally generated decadal climate variability (e.g. Xie et al., 2013). There is also evidence that solar forcing can introduce decadal timescale variability (e.g., Menary and Scaife, 2014), although this is an area of continuing debate (e.g. Chiodo et al., 2019).

5.2 **Pacific Ocean**

The "ENSO-like" PDO and IPO patterns have been recognized in the literature since the late 1990s (e.g. Zhang et al., 1997). They are typically identified through empirical orthogonal function (EOF) analysis of monthly North Pacific SST anomalies for the PDO, and Pacific basin 13-year low-pass filtered SST anomalies for the IPO (or regional SST anomalies, e.g. the "tripole index" of Henley et al., 2015). If defined for the Pacific basin, the PDO and IPO are virtually indistinguishable (Han et al 2014). Both have Pacific basin-wide ENSO-like patterns (Chen and Wallace, 2015), and the IPO has been connected to GMST trends (Kosaka and Xie 2013; England et al., 2014; Thompson et al. 2015; Dai et al., 2015; Meehl et al., 2016c). While they have been often regarded as physical "modes" of variability, it has become increasingly clear that these patterns result from the superposition of different processes, including atmospheric teleconnections from the tropics, "re-emergence" of subsurface temperature anomalies to the ocean surface during periods of deepening of the mixed layer, and midlatitude westward propagation of baroclinic oceanic Rossby waves (Newman et al., 2016). The agents in the system that produce such variability are crucial to understand in the context of validating initialized S2D predictions.

Decadal variability in the tropical Pacific is of particular interest to S2D predictions as it is associated with decadal ENSO modulation (Okumura et al., 2017). ENSO events tend to have a larger amplitude and be centered in the eastern Pacific during warmer decadal epochs (positive IPO phases), while they are weaker and primarily peaking in the central Pacific during colder decadal periods (negative IPO phases; Newman et al., 2016). These differences in ENSO characteristics are thus relevant to the credibility of S2I initialized predictions as well, and have been related to changes in the equatorial Pacific mean state, particularly changes in the zonal wind forcing and zonal thermocline slope (Fedorov and Philander, 2000; Capotondi and Sardeshmukh, 2015). In the observational record, decadal changes in ENSO appear to be associated with changes in the system dynamics (Capotondi and Sardeshmukh, 2017), while long model simulations suggest a purely stochastic origin, withdecadal epochs characterized by different ENSO behaviors (Wittenberg et al., 2014). High-resolution paleoclimate records provide further evidence for a highly variable ENSO system (Tudhope et al. 2001; Cobb et al. 2003; Cobb et al. 2013; Grothe et al. 2019); nevertheless, the growing network of records provides support for potential forced changes in ENSO, including weakened ENSO variability between 3-5ka and enhanced ENSO variability over the past 5 decades (McGregor et al. 2013; Grothe et al. 2019). However, it is also unclear whether ENSO is responding to the slow changes in the mean tropical conditions, or whether those conditions result from changes in ENSO itself (Rodgers et al., 2000).

Various ocean processes have been linked to decadal SST variations in the tropical Pacific which, if simulated adequately, can contribute to S2D initialized prediction skill. These include changes in the strength of the upper-ocean wind driven circulation (the Subtropical-Tropical Cells, or STCs; McPhaden and Zhang, 2002; Capotondi et al., 2005), propagation of salinity compensated temperature anomalies (“spiciness” anomalies) from subtropical regions to the equator in the ocean interior (Schneider, 2000), the recharge-discharge of heat content from the “reservoir” in the western off-equatorial tropics (Meehl et al., 2016b), influences from the South Pacific (Okumura, 2013), or stochastic interactions with ENSO (Okumura et al., 2017). Tropical and subtropical wind variations associated with tropical-midlatitude interactions play a critical role in forcing the above processes, but it is unclear if these wind variations are stochastic in nature or are a response to the decadal SST anomalies themselves (e.g., Meehl and Hu, 2006; Farneti et al., 2014). It is also unclear how the patterns of S2D SST variability in the Pacific associated with meridional modes or the North Pacific Oscillation (NPO) and associated NPGO, which share some characteristics with the IPO/PDO, are related in the context of overall PDV phenomena (Furtado et al., 2012; Di Lorenzo et al., 2015).

5.3 Atlantic Ocean

North Atlantic basin-wide SST variability exhibits clear multi-decadal variability, over the past century and a half instrumental record, even if no time filtering is applied (Kushnir, 1994; Enfield et al., 2001). If such variability could be predicted on S2D timescales, there would be improved skill of S2D initialized predictions over this region and possibly the surrounding continents (Zhang et al., 2019). As noted earlier, this multidecadal change has been referred to as the AMO and more recently more generically as AMV emphasizing its irregular, non-periodic behavior. Early investigators emphasized its largely uniform spatial structure, in contrast to the banded multi-polar pattern of interannual SST variability. This was thought to involve decadal-timescale variations of the ocean circulation (Bjerknes, 1964; Delworth et al., 1993; Knight et al. 2005 and 2006), in particular the fluctuations of the AMOC, an association largely based on coupled model analyses (e.g. Kim et al, 2018; Zhang et al., 2019; Yeager and Robson, 2017). Research has linked the AMV and AMOC to the broad spectrum variability of the NAO, where the latter is seen as forcing the former (Delworth and Greatbatch, 2000; Delworth and Zeng, 2016; Delworth et al., 2016, 2017). Whether the interaction is coupled remains uncertain although a model for such relation has been proposed (Goodman and Marshall, 1999; Czaja and Marshall, 2001). Predictions of AMV could thus play a role in skillful predictions of the NAO (Smith et al., 2020) and blocking, and thus improve predictions for weather and climate over Europe (Scaife et al., 2014; Athanasiadis et al., 2019). However, a recent study shows high decadal NAO skill that is not solely forced by AMV (Smith et al 2020). Furthermore, recent studies sparked an intense debate by pointing at the likelihood that external forcing from a combination of anthropogenic and natural aerosols and changes in greenhouse gas concentrations, played a role in the observed AMV time evolution during the 20th century (e.g. Booth et al., 2012; Bellomo et al., 2017; Murphy et al., 2017) and perhaps as far back as the Little Ice Age (Knudsen et al., 2014). Part of the uncertainty regarding the origin of the AMV could be related to the metric used to identify the phenomenon, namely one that derives from measuring it by averaging the SST over the entire North Atlantic Basin and thus possibly pooling together the impact of several mechanisms (Terray, 2012). In particular, the connection between AMOC and SSTs in the subpolar gyre could be stronger than the influence of external forcing (Watanabe and Tatebe, 2019). This may explain why coupled model, initialized decadal prediction of subpolar gyre SST was shown to be successful (Msadek et al., 2014; Robson et al., 2012 and 2014; Yeager and Robson, 2017).

