DECADAL CLIMATE VARIABILITY, PREDICTABILITY AND PREDICTION: OPPORTUNITIES AND CHALLENGES.

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1. INTRODUCTION

The scientific understanding of Earth's climate system is now sufficiently developed to show that climate change from anthropogenic greenhouse gas forcing is already upon us, and the rate of change as projected exceeds anything seen in nature in the past 10,000 years. The indisputable evidence of global warming and the knowledge that surface temperatures will continue to rise over the next several decades under any plausible emission scenario is now a factor in the planning of many governments, businesses, and socio-economic sectors for which climate sensitivity and vulnerability is high. It does not imply, however, that future changes will be uniform around the globe. On the time scale of a few years to a few decades ahead, regional and seasonal variations in weather patterns and climate, and their corresponding impacts, will be strongly influenced by natural, internal variability [1]. Decision makers in diverse arenas thus need to know the extent to which the climate events they are seeing are the product of this natural variability, and hence can be expected to reverse at some point, or are the result of potentially irreversible, forced anthropogenic climate change.

Efforts to predict the evolution of climate over the next

several decades that take into account both forced climate change *and* natural decadal-scale climate variability are in their infancy [2]. Many formidable challenges exist. For example, climate system predictions on the decadal time scale will require initialization of coupled general circulation models with the best estimates of the current observed state of the atmosphere, oceans, cryosphere, and land surface – a state influenced both by the current phases of modes of natural variability and by the accumulated impacts to date of anthropogenic radiative forcing. However, given imperfect observations and systematic errors in models, the best method of initialization has not yet been established, and it is not known what effect initialization has on climate predictions. It is also not clear what predictions should be attempted or how will they be verified. The brevity of most instrumental records furthermore means that even the basic characteristics and mechanisms of decadal variations in climate are relatively poorly documented and understood. As a consequence, the representation of natural variability arising from the slowly-varying components of the climate system differs considerably among models, so the inherent predictability of the climate system on the decadal time scale is also not well established. Demands will therefore be made on observations, particularly ocean observations, not only to describe the state of the climate system and improve knowledge of the mechanisms that give rise to decadal fluctuations in climate, but also to provide the optimal observations for decadal climate predictions and their verification.

The purpose of this paper is to outline the most significant issues and the challenges of producing skillful predictions of the evolution of the climate system on the time scale of years to decades ahead. A very brief overview of observed decadal variability and its associated impacts is presented in the following section, while a concise description of the processes that give rise to such variability is presented in Section 3 (see also [3]). Different sources of predictability on decadal time scales are described in Section 4, while Section 5 describes issues associated with initializing coupled climate models (see also [4]). First attempts at initialized, decadal predictions and the challenge of verifying such predictions are summarized in Sections 6 and 7, while the paper concludes with some brief comments on the particular importance of ocean observations for emerging decadal prediction systems.

2. OBSERVED DECADAL VARIABILITY AND IMPACTS

Global warming will continue over the next several decades under any plausible emission scenario but will inevitably be accompanied by regional scale variability and change, which can have profoundly important impacts. Examples include the Dust Bowl drought of the 1930s, the Sahelian drought of the 1970s and 1980s, the ongoing drought in the southwestern US, and decadal scale changes in Atlantic hurricane activity. They are associated with differences in land and ocean temperatures, as well as differences among the oceans (Fig. 1). It is a central challenge of climate science to attempt to predict such regional scale climate variability and change over time scales of decades.

The most prominent example of a natural, coupled ocean-atmosphere phenomenon is the El Niño-Southern Oscillation (ENSO). El Niño events are typified by very strong warming of the central and eastern tropical Pacific Ocean with cooling over portions of the subtropics and the tropical western Pacific. These differences in regional sea surface temperature (SST) perturb the global atmospheric circulation so that some regions become warmer and drier, while other regions cool and become wetter. Historically, El Niño events occur about every 3 to 7 years and alternate with the opposite phase of below-average temperatures in the eastern tropical Pacific (La Niña).

The nature of ENSO has varied considerably over time, however, and in recent years many studies have documented decadal and longer-term variability of ENSO and Pacific climate in general [5]. Decadal to inter-decadal variability in the atmospheric circulation is especially prominent in the North Pacific [6] where fluctuations in the strength of the wintertime Aleutian Low pressure system co-vary with North Pacific SST (Fig. 1) in what has been termed the "Pacific Decadal Oscillation" or PDO [7]. Very similar time scale fluctuations in SST and atmospheric and ocean circulation are present across the whole Pacific Basin, and these variations are known as the Inter-decadal Pacific Oscillation (IPO; [8], [9]). Phase changes of the PDO/IPO are associated with pronounced changes in temperature and rainfall patterns across North and South America, Asia and Australia ([10], [11], [12]), as well as important ecological consequences, including major shifts in distribution and abundance of zooplankton and important commercial species of fish [13]. Furthermore, ENSO teleconnections on interannual time scales around the Pacific basin are significantly modified by the PDO/IPO.

Over the Atlantic sector, in contrast to the tropical Pacific, decadal variability has large amplitude relative to interannual variability, especially over the North Atlantic ([14], [15], [16]). Multi-decadal variability in the SSTs in the Atlantic has been termed the "Atlantic Multi-decadal Oscillation", or AMO (Fig. 1). Instrumental records are not long enough to determine whether this variability has a well defined period rather than a simpler character, such as "red noise". The robustness of the signal has therefore been addressed using paleoclimate records, and similar fluctuations

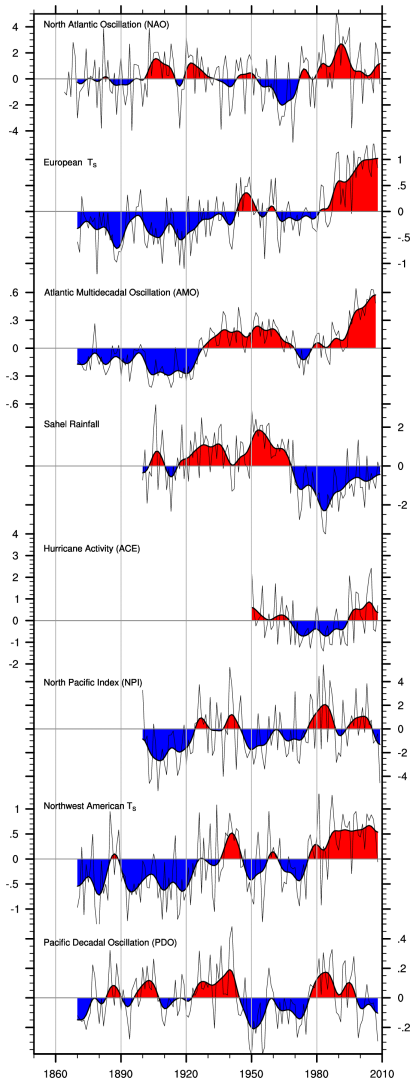

Figure 1. From top to bottom: Station-based index of the North Atlantic Oscillation (NAO;[50]); European (5°W-10°E, 35-60°N) surface air temperature; Atlantic Multidecadal Oscillation, as denoted by the low-pass filtered time series of SST anomalies averaged over the North Atlantic (0-60°N, 0-80°W) and updated from [31]; boreal summer Sahel rainfall; and Atlantic hurricane activity (ACE index). The bottom three panels show the (inverse) North Pacific Index [6]; western United States (145°W-110°W, 30-65°N) surface air temperature; and the Pacific Decadal Oscillation index, as denoted by SST based on the leading EOF SST pattern for the Pacific basin north of 20°N (updated from [7]). All time series are deviations from long-term means, and temperature time series are annual means in units of °C. The NAO index, Sahel rainfall and the ACE index were normalized by the long-term standard deviation. The NP index has units of hPa. The color fill in all panels is from a low-pass symmetric filter with 13 total weights and a half-power point at 16 year periods, with the end points reflected.

have been documented through the last four centuries [17]. Numerous modelling studies have examined potential links between the AMO and the Atlantic Meridional Overturning Circulation (MOC; see also Section 3), but the nature of the observed relationship is unclear owing to a lack of long-term, continuous, records of the MOC ([18], [19]). There is clear evidence, however, of decadal variability in the heat and freshwater content of the Atlantic Ocean ([20], [21], [22]) as well as evidence of ocean circulation changes in recent decades ([18], [23], [24]) that have likely played an important role in the evolution of the Atlantic SSTs.