5.4 Indian Ocean

Although of lower amplitude compared to decadal fluctuations in the Pacific or Atlantic, prominent decadal variability has been detected in the Indian Ocean (Han et al. 2014a). Although it remains unclear whether or not the Indian Ocean possesses a decadal mode with a physical mechanism, the basin-wide warming/cooling patterns of decadal SSTs and upper ocean heat content (0-400m averaged temperature) have recently been shown to characterize decadal-timescale variability in the Indian Ocean (Han et al., 2014a,b; Li Yuanlong et al. 2019). Significant decadal variations of the IOD have also been shown (Song et al. 2007; Tozuka et al. 2007, Abram et al. 2020). Furthermore, a rapid rise in Indian Ocean subsurface heat content in the 2000s in observations and model simulations is associated with a redistribution of heat from the Pacific to the Indian Ocean and has been suggested to account for a large portion of the global ocean heat gain during that period (Lee et al., 2015, Nieves et al., 2015). IPO variability could thus be modulating Indian Ocean variability, transmitted through both the atmospheric and oceanic bridge (e.g., Jin et al., 2018a,b). These low-frequency modulations have been implicated in modulating interannual variability associated with the Indian Ocean Dipole mode on decadal timescales (Annamalai et al., 2005, Ummenhofer et al., 2017). The interactions between the Indian Ocean and the two other ocean basins have been described in observations,model simulations, and paleo-climate records (e.g., Ummenhofer et al., 2017; Abram et al. 2020), and are discussed next.

5.5 **Interactions between ocean basins**

One of the most compelling science questions that has arisen regarding the origins and nature of decadal climate variability, with implications for initialized prediction skill, is how and in what way processes in the various ocean basins affect one another (Cassou et al., 2018; Cai et al., 2019). The issue for initialized prediction is that if a skillful prediction of climate in one basin is achieved, then skillful simulations in the other basins could follow (that is, if the models capture these connections realistically), thus potentially improving the skill of initialized S2D predictions. Various studies have shown how SST variability in one ocean basin can affect the others through the tropical large-scale east-west atmospheric Walker Circulation, though the direction of those influences differs. Model simulations have indicated that decadal timescale variability in the Atlantic could produce decadal timescale variability in the Pacific (McGregor et al., 2015; Chikamoto et al., 2016; Ruprich-Robert et al., 2017; Levine et al., 2017). Pacific decadal variability can also affect the Atlantic (Kumar et al., 2014; Taschetto et al., 2016; Meehl et al., 2016) and control a large fraction of decadal variability in the Indian Ocean (Frankcomb et al. 2015; Ummenhofer et al. 2017; Han et al. 2017, 2018; Li et al. 2018; Deepa et al. 2019; Abram et al. 2020). Similarly, the Indian Ocean could be playing a role in decadal variability in the Pacific (Han et al., 2014b; Ummenhofer et al., 2017; Cai et al., 2019; Zhang et al., 2019). There also could be staggered responses based on decadal timescales, with the tropical Pacific driving the tropical Atlantic on interannual timescales, with the Atlantic then affecting the Indian Ocean and subsequently the Pacific on decadal timescales (Li et al., 2015; 2016). More recently it has been postulated that the tropical Atlantic and Pacific Oceans are mutually interactive, with each alternately affecting the other (Meehl et al., 2020), and thatthe tropical Pacific could be driving the extra-tropical Pacific (e.g., Jin and Kirtman 2010).

Another factor noted above is external forcing, particularly from time-evolving anthropogenic aerosols, that could produce decadal climate variability and inter-basin connections (Booth et al 2012; Smith et al., 2016; Zhang et al. 2018). Such fundamental interactions all currently fall under the heading of a compelling research frontier that, with increased understanding, will certainly advance the science of initialized prediction.

6. Challenges and future perspectives

Despite progress in predictions and processes therein noted earlier, there are still many challenges, and we outline some of these here.

6.1 Model error

Certainly almost every science-related aspect of understanding subseasonal to decadal climate variability has considerable uncertainty associated with it and, consequently, there is a high level of new and exciting research taking place. However, perhaps the number one obstacle to progress in this field, other than fundamental scientific understanding, is model error. Just one of the factors involved with the difficulties involved with reducing model error is that some of the phenomena that give rise to predictability (such as MJO and ENSO) are coupled ocean/atmosphere phenomena and hence particularly difficult to simulate. Model development historically has been done for each component individually, and only in recent years has the focus been on model development in a coupled system. Consequently, drift in any one component is often exacerbated when coupled with other components.

Because of model errors, a climate model initialized with observations will drift away from that observed state due to errors in its formulations that take the model to its own preferred state that is some distance from the observations (Fig. 4). This drift is evident in S2S, S2I and S2D with the pattern of biases already established in the first month (Jin and Kinter 2009). To deal with this in an initialized prediction, ad hoc bias adjustments are applied that differ across the different modeling groups and timescales.

Clearly the way forward involves improving the models to reduce the biases and drifts. But this is a major challenge that historically involves incremental progress in gaining new understanding of processes and mechanisms through analyses of observations. A second aspect that has shown to improve model bias is increased model resolution, though such increases in resolution, particularly in the atmosphere, must be accompanied by comparable increases in the quality of the physical parameterizations in the models (Meehl et al., 2019).

6.2 Initialisation techniques

How to best initialize an Earth system prediction system with observations is still a fundamental research question and the S2S, S2I and S2D communities are dealing with similar issues. The importance of atmosphere and land initialization in decadal prediction, the role of atmospheric, land, and ocean initialization in subseasonal to interannual predictions, best way to generate ensemble spread and optimal ensemble size at all prediction timescales are at this point not clear.

Modeling groups have applied a variety of approaches (Table 1) , and some are now re-assessing those methods to determine if additional skill can be obtained from different initialization techniques. Assessment of initialization techniques is in part difficult due to the extensive computational resources required to rerun the hindcast sets.

At this point this is a research problem with no clear conclusion as to what initialization technique will work best to produce the highest quality initialized predictions.

6.3 Internal variability

There is emerging evidence, that models may underestimate the magnitude of predictable signals relative to unpredictable internal variability, especially on seasonal and longer timescales in the extra-tropics and north Atlantic sector (Scaife and Smith 2018). Consequently, it is possible to make skillful forecasts, for example for the NAO, by taking the mean of a very large ensemble to extract the predictable signal and then adjusting its variance (Smith et al., 2019). As noted earlier, so-called “perfect model” techniques that assess a model's ability to predict a different realization of itself, will not provide an upper bound on skill as often assumed and may seriously underestimate the actual predictability of the climate system (e.g. Scaife and Smith, 2018; Boer et al., 2019). when the signal to noise ratio is larger in observations than models.

6.4 Climatic noise

One issue that remains to be resolved for S2D initialized predictions is whether there are indeed well-defined processes and mechanisms that, if initialized properly, could provide predictable signals that are distinct from the background of climatic noise. Such signals, such as PDV and AMV, offer the best prospect for long-term predictability. Strong low-frequency variability in paleoclimate "proxy" records, which is not captured by most climate models, suggests that either models do indeed underestimate low-frequency modes of variability, that proxy observations are characterized by non-climate memory or red noise, or some combination thereof (Ault et al. 2013, Laepple and Huybers 2014a, Parsons and Loope 2017, Loope et al., accepted; Loope et al. in review). Even if there is no distinct low-frequency (oscillating) phenomenon, predictability on decadal timescales could also come from memory and slowly varying components of the earth system, and initialization could be expected to contribute to skill in such cases.

6.5 Expanding predicted variables

There is interest, and corresponding applications, for expanding beyond the prediction of surface temperature, precipitation and sea surface temperatures. There have been efforts at predicting soil moisture with implications for drought prediction (Chikamoto et al., 2017) and ecosystem respiration (Lovenduski et al. 2020, in review). There is also a great societal need for prediction of sea-ice on S2D timescales. S2S models show a very wide range of skill in predicting the sea-ice edge in the Arctic, with the most skillful model producing useful forecasts up to 45 days (Zampieri et al. 2018). Air pollution and air quality are other very society-relevant applications which have been largely unexplored due to the lack of inclusion of interactive tropospheric chemistry in most S2S, S2I and S2D models. However, new comprehensive Earth System

Models, such as Community Earth System Model with the Whole Atmosphere Community Climate Model as its atmospheric component, CESM2(WACCM) (Gettelman et al. 2019) will be able to embark on this research area. Ocean heat content, which is important for monitoring Earth's energy imbalance, has shown higher predictability than SST in the North Atlantic, where the mixed layer is thick, based on analysis of observations and CMIP5 outputs (Buckley et al. 2019).

Variability of the mesosphere and lower thermosphere region drives a significant portion of space weather, and initialized predictions of those features will also be possible in future. There may be other quantities in the Earth system with predictability on longer timescales than seasonal that have yet to be explored. Yet, as noted earlier, model error remains a significant obstacle against which future progress will be measured, with profound implications for possible applications to stakeholder communities (Brasseur and Gallardo, 2016). Such applications could include energy supply (wind, solar) and demand (e.g. Thornton et al., 2019), agriculture (drought, freezing), transport (e.g. Palin et al., 2015) and numerous others spanning a range of timescales. Notably, S2S prediction could inform preparedness for specific large-scale extreme events weeks ahead (Vitart and Robertson 2018), and S2I and S2D initialized predictions are beginning to inform planning at ranges between the seasonal to multi-decadal climate change time scales (e.g. Towler et al., 2018).

In the broader Earth system, there is growing interest in predicting the biosphere and biogeochemical state variables and fluxes that may inform management decisions. Skillful initialized predictions of SST on S2S timescales may engender predictability of fish yields in the California Current System (Tommasi et al., 2017) and other Large Marine Ecosystems (Stock et al., 2015, Hervieux et al., 2019). S2S initialized predictions of heat stress and coral bleaching risk have also demonstrated considerable skill and have provided critical advanced warning for coral reef scientists, managers, and stakeholders (e.g., Griesser and Spillman 2016; Liu et al., 2018). Emerging literature on S2D predictions of biogeochemistry in the terrestrial biosphere and ocean suggests that slowly evolving state variables may enable prediction of biogeochemically relevant quantities with greater skill than climate model state variables such as temperature and precipitation. Predictions of marine net primary production by photosynthesizing phytoplankton (including algae, eukaryotes and cyanobacteria) may foretell future potential fisheries catch, predict harmful algal blooms (Wells et al., 2015), and aid with fisheries management strategies (Séférian et al., 2014; Wells et al., 2015; Park et al., 2019; Krumhardt et al. 2020, in review). Skillful predictions of ocean oxygen content or acidity may similarly aid in fisheries and coral reef management (Siedlecki et al., 2016; Donner et al., 2018; Brady et al. 2020, in review). Reliable forecasts of the changing global carbon budget, such as, for example, the rate of ocean carbon absorption (Li et al., 2016; Séférian et al., 2018; Lovenduski et al. 2019; Li et al., 2019) or the rate of terrestrial biosphere-atmosphere net ecosystem exchange (Séférian et al., 2018; Lovenduski et al., 2020, in revision) may help to generate forecasts of atmospheric CO_2 growth rate and thus contribute to CO_2 emissions management strategies.

SST anomalies in the western tropical Pacific and northern subtropics, often associated with ENSO events, appear to be skillful precursors for variations in temperature and related biological productivity along the U.S. West Coast at S2I timescales (Capotondi et al., 2019a). Slowly propagating subsurface salinity anomalies in the North Pacific Ocean may provide predictability in the California Current oxygen concentration on S2D timescales (Pozo Buil and Di Lorenzo, 2017). Recently reported skillful predictions of chlorophyll concentrations over the global oceans at seasonal to multi-annual timescales have been related to the successful simulation of the chlorophyll response to ENSO, and to the winter re-emergence of subsurface nutrient anomalies in the extra-tropics (Park et al., 2019). Chlorophyll not only responds to ENSO, but can also constitute a potentially useful ENSO precursor (Park et al., 2018).

In the ocean biogeochemical system, variables of interest for prediction are rarely directly observed at the spatial and temporal scales needed for forecast verification, regardless of the timescale of the prediction (Capotondi et al., 2019b; Fennel et al., 2019). Thus, most of the literature is focused on the potential to make predictions of these quantities, rather than on skill as measured by historical observations (Séférian et al., 2014; Seferian et al., 2018; Lovenduski et al. 2019, Lovenduski et al. 2020, in review; Krumhardt et al. 2020, in review). Exceptions include regional studies, such as those that provide S2S initialized predictions of coastal biogeochemistry in the northern California Current (Siedlecki et al., 2016), S2D prediction of ocean acidity in the California Current (Brady et al. 2020, in review), S2D prediction of the surface ocean partial pressure of CO2 in the North Atlantic (Li et al., 2016), and S2S thermal stress forecasts in the western Pacific Ocean (Griesser and Spillman 2016). On the global scale, verification is limited to variables measured or derived from satellite observations, such as ocean chlorophyll (Park et al., 2019), marine primary productivity (Yeager et al., 2018), or interpolated estimates of the surface ocean partial pressure of CO2 (Li et al., 2019). Nevertheless, there is promising potential to make ocean biogeochemical initialized predictions across multiple timescales.

7. Summary

Numerical models initialized with observations for specific time periods and integrated forward in time provide a continuum of predictions on different timescales from S2S, S2I and S2D. Since all rely on similar methodologies of initialization, and experience model drift due to model error, all face similar challenges, and all are still in the early stages of the scientific research necessary to make improvements. Certainly reducing model error is very high on the list of challenges that need to be overcome to produce skill and reliability of initialized predictions on all timescales. Results so far indicate promise for initialized prediction skill certainly for surface temperature and in some cases precipitation and atmospheric circulation. As the scope of research into initialized prediction expands, there are indications that other quantities in the climate system, particularly from biogeochemistry, may have greater predictability than surface temperature and precipitation. This opens up new avenues for initialized prediction for stakeholder-relevant quantities that affect the ocean state with implications for fisheries and other applications.

However, for S2S, S2I, and S2D initialized predictions to be useful, they must be shown to be not only skillful but reliable (Weisheimer and Palmer, 2014), and this is a considerable challenge that the community is only starting to attempt to address (Vitart and Robertson, 2018; Smith et al., 2013). The ultimate challenge in this emerging area of research, and one that is igniting excitement and interest in the scientific community is to provide predictions with maximum skill, taking into account all relevant processes across subseasonal to decadal timescales. Improvements in understanding and prediction capability are still being provided, driving rapid advances in this burgeoning field.