The slow changes in Atlantic SSTs have affected regional climate trends over parts of North America and Europe ([15], [25]), hemispheric temperature anomalies [26], sea ice concentration in the Greenland Sea [27], Arctic Ocean conditions [28], hurricane activity in the tropical Atlantic and Caribbean ([29], [30], [31]) and fisheries production in the northern North Atlantic [32]. In addition, tropical Atlantic SST anomalies have contributed to rainfall anomalies over the Caribbean and the Nordeste region of Brazil, and severe multi-year droughts over parts of Africa including the Sahel ([33], [34], [35], [36]). Tropical Atlantic SST variations are also a factor in producing drought conditions over portions of North America, although tropical Pacific SST variations appear to play a more dominant role ([37], [38], [39]).

This brief survey of observed decadal climate variability makes it clear that, on the regional scales on which most planning decisions are made, anthropogenic climate change signals will be strongly modulated by natural climate variations, and especially those driven by the slowly varying oceans on a time scale of decades. This non-uniformity of change highlights the challenges of regional climate change that has considerable spatial structure and temporal variability. Moreover, it illustrates the need to predict not just the change in global mean temperature, but the patterns of SSTs around the globe as accurately as possible. A robust global ocean observing system, including not only maintaining recent advances in upper ocean measurements from Argo and satellite remote sensing [40], but also improving and expanding deep ocean measurements through repeat hydrography [22], moored arrays [18] and other technologies ([19], [21]) will be crucial to such decadal climate predictions.

3. MECHANISMS FOR DECADAL VARIABILITY

A large body of literature exists on the processes that potentially give rise to decadal climate variability. In the following, it is only briefly summarized (see also [3]). Reference [41] concluded from his observational analyses of the middle latitudes of the Atlantic region that the atmosphere drives the ocean on interannual time

scales, while on decadal-to-multi-decadal time scales ocean dynamics are most important. Many subsequent observational and modeling studies basically agree with this view (e.g., [42], [43]; and references therein), so the predictability potential in the Atlantic sector is possibly large at these time scales. Although the mechanisms behind the Atlantic decadal variability are still not well understood, there is some consensus that a significant fraction of it is driven by variations in the MOC. Over

the North Pacific, a strong overturning circulation does not exist, and variability of the wind-driven circulation is the most likely candidate for the generation of decadal to multi-decadal climate variability (e.g., [43], [44], [45]). In the following, we concentrate on only these two regions, although it is important to note that other regions, such as the Southern Ocean, also exhibit relatively high potential predictability on decadal and longer time scales [46].

3.1 The zero-order stochastic climate model

Reference [47] introduced an approach to modeling the effect of the fast variables on the slow in analogy to Brownian motion. He suggested treating the former not as deterministic variables, but rather as stochastic variables, so that the slow variables evolve following dynamical equations with stochastic forcing. The chaotic components of the system often have well-defined statistical properties and these can be built into approximate stochastic representations of the high-frequency variability. The resulting models for the slow variables are collectively referred to as *stochastic climate models*, although the precise time scale considered as slow may vary greatly from model to model.

In the simplest case, the atmosphere can be considered as the fast component of the climate system and treated as a *white noise* process (i.e., the spectrum of the atmospheric forcing does not vary with frequency), while the ocean-sea ice system is the slow component. The atmospheric forcing at one location drives only changes in the ocean-sea ice system at that location, and neither the atmosphere nor the ocean-ice system exhibit spatial coherence. The resulting spectrum of an ocean variable, such as SST, is *red*, which means that the power increases with time scale. It has been shown ([48], [49]) that such a local model can explain much of the observed SST and salinity variability in parts of the middle latitudes, away from coasts and fronts, and climate models also reproduce this behavior. In regions where mesoscale eddies or advection is important, however, this simple stochastic model fails. Nevertheless, it demonstrates that decadal variability in the ocean-sea ice system can be generated by the integration of atmospheric weather noise. This simple model thus serves as a useful null hypothesis for the generation of decadal variability.

3.2 Stochastic models with mean advection

Atmospheric variability on time scales of a month or longer is dominated by a small number of large-scale spatial patterns whose time evolution has a significant stochastic component. One prominent example is the North Atlantic Oscillation (NAO, [50]), and one may expect such atmospheric patterns to play an important role in ocean-atmosphere interactions. Advection in the ocean-sea ice system also plays an important role. Reference [51] fit a stochastic model incorporating horizontal transport to observed polar sea ice variability. A local stochastic model, including the effects of advection by the observed mean current, was employed by [52] to predict the statistical characteristics of observed SST anomalies in the North Pacific on time scales of several months. Their results indicated mean advection had only a small effect in general, although in regions of large currents advection effects were more important at longer time scales (see also [53]).

A simple one-dimensional stochastic model of the interaction between spatially coherent atmospheric forcing patterns and an advective ocean was developed by [54]. A slow–shallow regime, where local damping effects dominate, and a fast–deep regime, where nonlocal advective effects dominate, were found. An interesting feature of the fast–deep regime was that the ocean–atmosphere system exhibited preferred time scales of variability, although there was no underlying oscillatory mechanism in either the atmosphere or ocean. The existence of the preferred time scale in the ocean did not depend on the existence of an atmospheric response to SST anomalies; rather, it was determined by the advective velocity scale associated with the upper ocean and the length scale associated with low-frequency atmospheric variability. This mechanism is often referred to as "spatial resonance" or "optimal forcing."

For the extratropical North Atlantic basin, the preferred time scale would be of the order of a decade. Interestingly, [55], [56], [57] documented variability in surface observations of the North Atlantic on the decadal time scale. However, their studies differed in the derived propagation characteristics. The stochastic-advective mechanism may also underlie variability of the Antarctic Circumpolar Wave (e. g., [58]) as shown in the model study of [59].

3.3 Stochastic wind stress forcing of a dynamical ocean

Only heat and freshwater forcing, and not varying ocean dynamics, have been considered as a mechanism for

producing decadal variability in the preceding discussion. Using a simple linear model to estimate the dynamical response of the extratropical ocean to stochastic wind stress forcing, [60] found the barotropic fields were governed by a time-dependent Sverdrup balance while the baroclinic fields were governed by the long Rossby wave equation. The baroclinic response consisted of a forced response plus a Rossby wave generated at the eastern boundary. For zonally-uniform forcing, the response propagated westward at twice the Rossby phase speed. The model also predicted the shape and level of the frequency spectra of the oceanic pressure field and their variation with longitude and latitude. The baroclinic response was spread over a continuum of frequencies, with a dominant timescale determined by the time it takes a long baroclinic Rossby wave to propagate across the basin and thus increased with basin width. The baroclinic predictions for a white wind stress curl spectrum were broadly consistent with the frequency spectrum of sea level changes and temperature fluctuations in the thermocline observed near Bermuda. Evidence for the accumulation of stochastic atmospheric forcing along Rossby wave trajectories in the North Pacific has also been documented [61]. Stochastic wind stress forcing may thus explain a substantial part of the decadal variability of the oceanic gyres.

The importance of stochastically-driven Rossby waves was also noted in a study of multi-decadal variability in the North Pacific, using a coupled ocean-atmosphere general circulation model [45]. Results suggested the simulated multi-decadal variability could be partly explained by the dynamical ocean response to stochastic wind stress forcing. Superimposed on the red background variability, a multi-decadal mode with a period of about 40 years was simulated, which was understood through the concept of spatial resonance between the ocean and the atmosphere, as described above. In summary, the bulk of the potential predictability found in the North Pacific (e.g., [46]) is probably related to the propagation of long baroclinic Rossby waves (e.g., [44]). The degree of air-sea coupling, however, needs to be considered in this context (e.g., [62]), as well as the role of remote forcing by the Tropics (e.g., [63], [64]).

3.4 Hyper modes

Next the case considered is one in which the atmosphere is no longer represented by a simple stochastic model, but rather deterministically by an atmospheric general circulation model, and the ocean is represented by a vertical column model that includes only vertical diffusion. Since varying ocean dynamics are not considered, air-sea interactions are purely local. Some important aspects of the space-time structure of observed multi-decadal SST variability can be explained by such a model, which was also used to formulate the concept of "Global Hyper Climate Modes" [65]. In this paradigm, surface heat flux variability associated with regional atmospheric variability is integrated by the large heat capacity of the extratropical oceans, leading to a continuous increase of SST variance towards longer time scales. The extratropical signals are then communicated to tropical regions via atmospheric processes and, once tropical SST anomalies develop, global atmospheric teleconnections spread the signal around the world, thereby creating a global hyper climate mode. Estimates with a further reduced model suggest that hyper climate modes can vary on timescales longer than 1,000 years.

The SST anomaly patterns simulated at multi-decadal time scales in the model of [65] are remarkably similar to those derived from observations and from long control integrations with sophisticated coupled ocean-atmosphere general circulation models. The hyper mode mechanism could, for instance, underlie the PDO (Fig. 2). Ocean dynamics and large-scale ocean-atmosphere coupling may amplify the hyper modes, especially in the Tropics, and may influence the regional expression of the associated variability. Equatorial ocean dynamics, such as those operating in ENSO for instance, could further enhance the variability in the eastern and central equatorial Pacific. Such feedbacks would make the simulated variability even more realistic, but they are not at the heart of the mechanism which produces the hyper modes.

3.5 Stochastically driven variability of the thermohaline circulation

Competing mechanisms have been proposed to explain the variability of the North Atlantic MOC. One idea is that multi-decadal MOC variability is driven by the low-frequency portion of the spectrum of atmospheric flux forcing. Reference [66] describes results from a multi-millennial integration with an ocean general circulation model driven by spatially correlated white-noise freshwater flux anomalies. In addition to the expected red-noise character of the oceanic response, the model simulated pronounced variability in a frequency band around 320 years in the Atlantic basin due to the excitation of a damped oceanic eigenmode. The physics behind the simulated variability involved a dipole-like salinity anomaly interacting with and advected by the mean thermohaline circulation. In the same experiment, [67] describe variability with a time scale of 10-40 years produced by salinity anomalies in the Labrador Sea and their discharge into the North Atlantic. The generation of the salinity anomalies was mainly due to an almost undisturbed local integration of the white noise freshwater fluxes. The time scale and damping term of the integration process were determined by the flushing time of the well-mixed upper ocean layer. The decadal

mode affected the Atlantic MOC and represented a "discharge process" that depended nonlinearly on the modulated circulation structure rather than a regular linear oscillator.

North Atlantic multi-decadal variability was also present in the coupled model simulation of [42], involving interactions of the gyre and thermohaline circulations in which the anomalous salt advection into the oceanic sinking region played a crucial role in determining deep convection. In their analysis of those

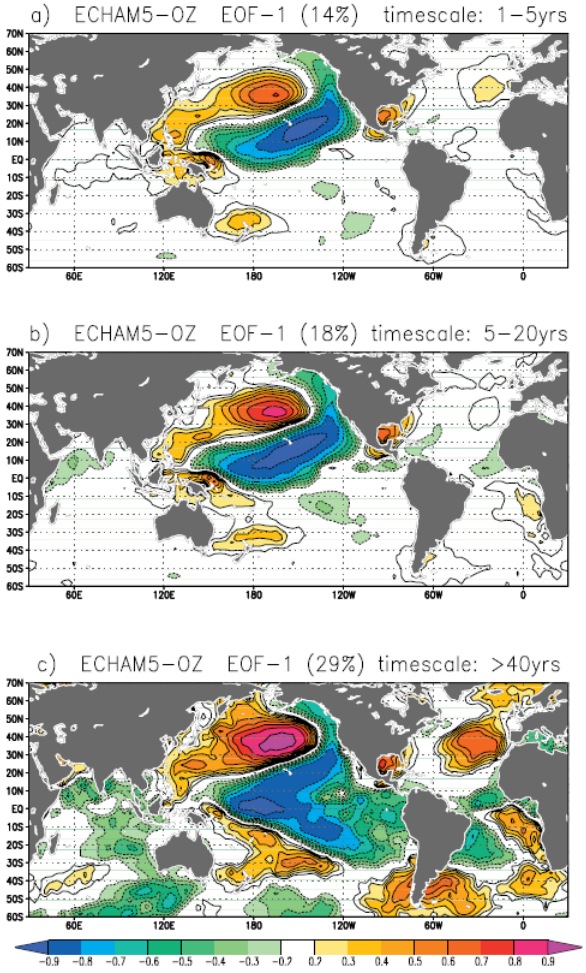

Figure 2. Correlations maps of SST with the leading principal component time series of SST from the simple climate model described in Section 3.4 at various time scales. Filtering was performed by applying and/or subtracting running means. The hyper mode is fully developed at multi-decadal time scales. See [65] for full details.

same simulations, [68] showed that multi-decadal MOC fluctuations were driven by a spatial pattern of surface heat flux variability that bore a strong resemblance to the NAO. No conclusive evidence was found, however, that the MOC variability was part of a dynamically coupled atmosphere-ocean mode in this particular model.

Reference [69] interpreted the same coupled model simulation in terms of a stochastically forced four-box model of the MOC. The box model was placed in a linearly-stable, thermally-dominant mean state under mixed boundary conditions [70]. A linear stability analysis of this state revealed one damped oscillatory thermohaline circulation mode in addition to purely damped modes. Direct comparison of the variability in the box model and the coupled ocean-atmosphere model revealed common qualitative aspects, supporting the hypothesis that the latter's MOC variability could be described by the stochastic excitation of a linear damped oscillatory mode.

Coupled air-sea modes have also been proposed as a mechanism for decadal variability. For instance, [71] described coupled variability with a 35 year period in a multi-century integration of a sophisticated climate model. In their experiments, an anomalously strong MOC drove positive SST anomalies in the North Atlantic. The atmospheric response to the warmer SSTs involved a strengthened NAO, which led to anomalously weak evaporation and Ekman transport off Newfoundland and in the Greenland Sea, as well as the generation of negative sea surface salinity (SSS) anomalies. Reduced deep convection in the oceanic sinking regions and a subsequently weakened MOC eventually led to the formation of negative SST anomalies.