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Competing Interests

Author contributions (if wanted)

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Timescale	Number models	Atmospheric resolution/levels	Ocean resolution/levels	Components initialized	Initiali-zation	Number ensembles	Prediction length
S2S	18	25 200 km 17 91 levels	8 200 km 25 75 levels	Most initialize atmosphere, ocean, land and sea ice	Full field	4 51	31 62 days
S2I	13	36 200 km 24 95 levels	25 200 km 24 74 levels	All initialize atmosphere, ocean, land and sea ice	Full field	10 51	6 12 months
S2D	14	50 20 0km 26 95 levels	25 100 km 30 75 levels	Models range from initializing only ocean, to initializing atmosphere, ocean, land and sea ice	Full field, anomaly	10 40	5 10 years

Table 1. General characteristics of models used for S2S, S2I and S2D initialized predictions. A full and more complete accounting of model features is given for S2S models in Table S1, for S2I in Table S2, and for S2D in Table S3.

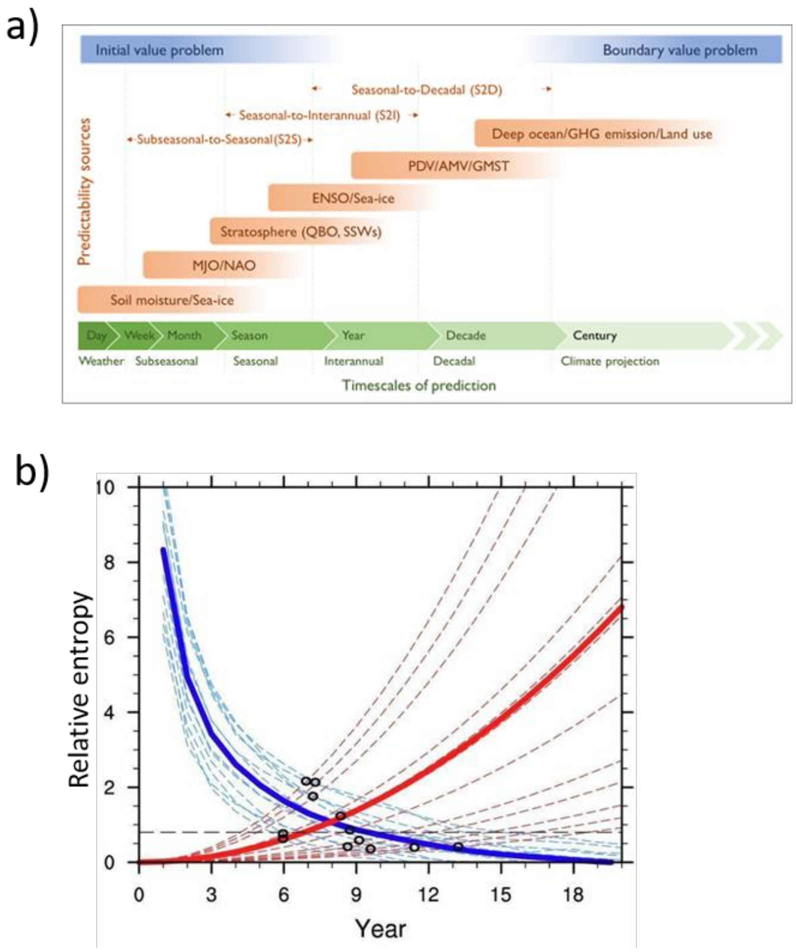

Figure 1. Timescales and processes involved with initialized predictions. a) Predictability sources and timescales of prediction for S2S, S2I, and S2D. Lighter green shading indicates larger uncertainty. A seamless prediction methodology would involve integrations with the same model spanning weather to decadal time frames; b) Skill from the initial state measured by relative entropy (blue line, larger values indicate higher skill in this generalized measure) in initialized predictions is high for S2S and S2I (timescales less than about 2 years), but decreases for S2D from about year 3 to year 9 until skill increases from external forcing (red line) around year 9 in the latter part of S2D predictions (dashed lines indicate uncertainty measured from various models; black circles indicate when decreasing skill from the initial state crosses over increasing skill from external forcing).

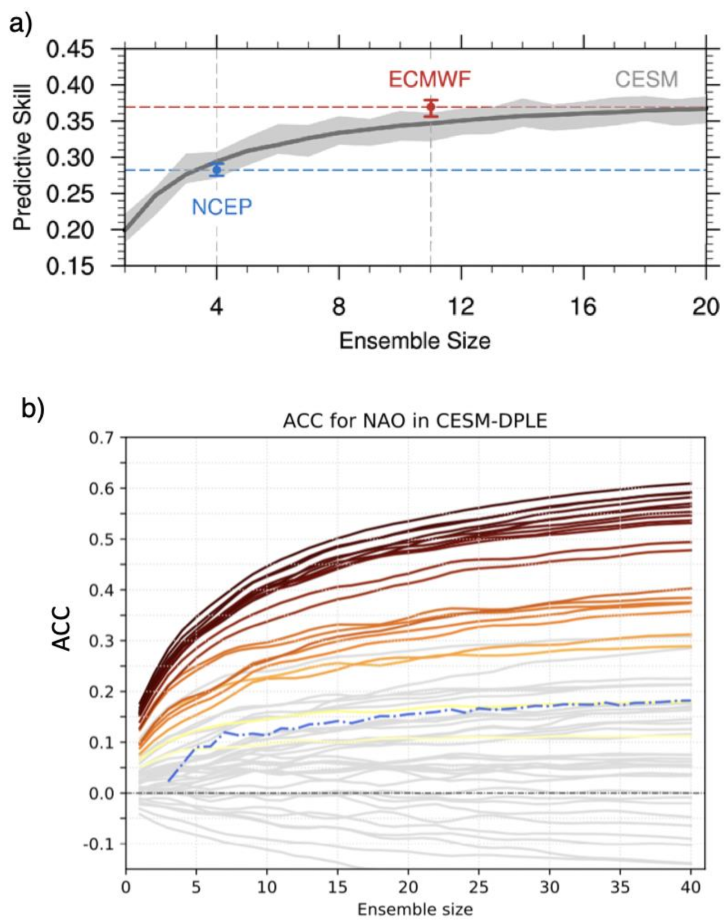

Figure 2. Predictive skill of predictions increases with larger ensemble size. a) An example for S2S predictions, NDJFM surface air temperature, initialized predictions for week 3-6 with higher prediction skill having larger values of the skill metric on the y axis (anomaly correlation coefficient, ACC) averaged over global land (excluding the Antarctic) as a function of ensemble size for NCEP CFSv2 (blue whisker), ECMWF (red whisker), and CESM subseasonal hindcasts (grey line; shading denotes the 5% and 95% significance levels). Data are used between the common period of 1999 to 2015. Blue (red) error bars indicate the 5% and 95% statistical level of NCEP and ECMWF hindcasts, respectively (based on analyses in Kim et al., 2019b); b) An example from S2D, predictive skill for winter (measured by Anomaly Correlation Coefficient, ACC) from the Decadal Prediction Large Ensemble (DPLE) for the NAO as a function of ensemble size, each line indicates a different lead year range, indicating the more ensemble members, the higher the skill, with colored lines corresponding to statistically significant correlations for longer lead year ranges, with largest ACC values of 0.6 with 40 members for lead year ranges for an average of years 2 to 8.