Results from a simple stochastic atmosphere model coupled to a realistic model of the North Atlantic Ocean were described by [72]. A north-south SST dipole, with its zero line centered along the sub-polar front, produced a NAO-like atmospheric response which, in turn, forced the ocean model and produced a damped decadal oscillation. The mechanism consisted of a fast, wind-driven positive feedback of the ocean and a delayed negative feedback orchestrated by shallow overturning circulation anomalies. The positive feedback distinguishes the coupled oscillation from that in a model without an ocean-to-atmosphere feedback. Anomalous geostrophic advection appeared to be important in sustaining the oscillation.

Uncertainties in the atmospheric response to middle latitude SST anomalies and, thus, the strength of air-sea coupling is still an open scientific question and likely explains some of the major differences between the aforementioned model results. Recent studies suggest that the resolution (horizontal and vertical) of atmospheric models may not be sufficient to resolve phenomena such as variations in the position of the polar front [73]. Furthermore, stratospheric and tropospheric variability are linked on seasonal time

scales, as shown by observational and modeling studies. It thus follows that low-frequency stratospheric change, of either natural or anthropogenic origin, can influence the tropospheric circulation. This has recently been highlighted in experiments that indicate the observed strengthening of the stratospheric jet over recent decades could account for observed changes in the phase and amplitude of the NAO and other associated changes in North Atlantic climate [74].

4. SOURCES OF PREDICTABILITY

4.1 External Forcing

A significant source of predictability on the decadal time scale is associated with radiative forcing changes [2]. Past emissions of greenhouse gases have committed the climate system to future warming as the ocean comes into equilibrium with the altered radiative forcing ([75], [76]). Changes in solar irradiance and volcanic activity in the recent past also can provide some level of decadal predictability as the climate system responds to these forcing changes on decadal scales.

The best possible estimates of future radiative forcing changes are also needed for predictions. Estimates of future emissions of radiatively important pollutants are needed for making predictions, as well as modeling capabilities to accurately simulate both how these pollutants affect the global energy, carbon and sulfur cycles, and how the climate system subsequently responds to that altered forcing. In this regard, future external forcing from greenhouse gases is likely to provide significant regional decadal predictability [77], since the increase of concentrations over the next 30 years is about the same no matter what emission scenario is followed [78]. While man-made aerosols can be washed out of the atmosphere by rain in just a few days, they tend to be concentrated near their sources such as industrial regions, and can affect climate with a very strong regional pattern. Future changes in anthropogenic aerosols, therefore, could have very significant regional climatic impacts on decadal scales. Unpredictable volcanic eruptions can be a significant "wild card" to decadal climate predictions, although techniques to handle this aspect are under consideration [79]. Similarly, only very general features of the 11-year solar cycle can be projected, but could provide some decadal scale predictability. The influence of the stratosphere, by transmitting external forcing signals to the troposphere, might also be a significant source of predictability.

4.2 Natural Internal Variability

There have only been a handful of efforts to assess the predictability of the tropical and extratropical ocean state, especially on decadal to inter-decadal time scales. A classic measure of predictability is how rapidly two similar states diverge from each other with predictability being lost when the two states are as far apart as two randomly chosen states. Using a 40-member ensemble of Community Climate System Model (CCSM-3; [80]) simulations that differ only in their initial atmospheric states, for the globe as a whole the limit of predictability for annual means of average upper-ocean temperature is about a decade (Fig. 3).

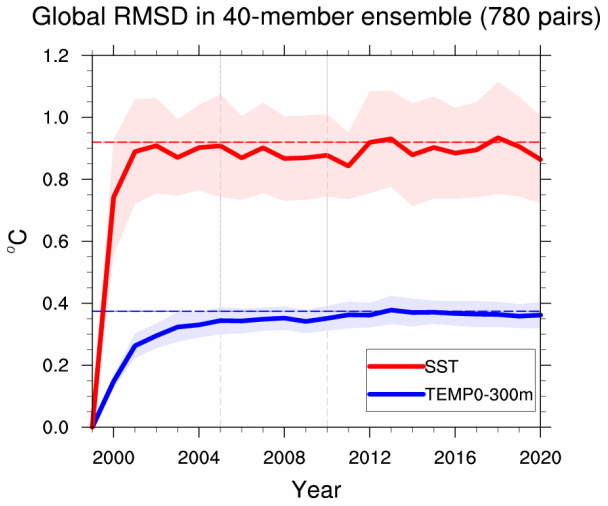

Figure 3. Global Root-Mean-Square-Difference (RMSD) in surface and upper-ocean (0-300 m) temperature from 780 pairs of coupled climate model simulations, derived from an ensemble of 40 simulations. Each simulation differs only in the specification of the initial atmospheric state. The RMSD from completely random states are given by the horizontal, dashed lines. Courtesy of Grant Branstator and Haiyan Teng.

There is less predictability of the global SST field because of the stronger influence of high-frequency atmospheric variability on surface temperature. The results in Fig. 3 are model dependent and could change with better models.

Regionally, the predictability of SST can be higher than for the global field (not shown), with the highest levels on decadal time scales over the middle to high latitude ocean areas of both hemispheres, especially in regions where the surface layer makes contact with the deeper ocean beneath [46]. A fundamental precept in predictability is the notion that long-lived variations, such as those associated with the PDO or changes in the strength of the Atlantic MOC, can be predicted for a significant fraction of their lifetimes. This is simply a reflection of the fact that the persistence of the variation implies a stable balance that permits the variation to have an extended lifetime. Thus, there is some confidence that naturally occurring climate variations with decadal time scales can, at times, be predictable

given an accurate initial state. These times are likely to be when a significant amplitude variation exists. At other times, particularly the nascent phase of variation growth, the predictability of variations is likely to be quite delicate and require a very accurate depiction of the current state of the climate system if there is to be any hope of accurate prediction.

Studies of simulated variability help to identify signals of potential predictability. For the Atlantic MOC, [42] found damped oscillatory MOC variability with a 50-year time scale. Reference [81] demonstrated decadal predictability for several ocean fields in the GFDL model, and [82] found comparable levels of predictability in several independent climate models. Such studies, while provocative, are however limited by the fidelity of the models used and insufficient observations [18] to fully evaluate the physical relevance of the simulations [83].

The Atlantic MOC index is shown from eight different coupled climate model simulations in Fig. 4. Several points are salient to the decadal prediction problem:

- The amplitude and spectra (not shown) of the MOC variability span a wide range, with some models showing periods of quasi-regular multi-decadal oscillations and others showing highly-damped variations whose power is focused more on interannual time scales. Perfect model predictability experiments would likely show correspondingly distinct behaviors.

- The GFDL simulations CM2.1, CM2M, and CM2G use identical atmosphere, sea ice, and land models. Only the ocean model configurations differ; yet, the simulated Atlantic MOC variations exhibit considerable differences, with CM2G illustrating very little power at the decadal time scale. Such results illustrate the potential sensitivity of simulated variability to details of the ocean configuration and the corresponding representation of ocean processes.

- In the CCSM-3 simulations, both the mean value of the Atlantic MOC and the amplitude of its variability have significant dependency on the atmospheric resolution ([84], [85]). There is a ~20 year period of variability in both model configurations, in contrast to the longer-term variability evident in CCSM-4.

- The paucity of observational data precludes a definitive statement as to which simulation best approximates nature. However, no model replicates time series like the observed AMO.

The above results highlight some fundamental challenges and requirements, since the feasibility of decadal predictions largely stems from the role the ocean plays in the predictability of slowly evolving modes of variability. The challenge then is to have the capability to accurately represent this low frequency climate variability within climate models [83], so that initializing them offers the potential to predict the internal variability of the real climate system [4]. To improve the representation of the internal variability in models, it will be necessary to compare and contrast the physical mechanisms that give rise to the simulated variability, with the goal of establishing organizing principle(s) to rationalize the wide ranging simulation behaviors evident in Fig. 4. Such analyses will ultimately lead to an assessment of the importance of certain physical processes for setting the simulated variability, as well as to an improved representation of those processes in models. Paleoclimate reconstructions will also play an important role in constraining the model simulated variability.

Finally, it should be noted that many climate and biogeochemical variables exhibit long-term persistence that could be exploited using statistical forecasting schemes. Physical damping of high-frequency variability increases the decadal signal to noise ratio and hence the potential predictability on decadal timescales. Simple linear multivariate decadal prediction schemes that exploit the long-term damped persistence of certain physical processes may, in fact, be quite successful [86], but they rely heavily on long-term data sets to accurately estimate the covariance matrix. With their potential for long records, paleoclimate reconstructions may be of use in estimating such statistical relationships and developing predictive models. For example, a statistical model for predicting regime shifts in the AMO has been developed [87]; similar methodology could be applied for other climatic shifts.

5. INITIAL CONDITIONS

An important research question is "How accurately must the initial state be described to yield outlooks that are useful to society?" Prediction of the full coupled climate system requires an initial state to be specified based upon observations and a data assimilation system. All sorts of atmospheric observations are routinely processed in real time for numerical weather prediction purposes, and surface fields, including fluxes potentially useful for coupling, result from these analyses. However, surface fluxes of a reanalysis atmospheric model with specified SSTs are typically biased [88] and can be very wrong as the ocean acts as an infinite heat and moisture source or sink. Very useful diagnostics can be obtained on the performance of coupled models, nevertheless, through comparison with good quality surface fluxes [89], such as those from the moored buoy OceanSITES measurements [90].

For climate predictions, the initial state of the atmosphere is less critical, but the initial states of other climate system components are vital. For predictions of a season to a year or so, the SSTs, sea ice extent and upper ocean heat content, soil moisture, snow cover, and state of surface vegetation over land are all important. Such initial value predictions are already operational for forecasting El Niño, and extensions to the global oceans are under way. For the decadal prediction problem, increased information throughout the ocean could be essential ([2], [91], [92], [93]).

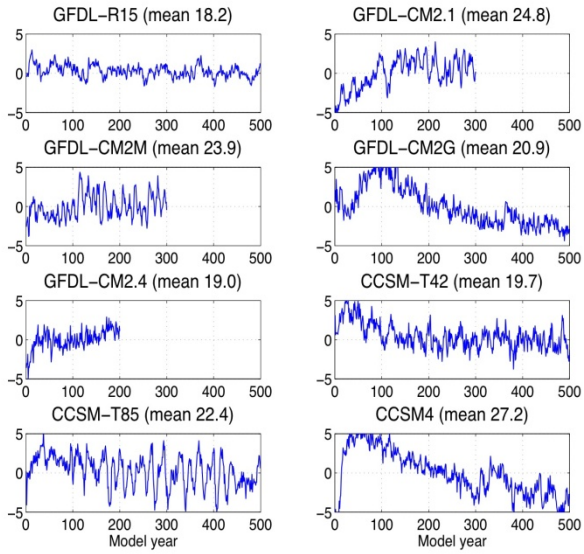

Figure 4. Atlantic MOC index from a suite of coupled climate models. Values plotted are departures from the respective long-term means (listed along top of each graph). Units are Sverdrups (Sv; 1 Sv = 10^6 m^3 s^{-1}). GFDL-R15 is from [42]; GFDL-CM2.1 is from [94]. CM2M and CM2G are prototype models developed for the AR5 IPCC simulations, with each model using the same atmosphere, sea ice, and land used in CM2.1, but with CM2M using updated ocean physics and CM2G using an isopycnal coordinate ocean. CM2.4 uses a ¼° square grid ocean component (with roughly 12km horizontal resolution in the North Atlantic) and a 1° atmosphere that uses the same physics as the 2° CM2.1 atmosphere. CCSM-3 T42 and T85 [80] use the same atmosphere, sea-ice, land, and ocean models, but differ in the horizontal resolution of the atmospheric model. In both, the ocean model has a nominal 1° horizontal resolution. CCSM4 represents a prototype simulation that uses newer physics in all components with a nominal 2° horizontal resolution, finite-volume dynamical core atmosphere and a nominal 1° ocean model.

Initialization has three main components: the observing system, the assimilation method, and the model. These three components are combined to produce initial conditions for the climate model. One needs to keep in mind that the initialization problem is different from the state estimation problem. Next we examine each component and its relation to decadal prediction problem, focusing on the role of the ocean.

5.1. The Observing System

Historically the sub-surface ocean has been very sparsely observed, and some of the data appear to be significantly biased [18, 95], making the development and testing of ocean initialization schemes difficult. For instance, the non-stationary nature of the ocean

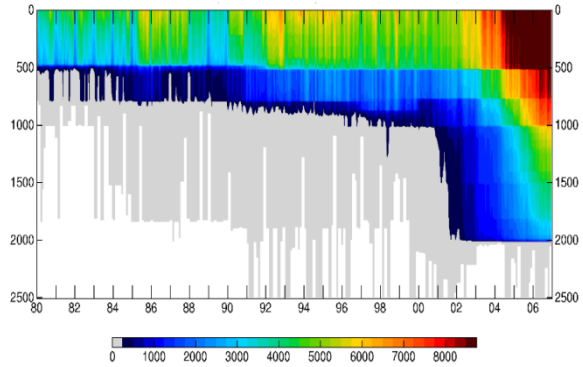

Figure 5. The global number of temperature observations per month as a function of depth. The data sources are XBTs, fixed tropical moorings (TAO (Pacific), TRITON (Pacific), PIRATA (Atlantic), and the developing Indian Ocean array) and Argo floats. The apparent horizontal strata reflect the successive influence of 450 m XBTs, 750 m XBTs, 500 m TAO-class moorings and 1000 m and 2000 m Argo floats.

observing system (Fig. 5), particularly due to the paucity of salinity data as well as XBT data only going to 500 m, can give rise to spurious decadal variability making the assessment of forecasts difficult.

Studies of historical periods are important in order to assess the likely skill of forecasts over a range of different climate states. Recent and planned improvements to the observational network, however, offer significant potential for improvements in future forecast skill. Perhaps most important among these is the recent (2003) deployment of a global array of profiling floats by the Argo program [96]. These provide for the first time contemporaneous measurements of both temperature and salinity over the upper 2 km of the global ocean, potentially offering a step change in our ability to initialize ocean heat and density anomalies. These measurements, for instance, are likely critical in order to make useful predictions of the Atlantic MOC (see Fig. 5 of [4]). Another important recent contribution is the altimetry data that, in addition to its own merits, holds great promise in conjunction with Argo.

5.2 The Assimilation Method

A simple approach that avoids the difficulties with historical sub-surface ocean observations is to initialize models by assimilating only SSTs [97], thus relying on ocean transport processes in the model to initialize the sub-surface ocean indirectly. An alternative approach (being tested at NCAR and MPI) is one in which sub-surface ocean temperature and salinity are diagnosed from an ocean model forced by atmospheric observations, then nudged into a coupled model to produce initial conditions for forecasts. The direct use of sub-surface ocean observations, however, would be expected to improve forecast skill.