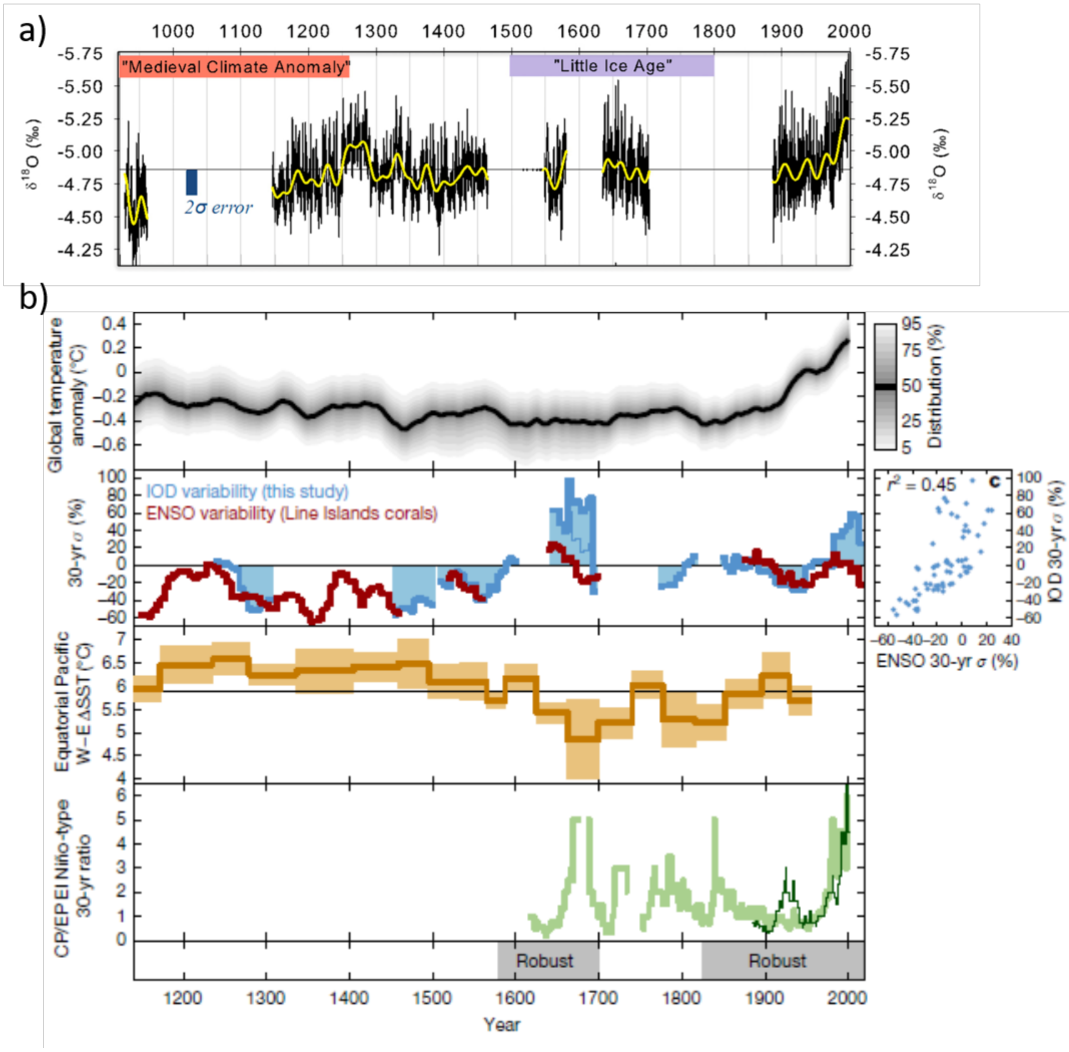

Figure 3. Extending proxy observations of S2D variability back in time. a) Delta 18 oxygen isotope reconstruction from corals on Palmyra Island (6N, 162W) as a proxy for temperature in the tropical Pacific, pre-1000 to 2000 CE; monthly means (black line). The 10-year running mean (yellow line) highlights decadal timescale variability in different epochs like the "Medieval Climate Anomaly" and "Little Ice Age". Such proxy records are an invaluable supplement to the short instrumental observational period of the most recent century. More realizations of S2D variability from this proxy record provides quantitative information on amplitude and frequency of S2D variability to enable better evaluation of S2D initialized predictions for the present century (Cobb, et al., 2003; National Academies of Sciences, Engineering and Medicine, 2016); b) 30 year running means, global mean surface temperature anomalies (black line), coral based IOD (blue) and ENSO (red), scatter plot (blue dots) of coral-based IOD and ENSO showing strong connections, equatorial Pacific west-east SST gradient (orange), and central and eastern Pacific El Nino derived from teleconnected climate patterns, all showing strengthening of IOD-ENSO decadal variability after about 1590 (Abram et al., 2019).

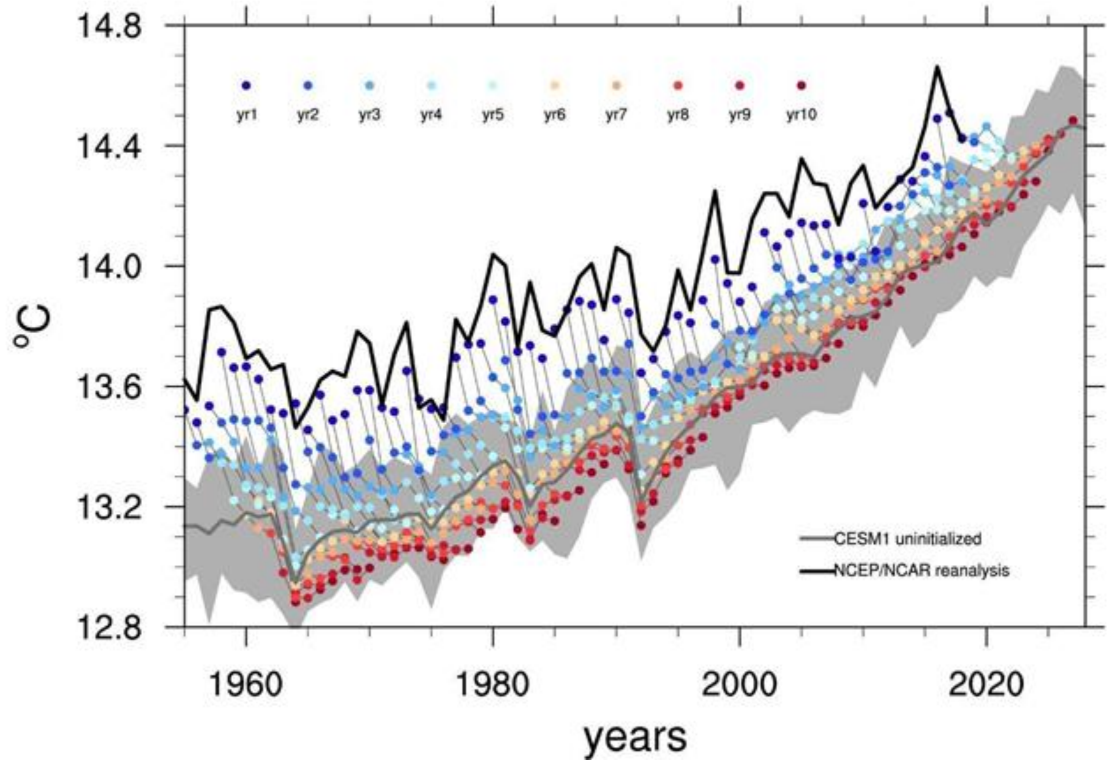

Figure 4. Model drift from initial states due to model error occurs rapidly and thus affects S2S, S2I and S2D initialized predictions. The CESM1 model initial states (blue dots) are close to the observations (black line); the predictions drift (progression of blue dots to red dots) toward the model's systematic error state represented by the uninitialized state (dark gray line; gray shading is range of uninitialized projections). Bias adjustment techniques must then be applied to correct for this drift that is the result of model error. Model data are from the Decadal Prediction Large Ensemble (DPLE, Yeager et al., 2018).