Several reanalyses of historical ocean observations have been constructed and are being evaluated through the CLIVAR GSOP (Global Synthesis and Observations Panel) intercomparison project. Temperature and salinity from two of these have already been used to initialize models for decadal forecasts ([91], [98]). In this way, modeling groups without data assimilation schemes can perform initialized climate predictions. Ocean data assimilation is used operationally in several prediction centers around the world to initialize seasonal forecasts with coupled models, and it is from that experience that decadal prediction efforts will build [4]. Ultimately, however, fully-coupled data assimilation schemes that take advantage of covariances between ocean and atmospheric variables to generate an optimal estimate of the climate system are expected to offer the greatest forecast skill. Such schemes are under development with some encouraging results [99].

5.3 The Model

Although idealized model experiments show considerable promise for predicting internal variability, particularly in the North Atlantic ([82], [100]), there are technical obstacles that must be overcome if such potential predictability is to be achieved in reality. The problem of model error, as discussed in Section 3, is critical for decadal prediction, since the sub-surface ocean state associated with the initial condition may be significantly different than the climate of the free running coupled model. As a consequence, at forecast initialization, the coupled model rapidly adjusts away from the observed climate estimate towards the coupled model climate that is itself a product of its own systematic errors. This is often referred to as an "initialization shock" or "coupling shock". Is simple bias correction sufficient to remove the effects of model drift, or is the non-linearity of climate such as to cause bias to destroy any useful predictability that may exist on the decadal timescale?

Another approach, known as "anomaly initialization" [101], has therefore been tried ([91], [97], [98]) to avoid the systematic error. In this, models are initialized with observed *anomalies* added to the model climate, rather than initialized with observed *values,* and the model climate is removed to obtain forecast anomalies. However, the relative merits of bias correction and anomaly assimilation have yet to be quantified on decadal timescales. Nevertheless, with the current generation of ocean data assimilation systems and coupled models, it is possible to demonstrate the benefits of assimilating ocean data for the decadal forecast skill.

6. DECADAL PREDICTIONS

6.1 First Attempts

Prediction of observed decadal variations in climate is in its infancy ([2], [102]). To date there have been two sensitivity studies ([103], [104]) and three extended hindcast experiments ([91], [97], [99]) that investigated the impact of initializing climate projections from an observed state. The sensitivity studies found little additional predictability from initialization over that due to changes in external radiative forcing on global [103] and regional scales [104]. However, neither study considered more than two start dates.

The extended hindcast experiments indicated enhanced skill from initialization at global scale [91] and over the North Atlantic ([97], [98]). These studies took a very similar approach: initializing a global climate model using observed anomalies and running it forward ten years, while accounting for changes in external forcing (natural and anthropogenic). However, the initialization technique, data and models were different and gave rise to different results. Whereas [91] demonstrated that initialization leads to better predictions for global mean temperature over the past nearly three decades of recent warming, the results of [97] and [98] were less convincing over the longer period (Fig. 6, top). The latter two studies demonstrated enhanced skill, however, in the North Atlantic Sector (Fig. 6, bottom). Predictability of global mean temperature arose from initialization of upper ocean heat content [91], whereas for North Atlantic SST it was from the Atlantic MOC. Hence, it may be speculated that differences among these systems comes primarily from different initialization strategies, which is partly supported by the fact that [97] and [98] used essentially the same model. Future ten-year projections from these systems also came to somewhat different outcomes (Fig. 6).

6.2 Single versus Multiple Model Predictions

Differences in the results from the initial decadal prediction efforts discussed above also likely arise from model differences, highlighting the potential importance of a multi-model approach to prediction as is being

investigated, for instance, in the EU-Project ENSEMBLES (http://www.ensembles-eu.org). The need for ensemble prediction for weather is well established based on the fact that the atmosphere is chaotic and therefore sensitive to initial condition uncertainty.

There has been considerable debate in the literature regarding ensemble generation techniques. In terms of sub-seasonal to interannual time scale variability, the climate system clearly exhibits sensitive dependence on initial conditions. For example, [105] argue that forecast errors in some ENSO predictions are dominated by initial condition errors. On decadal to multi-decadal time scales, the sensitivity to initial conditions is not firmly established, but could very well be important, particularly when considering quantifying the climate change commitment.

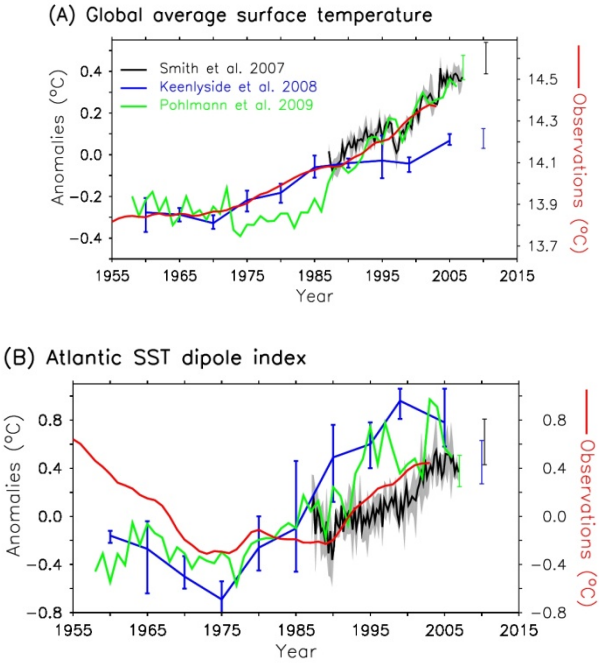

Figure 6. Observed and hindcast ten year mean (top) global surface temperature and (bottom) Atlantic SST dipole indices. The latter is sometimes used as a proxy for MOC fluctuations and is defined as the SST average difference 60-10W, 40-60N minus 30W-10E, 10-40S. Hindcasts for [91] begin in 1982, with one per season and four ensemble members (spread shaded); [97] begin in 1955, with one every five years and three ensemble members (vertical bars); and [98] begin in 1953, with one per year. Separate vertical bars centered on the predicted period show future forecasts. The [98] forecast has seven ensemble members. References [91], [97], and [98] hindcasts have been adjusted to have the observed means over the 1979-2001, 1955-2005, and 1953-2001 periods, respectively. Observations are from HadISST 1.1 and HadCRU3.

Sensitivity due to uncertainty in model formulation can also have a significant impact on predictability [106]. This sensitivity is associated with the uncertainty in sub-grid scale parameterized physics and model numerics. The recognition of the importance of this sensitivity has led to a number of efforts that have demonstrated that a multi-model ensemble strategy is the best current approach for adequately resolving forecast uncertainty and the forecast probability distribution in seasonal-to-interannual predictions ([107], [108], [109], [110], and [111]). Another recently proposed methodology is to use stochastic-dynamic parameterization techniques which perturb parameterizations in such a way as to improve on the benefits of a multi-model ensemble by using a single model [112].

7. VERIFICATION

How to evaluate decadal hindcasts and predictions is a major challenge. A quick scan through the literature reveals a dizzying array of different climate metrics both interesting and important. Furthermore, the attraction to use metrics to select the "best" model for a climate application is problematic [113]. Metrics differ in variable, time scale, space scale, or functional representation. The same is not true in weather prediction, where some estimates of both prediction limits and the impact of different weather prediction metrics can be determined. Moreover, the skill of daily weather forecasts can be verified many times and a quantification of model skill is relatively straightforward.

The problem is more difficult for seasonal prediction, since a large number of seasons and those forecast states must pass in order to build up forecast verification statistics. For decadal and longer time scales, the problem of quantifying prediction skill becomes even more difficult, and the metrics will likely involve how the forecasts are used in applications [114]. One important issue is how to accumulate enough forecasts for quality assessments. The use of hindcasts is a typical approach (Section 5); however, the lack of initialization data and the non-stationary nature of observing systems, as well as the climate system itself, are difficult issues that must be addressed. For instance, forecasts benefiting from Argo data are potentially significantly more skillful than hindcasts based on very sparse historical observations ([4] see also Section 5). Extending the climate record back in time using paleo-proxy data-based climate reconstructions is hence of paramount importance and should be an integral part of decadal prediction research.

In general, decadal forecasts will be probabilistic in nature. There are two key elements in determining the quality of a probability forecast: reliability and resolution [115]. Reliability can be described as follows:

in a set of forecasts where an event is predicted with a (say) 60% probability, the forecast system is reliable if the event occurs in reality, within this set, 60% of the time. In practice, because of model bias and other generic model shortcomings, single model ensembles are not reliable in this sense. Multi-model ensembles are more reliable than single model ensembles [111] but also cannot be said to be fully reliable [112]. Empirical corrections can be made to make the ensembles more reliable, but having to apply such empirical corrections is undesirable, especially since the decadal prediction problem is a nonlinear problem and the empirical correction methods are essentially linear. Evidence is starting to emerge that stochastic parameterization provides an alternative to the multi-model technique, in which reliability is improved [112].

The second element in determining the quality of a probability forecast is resolution. A system with "resolution" will forecast different probabilities according to whether the forecast event verifies or not. Hence a system that always predicts the climatological probability for some binary event, irrespective of whether or not the event verifies, will be reliable but have no resolution. A key goal of decadal prediction research is to establish that decadal prediction probabilities do indeed have some resolution, arising from predictable elements of the climate system such as the Atlantic MOC.

8. CONCLUDING REMARKS

Ocean observations will be at the heart of decadal climate prediction systems. Major challenges will, therefore, be to continually assess whether existing and planned ocean observing systems are also well suited for initialization and verification of decadal predictions and to address any identified deficiencies.

As for seasonal-to-interannual climate predictions, most likely a range of prediction approaches will be used for the decadal time scale. Some early results indicate that the overturning circulation in the ocean can provide some level of useful predictability [3]. Full water column observations will therefore likely be needed to properly initialize coupled system models [22]. A tremendous advance has been the measurements of temperature and salinity over the upper 2000 m of the global ocean currently provided by Argo profiling floats ([40], [96]). There exists, however, a need to assess whether observations from below 2000 m would be of use in decadal climate predictions by more completely characterizing deep ocean conditions ([18], [19], [21]). Verification of decadal predictions will also benefit from sustained moored time series observations, such as those already partially implemented by the oceanSITES group (see [90]; www.oceanSITES.org).

Instrumental errors of roving observing systems (e.g., Argo) remain a challenge [40], as do aliasing effects (due to mesoscale ocean eddies) from course resolution observations in time and space. It might be beneficial to sustain a dense observing system in critical regions for a decade or so in order to assess the requirements on spatial scales and depth resolution for decadal information. An excellent recent example is the RAPID/MOCA array, which will help verify model-based predictions and assessments of meridional ocean transports in the Atlantic ([18], 19]). Other regions requiring long-term intensive observations to help understand the fundamental mechanisms of decadal variability and establish predictability exist as well, such as the Kuroshio Oyashio Extension (KOE) [116], regions connecting middle latitude and tropical ocean circulations [3], the Arctic Ocean [117], the Antarctic Circulation Current System [18], and the exchange through the Indonesian Archipelago [118].

Despite the many issues and challenges outlined above, opportunities exist for major advancements in decadal climate prediction over the next several years. As part of the Coupled Model Intercomparison Project phase 5 (CMIP5) [119], modelling centers around the world are planning coordinated suites of decadal hindcast and prediction experiments covering the period from 1960 to 2035. The results from these prediction experiments will be available to the international research community, and analysis of these results should prove valuable in advancing our understanding of decadal scale variability and predictability. These initialized climate predictions will complement suites of longer term simulations that will explore other aspects of climate system change, including the carbon cycle and other biogeochemical processes and feedbacks that will determine the ultimate degree of climate change in the second half of the 21st century ([78], [120]). Ultimately, combining such approaches, including the use of higher resolution models capable of simulating regional scale climate phenomena, will provide a unified pathway for ever-improving decadal to centennial climate change predictions.

Skillful decadal predictions will prove invaluable to numerous aspects of society [114]. Examples include: climate-related health issues, such as the preparation for and possible prevention of the spread of viruses and diseases; planning for possible disasters from increased forest and bush fires, heat waves, droughts, floods and major storms including hurricanes; long-term resource management decisions in industries such as agriculture, forestry, and fisheries; and development of freshwater allocation strategies. Since the decadal time scale is of the same order as monetary investments, financial institutions could use such climate predictions for planning investment strategies.

8. REFERENCES

1. Hawkins, E. and R. Sutton, 2009: The potential to reduce uncertainty in regional climate predictions. *Bull. Am. Meteorol. Soc.*, **90**, 1095, doi:10.1175/2009BAMS2607.1

2. Meehl, G. A., L. Goddard, J. Murphy, R. J. Stouffer, G. Boer, G. Danabasoglu, K. Dixon, M. A. Giorgetta, A. Greene, E. Hawkins, G. Hegerl, D. Karoly, N. Keenlyside, M. Kimoto, B. Kirtman, A. Navarra, R. Pulwarty, D. Smith, D. Stammer, and T. Stockdale, 2010: Decadal prediction: Can it be skillful? *Bull. Amer. Meteorol. Soc*., 10.1175/2009BAMS2778.1

3. Latif, M., and co-authors, 2010: Dynamics of decadal climate variability and implications for its prediction. In these proceedings (Vol. 2).

4. Balmaseda, M. A., and co-authors, 2010: Initialization for seasonal and decadal forecasts. In these proceedings (Vol. 2).

5. Trenberth, K. E., P. D. Jones, P. Ambenje, R. Bojariu, D. Easterling, A. Klein Tank, D. Parker, F. Rahimzadeh, J. A. Renwick, M. Rusticucci, B. Soden, and P. Zhai 2007: *Observations: Surface and Atmospheric Climate Change.* In: *Climate Change 2007. The Physical Science Basis*. Contribution of WG 1 to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. [S. Solomon, D. Qin, M. Manning, Z. Chen, M. C. Marquis, K. B. Averyt, M. Tignor and H. L. Miller (Eds.)]. Cambridge University Press. Cambridge, U. K., and New York, NY, USA, 235–336, plus annex online.

6. Trenberth, K. E., and J. W. Hurrell, 1994: Decadal atmosphere-ocean variations in the Pacific. *Clim. Dyn*., **9,** 303-319.

7. Mantua, N. J., S. R. Hare, Y. Zhang, J. M Wallace, and R. C. Francis R C, 1997: A Pacific interdecadal climate oscillation with impacts on salmon production. *Bull. Amer. Meteor. Soc.,* **78**, 1069-1079.

8. Power, S., T. Casey, C. Folland, A. Colman, and V. Mehta, 1999a: Inter-decadal modulation of the impact of ENSO on Australia. *Clim. Dyn.,* **15**, 319-324.

9. Folland, C. K., and co-authors, 2002: Relative influences of the interdecadal Pacific oscillation and ENSO on the South Pacific convergence zone. *Geophys. Res. Lett.*, **29**(13), doi:10.1029/2001GL014201.

10. Power, S., F. Tseitkin, V. Mehta, B. Lavery, S. Torok, and N. Holbrook, 1999b: Decadal climate variability in Australia during the twentieth century. *Int. J. Climatol.,* **19**, 169-184.

11. Deser, C., A. S. Phillips, and J. W. Hurrell, 2004: Pacific interdecadal climate variability: Linkages between the tropics and the north Pacific during boreal winter since 1900. *J. Climate*, **17**, 3109–3124.