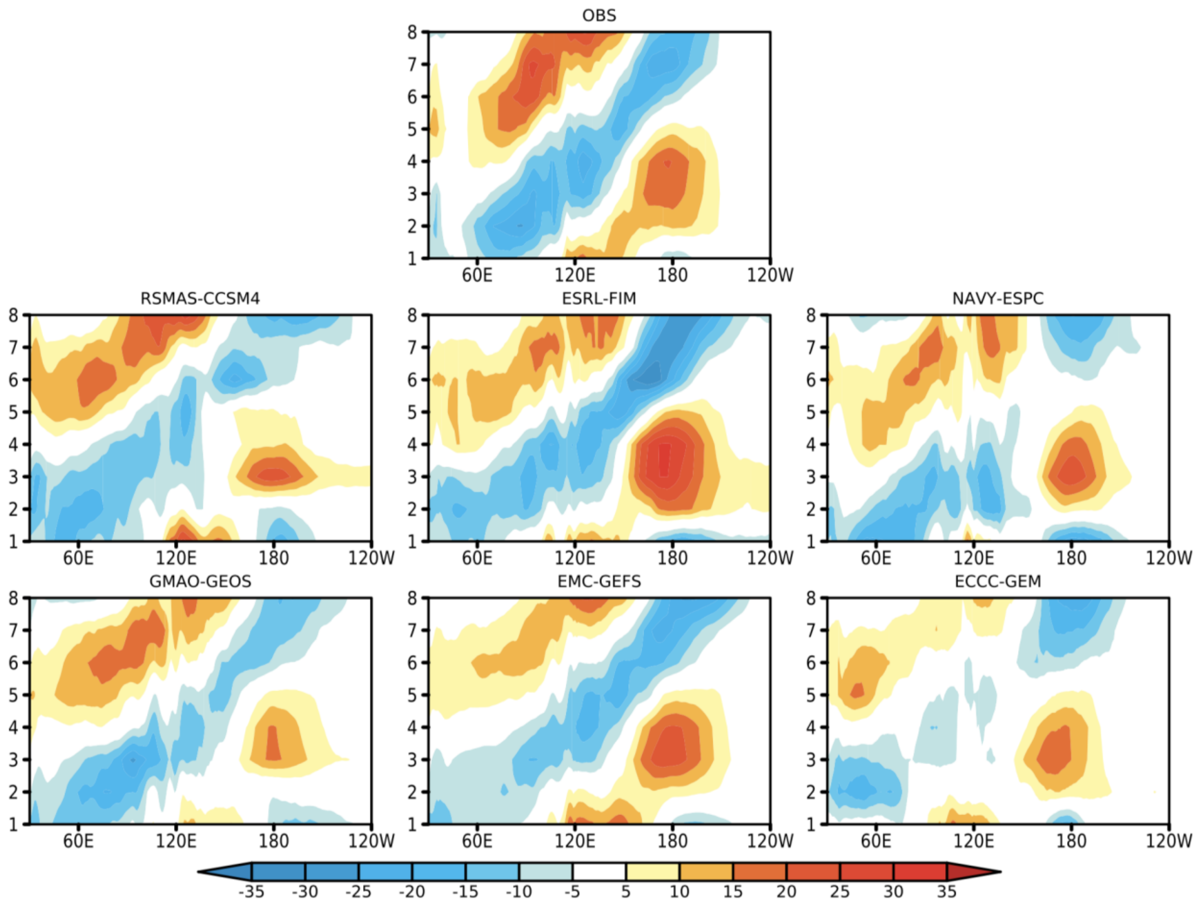

Figure 5. Eastward progression of outgoing longwave radiation (OLR, a proxy for precipitation) anomalies for the observed MJO (top panel) is captured in the initialized predictions from six models. Example of S2S initialized predictions for week 3 (average of days 15-21) from six models (lower panels) compared to observations (top panel) for MJO events represented by OLR anomalies averaged over 5S to 5N with longitude on the x axis, and a time evolution index of the MJO on the y axis with time increasing upward. (Pegion et al., 2019).

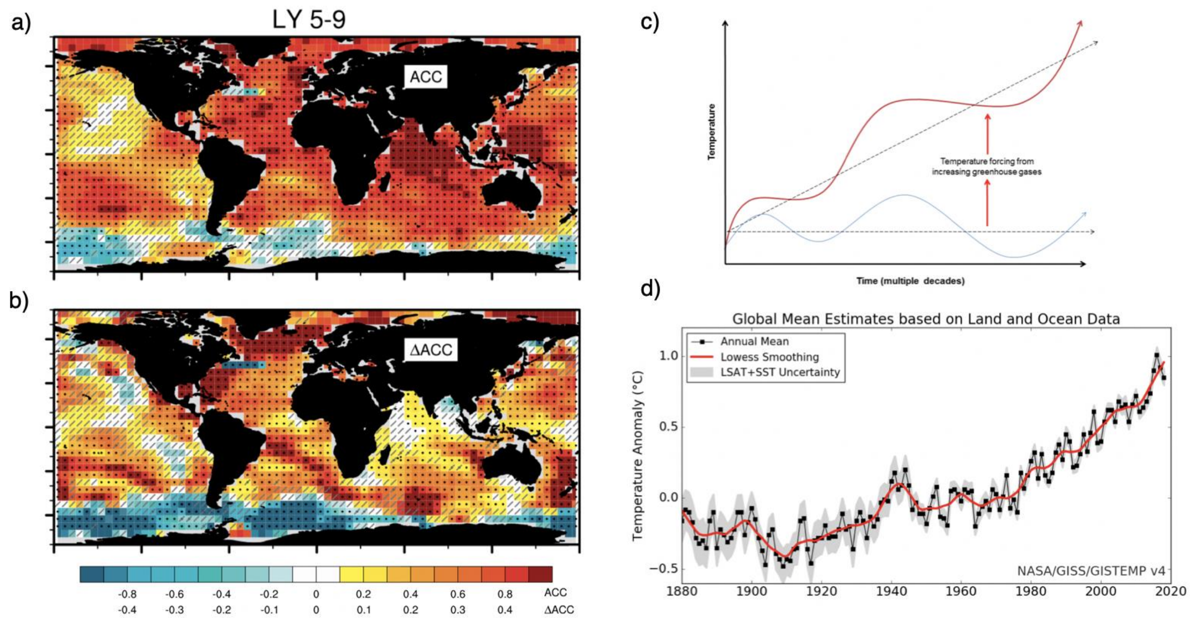

Figure 6. Skill of S2D predictions involves credible simulation of aspects of time-evolving globally averaged temperature. a) Example of S2D skill for SST predictions averaged over years 5-9 from a decadal prediction large ensemble, anomaly correlation coefficient for predicted SSTs compared to observations (darker red indicates higher skill); b) skill improvement from initialized predictions over persistence that does not involve initialized prediction (darker red indicates better skill in the initialized predictions) (Yeager et al., 2018); c) Schematic diagram of the "rising staircase": naturally-occurring decadal variability of GMST (blue line) would occur without any human influence and thus would have little long-term trend (dashed line through blue line). Human-produced GHGs produce an increasing long-term temperature trend (dashed line through red line) that tilts the natural decadal variability fluctuations upwards (red line) producing accelerated warming trends over certain decades and reduced warming trends over other decades, with a resemblance to a rising staircase (Kosaka and Xie, 2016; National Academies of Sciences, Engineering and Medicine, 2016); d) time series of observed global mean surface temperature anomalies showing characteristics of the rising staircase, with periods of accelerated rate of warming (e.g. 1980-2000), and periods of slow-down in the rate of warming (e.g. 2000-2014), and the recent acceleration of warming (2014-present) (from NASA: https://data.giss.nasa.gov/gistemp/graphs_v4/).

Supplementary Information

Table S1. Main characteristics of 18 currently used S2S initialized prediction models. Modeling center acronyms are described in the Appendix; origin refers to model originating either in the climate community (C) or from Numerical Weather Prediction (NWP) community; Operational or Research model is depicted by O and R respectively; Approximate atmospheric and ocean model horizontal resolution (current) is provided either in degrees, kilometers, or begins with ‘T’ for spectral models, number of vertical levels begins with ‘L’; The existence of ocean and sea-ice coupling is indicated by ‘Y’ (yes) or ‘N’ (no); Model components initialized with a state representative of observations are indicated by ‘A’ for the atmosphere, ‘L’ for land, ‘O’ for ocean, and ‘I’ for sea-ice; Initialization type refers to either ‘Full-field (FF)’ or ‘Anomaly(A).’ Initialization frequency for real time forecasts and reforecasts is indicated separately and often in different time units. ‘# Ens’ indicates the number of ensemble members for real time forecasts and reforecasts (Rfc); Forecast length is specified in number of days. Superscripts in the modeling center column depict the following: 1 indicates models included in the international S2S database, 2 indicates models included in the SubX project. * indicates that the full CFSv2 data (6 hourly initializations) are provided to the S2S database. The SubX version is a subset based on the SubX protocol (weekly initialization). For models that have used multiple versions and/or configurations, most recent configuration is described.

Model- ing Center	**Model Name**	**Origin (Cli- mate or NWP)**	**Ops. or Re- search**	**Atmos. Resolution /Vertical Levels**	**Ocean Res./ Levels**	**Ocean/ Sea Ice Coupling**	**Compo- nents Initial- ized**	**Init**	**Init. Frequency (Real time/Rfc)**	**# Ens Real time/ Rfc**	**Fore- cast Dur- ation (days)**
Models Providing Real Time Forecasts and Reforecasts											
BoM[1]	POAMA	C	O	2°x2°, L17	200 x 100 km / L25	Y/N	A, L, O	FF	2 per week/6 per month	33/33	62
CMA[1]	BCC CSM2-HR	C	O	T266, L56	0.25° L50	Y/Y	A, O, I	FF	Daily/Daily	4 /4	60

CNR ISAC[1]	GLOBO	C	O	0.8° 0.56°, L54	N/A	N/N	A, L	FF	weekly/every 5 days	41/1	31
ECCC[1,2]	GEPS, GEM	NWP	O	0.45°x0.45° / L40	N/A	N/N	A, L	FF	weekly/weekly	21/4	32
ECMWF[1]	ECMWF	NWP	O	0.25°x0.25° (days 0-10), 0.5°x0.5° (after day10) / L91	0.25° / L75	Y/N	A, L, O	FF	2 per week/2 per week	51/11	46
HMCR[1]	SLAV	NWP	O	1.1°x1.4° / L28	N/A	N/N	A	FF	Weekly/weekl y	20/10	61
JMA[1]	JMA GEPS, GSM	NWP	O	0.5°x0.5° / L60	N/A	N/N	A, L	FF	4 per week/3 per month	25/5	33
KMA[1]	GloSea5 GC2	C	O	0.5°x0.5° / L85	0.25° / L75	Y/Y	A, O, I	FF	daily/4 per month	4/3	75 or 240
Meteo France[1]	CNRM-CM	C	O	0.7°x0.7° / L91	1° / L42	Y/Y	A, L, O, I	FF	weekly/2 per month	51/15	61
NASA GMAO[2]	GEOS	C	R	0.5°x0.5° / L72	0.5° L40	Y/Y	A , L, O, I	FF	Every 5 days	4/4	45
NAVY[2]	ESPC	C	R	T359 / L50	0.08° / 41L	Y/Y	A,L,O,I	FF	4 per week/4 per week	4/4	45
NOAA EMC[2]	GEFS	NWP	O	T574 (days 0-8), T382 (days 8-35) / L64	N/A	N/N	A,L	FF	weekly/weekly	21/11	35
NOAA ESRL[2]	FIM	NWP	R	~ 60 km / L64	~ 60 km /L32	Y/Y	A,L,O,I	FF	weekly/weekly	4/4	32

NOAA NCEP[1,2]	CFSv2	C	O	T126 / L64	0.25° Eq, 0.5° global / L40	Y/Y	A, L, O, I	FF	6 hourly*/6 hourly*	16/1	45
RSMAS	CCSM4	C	R	0.9°x1.25° / L26	0.25° Tropics /1° global/ L60	Y/Y	A, L, O, I	FF	weekly/weekly	9/4	45
UKMO[1]	GloSea5	C	O	0.5°x0.8° L85	0.25° L75	Y/Y	A, L, O, I	FF	Daily/4 per month	4/7	45
Models Providing Reforecasts Only											
NCAR	30LCESM1	C	R	/ L30	0.25° Tropics /1° global/ L60	Y/Y	A, L, O, I	FF	weekly	NA/10	45
NCAR	46LCESM1	C	R	0.9°x1.25° L30	0.25° Tropics /1° global/ L60	Y/Y	A, L, O, I	FF	weekly	NA/10	45

Table S2. Main characteristics of 13 S2I initialized prediction models. Column labels are the same as in Table S1, except forecast length is in months. [3] indicates models participating in the NMME. [4] depicts models contributing to the Copernicus Climate Change Service (C3S).

Model ing Center	Model Name	Origi n (Clim - ate or NWP)	Ops. vs Re- earc h	Atmos. Resolution /Levels	Ocean Res./ Levels	Ocean / Sea Ice Coup- ling	Com- pon- Ents; Initial -ized	Init. Typ e	Initial- ization fre- quency (Real time/ Rfc)	# Ens (Rea l time/ Rfc)	Forcast Length, months
CMCC	CMCC SPS3[4]	C	O	1° / L46	0.25° /L50	Y/Y	A, L, O, I	FF	1 st of the month	50/40	
DWD	MPI-ESP[4]	C	O	T127 / L95	0.4° Eq / L40	Y/Y	A, L, O, I	FF	1 st of the month	50/30	12
ECCC	CanCM4i[3]	C	O	T63 / L35	.94°Eq / L40	Y/Y	A, L, O, I	FF	1 st of the month	10/10	12
ECCC	GEM-NEMO[3]	NWP	O	1.4° / L79	0.33°Eq /1°global/ L50	Y/Y	A, L, O, I	FF	1 st of the month	10/10	12
ECMWF	SEAS54	NWP	O	TCo319 (36km)/L91	0.25° /L75	Y/Y	A, L, O, I	FF			
GFDL	CM2.1[3]	C	R	2x2.5° / L24	2x2.5° L24	Y/Y	A, L, O, I	FF	1 st of the month	10/10	12

GFDL	CM2.5[3]	C	R	/ L32	0.3°Eq/ 1° Polar/ L50	Y/Y	A, L, O, I	FF	1 st of the month	10/10	12
JMA/ MRI	CPS24	C	O	T159/L60	0.3°Eq/L52	Y/Y	A, L, O, I	FF	12-13 mem every 5 days/5 mem every 15 days	51/10	12
Météo- France	System 7 4	C	O	TL359/L91	0.25° /L75	Y/Y	A, L, O, I	FF	1 st of the month	51/25	7
NASA	GEOSS2S[3]	C	R	0.5°/ L72	0.5°Eq/ L40	Y/Y	A, L, O, I	FF	1 mem ev 5 days; 6 members on last day of month	10/10	10
NCAR	RSMAS-CCSM4[3]	C	R	0.9x1.25° L26	0.25° Eq/L60	Y/Y	A, L, O, I		1 st of the month	10/10	12
NCEP	CFSv2[3,4]	C	O	T126 / L64	.25° Eq/L40	Y/Y	A, L, O, I	FF	4 members every 5 days	24/24	10
UKMO	GloSea5[4]	C	O	0.5°x0.8°/L85	0.25° /L75	Y/Y	A, L, O, I	FF	2 per day/7 4 times per month	62/28	7

Table 3. Main characteristics of 14 S2D initialized prediction models. Same as Table S1 but initialization frequency and ensemble size are used for research except as “operations” denoted via the WMO Lead Centres, and forecast length is in years.

Modeling Center	**Model Name**	**Origin (Climate or NWP)**	**Ops vs Research (Ops identified as WMO Lead Centers)**	**Atmos. Res. /Levels**	**Ocean Res. /Levels**	**Ocean/ Sea Ice Coupling**	**Comp-onents initialized**	**Initiali-zation Type**	**Initiali-zation Frequency**	**# Ens**	**Fore-cast Dur-ation, year)**
CCCma	CanESM5	C	R,O	2.8º / L49	1º, L45	Y/Y	A, L, O, I	FF	Nov of each year	40	10
CCSR/UT/ JAMESTEC/ NIES	MIROC6	C	R	1.4º / L81	1º, L62	Y/Y	A, O, I	A for Ocean; FF for Ice	Nov of each year	10	10
CMCC	CMCC-CM2-SR5	C	R	1º / L30	1º / L 50	Y/Y	A, L, O, I	FF	Nov of each year	10	10
CMA	BCC_CSM_MR	C	R	1º /L 46	1º / L40	Y/Y	O	A	Nov of each year	10	10
European EC-earth consortium	EC-Earth3 (BSC)	NWP	R	1º/ L91	1º / L75	Y/Y	A, L, O, I	FF	Nov of each year	10	10

European EC-earth consortium	EC-Earth3(BSC/SMHI/DMI)	C	R, O	1º/ L91	1º / L75	Y/Y	A, L, O, I	Two versions: FF (BSC) and AI (SMHI/DMI) with A for Ocean/Ice; FF for Atm/Land	Nov of each year	10	10
INM	INM-CM5	C	R	2º / L73	0.5º / L40	Y/Y	A, O	A	Nov of each year	10	10
LASG/IAP	FGOALS-g3	C	R	2º / L26	1º, L30	Y/Y	O	FF	Nov of each year	10	10
LASG/IAP	FGOALS-f3	C	R	1º / L32	1º, L30	Y/Y	O	A	Nov of each year	10	10
MPI	MPI-ESM-HR	C	R, O (via DWD)	1º / L95	0.4º /L40	Y/Y	A, L, O, I	A for Ocean/Ice; FF for atm	Nov of each year	10	10
MRI	MRI-ESM2	C	R	1º / L80	1x0.5º/L60	Y/Y	O	A	Nov of each year	10	10
NCAR	CESM1	C	R	0.9ºx1.25º / L30	0.25º Tropics /1º global/ L60	Y/Y	O	FF	Nov of each year	40	10
NCC	NorCPM1	C	R	2º /L26L	1º / L53	Y/Y	O	A	Nov of each year	10	10
UKMO	DePreSys4	C	R,O	0.5ºx0.8º/ L85	0.25º /L75	Y/Y	A, O, I	FF	Nov of each year	10	10

Modeling center names and countries:

BoM:	Bureau of Meteorology, Australia
CCMA:	Canadian Centre for Climate Modelling and Analysis, Canada
CCSR/UT/JAMSTEC/NIES:	Center for Climate System Research (CCSR), University of Tokyo, Japan Agency for Marine-Earth Science and Technology (JAMSTEC), and the National Institute for Environmental Studies (NIES), Japan
CMA:	China Meteorological Administration, China
CMCC:	Euro-Mediterranean Center on Climate Change, Italy
CNR-ISAC:	Institute of Atmospheric Sciences and Climate of the National Research Council, Italy
DWD:	Deutscher Wetterdienst, Germany
ECCC:	Environment and Climate Change Canada, Canada
ECMWF:	European Centre for Medium-Range Weather Forecasts, United Kingdom
HMCR:	Hydrometeorological Centre of Russia, Russia
INM:	Institute of Numerical Mathematics of the Russian Academy of Sciences, Russia
JMA:	Japan Meteorological Agency, Japan
KMA:	Korean Meteorological Administration, Korea
LASG/IAP:	Laboratory of Numerical Modeling for Atmospheric Sciences and Geophysical Fluid Dynamics (LASG), the Institute of Atmospheric

MPI:	Max Planck Institute, Germany
Meteo France:	Meteo France, France[2]
MRI:	Meteorological Research Institute, Japan Meteorological Agency, Japan
NASA GMAO:	National Aeronautics and Space Administration, Global Modeling and Assimilation Office, United States
NAVY:	United States Navy, United States
NCAR:	National Center for Atmospheric Research, United States
NCC:	Norwegian Climate Center, Norway
NOAA EMC:	National Oceanic and Atmospheric Administration, Environmental
NOAA ESRL:	National Oceanic and Atmospheric Administration, Earth System
NOAA NCEP:	National Oceanic and Atmospheric Administration, National Centers for
RSMAS:	Rosenstiel School for Marine and Atmospheric Science at the University
UKMO:	United Kingdom Met Office, United Kingdom