12. Micevski, T., S. W. Franks, and G. Kuczera, 2006: Multidecadal variability in coastal eastern Australian flood data. *J. Hydrol.,* **327**(1-2), 219-225, doi:10.1016/j.jhydrol.2005.11.017.

13. Hare, S. R., and N. J. Mantua, 2000: Empirical evidence for North Pacific regime shifts in 1977 and 1989. *Progr. Oceanogr*., **47**, 103–145.

14. Schlesinger, M. E., and N. Ramankutty, 1994: An oscillation in the global climate system of period 65–70 years. *Nature*, **367**, 723–726.

15. Enfield, D. B., A. M. Mestas-Nuñez, and P. J. Trimble, 2001: The Atlantic Multidecadal Oscillation and its relation to rainfall and river flows in the continental US. *Geophys. Res. Lett.*, **28**, 2077–2080.

16. Knight, J., and co-authors, 2005: A signature of persistent natural thermohaline circulation cycles in observed climate. G*eophys. Res. Lett*., **32**, L20708, doi: 1029/2005GL024233.

17. Delworth, T. L., and M. E. Mann, 2000: Observed and simulated multidecadal variability. *Clim. Dyn*., **16**, 661-676.

18. Rintoul, S. R., and co-authors, 2010: Deep circulation and meridional overturning: Recent progress and a strategy for sustained observations. In these proceedings (Vol. 1).

19. Cunningham, S., and co-authors, 2010: The present and future system for measuring the Atlantic Meridional overturning circulation and heat transport. In these proceedings (Vol. 2).

20. Lozier, M. S., S. J. Leadbetter, R. G. Williams, V. Roussenov, M. S. C. Reed, and N. J. Moore, 2008: The spatial pattern and mechanisms of heat content change in the North Atlantic, *Science*, **319**, 800-803.

21. Garzoli, S. L., and co-authors, 2010: Progressing towards global sustained deep ocean observations. In these proceedings (Vol. 2).

22. Hood, M., and co-authors, 2010: Ship-based hydrography: A strategy for a sustained global program. In these proceedings (Vol. 2).

23. Hakkinen, S., and P. B. Rhines, 2004: Decline of subpolar North Atlantic circulation during the 1990s. *Science*, **304,** 555–559.

24. Curry, R., and C. Mauritzen, 2005. Dilution of the northern North Atlantic in recent decades. *Science*, **308**, 1772-1774.

25. Sutton, R. T., and D. L. R. Hodson, 2005: Atlantic Ocean forcing of North American and European summer climate. *Science,* **309,** 115–118.

26. Zhang, R., T. L. Delworth, and I. M. Held, 2007: Can the Atlantic Ocean drive the observed multidecadal variability in Northern Hemisphere mean temperature? Geophys. Res. Lett., **34**, L02709, doi:10.1029/2006GL028683.

27. Venegas, S. A., and L. A. Mysak, 2000: Is there a dominant timescale of natural climate variability in the Arctic? *J. Climate*, **13**, 3412–3434.

28. Polyakov, I. V., G. V. Alekseev, L. A. Timokhov, U. S. Bhatt, R. L. Colony, H. L. Simmons, D. Walsh, J. E. Walsh, and V. F. Zakharov, 2004: Variability of the

Intermediate Atlantic Water of the Arctic Ocean over the Last 100 years. *J. Climate*, **17** (23), 4485-4497.

29. Webster, P.J., et al., 2005: Changes in tropical cyclone number, duration and intensity in a warming environment. *Science*, **309**, 1844–1846.

30. Zhang, R., and T. L. Delworth, 2006: Impact of Atlantic multidecadal oscillations on India/Sahel rainfall and Atlantic hurricanes. *Geophys. Res. Lett.,* **33**, L17712, doi:10.1029/2006GL026267.

31. Trenberth, K. E., and D. J. Shea, 2006: Atlantic hurricanes and natural variability in 2005, *Geophys. Res. Lett.*, **33**, L12704, doi:10.1029/2006GL026894

32. Drinkwater, K. F., 2006: The regime shift of the 1920s and 1930s in the North Atlantic. *Progr. Oceanogr.*, **68**, 134-151.

33. Bader, J., and M. Latif, 2003: The impact of decadal-scale Indian Ocean sea surface temperature anomalies on Sahelian rainfall and the North Atlantic Oscillation. *Geophys. Res. Lett.*, **30**, doi: 10.1029/2003GL018426.

34. Giannini, A., R. Saravanan, and P. Chang, 2003: Oceanic forcing of Sahel rainfall on interannual to interdecadal time scales. *Science*, **302**, 1027-1030.

35. Lu, J., and T. Delworth, 2005: Oceanic forcing of the late 20th century Sahel drought. *Geophys. Res. Lett*., **32**, L22706, doi:10.1029/2005GL023316

36. Hoerling, M. P., J. W. Hurrell, J. Eischeid, and A. Phillips, 2006: Detection and Attribution of 20th Century Northern and Southern African Rainfall Change. *J. Climate,* **19,** 3989-4008.

37. Schubert, S. D., M. J. Suarez, P. J. Pegion, R. D. Koster, and J. T. Bacmeister, 2004: Causes of long-term drought in the United States Great Plains. *J. Climate,* **17,** 485–503.

38. Seager, R., Y. Kushnir, C. Herweijer, N. Naik and J. Velez (Nakamura), 2005: Modeling of tropical forcing of persistent droughts and pluvials over western North America: 1856-2000. *J. Climate,* **18**(19), 4065-4088.

39. Seager, R., 2007: The Turn of the Century drought across North America: global context, dynamics and past analogues. *J. Climate*, **20,** 5527-5552.

40. Roemmich, D., and co-authors, 2010: Integrating the ocean observing system: Mobile platforms. In these proceedings (Vol. 1).

41. Bjerknes, J., 1964: Atlantic air-sea interaction. *Advances in Geophysics*, Academic Press, **10**, 1-82.

42. Delworth, T., S. Manabe, and R.J. Stouffer, 1993: Interdecadal variations of the thermohaline circulation in a coupled ocean-atmosphere model. *J. Climate*, **6**, 1993-2011.

43. Latif, M., 1998: Dynamics of interdecadal variability in coupled ocean-atmosphere models. *J. Climate,* **11**, 602-624.

44. Schneider, N. and B. Cornuelle, 2005: The forcing of the Pacific Decadal Oscillation. *J. Climate*, **18**, 4355-4373.

45. Latif, M. 2006: On North Pacific Multidecadal Climate Variability. *J. Climate*, **19**, 2906-2915.

46. Boer, G. J., and S. J. Lambert, 2008: Multi-model decadal potential predictability of precipitation and temperature. *Geophys. Res. Lett.,* **35**, doi:10.1029/2008GL033234.

47. Hasselmann, K., 1976: Stochastic climate models. Part I: Theory. *Tellus*, **28**, 473-485.

48. Frankignoul, C. and K. Hasselmann, 1977: Stochastic climate models. Part II: application to sea surface temperature anomalies and thermocline variability, *Tellus*, **29**, 284–305.

49. Hall, A. and S. Manabe, 1997: Can Local, Linear Stochastic Theory Explain Sea Surface Temperature and Salinity Variability? *Climate Dynamics,* **13**, 167-180.

50. Hurrell, J.W., 1995: Decadal trends in the North Atlantic Oscillation: Regional temperatures and precipitation. *Science,* **269**, 676-679.

51. Lemke, P., E. W. Trinkl, and K. Hasselmann, 1980: Stochastic dynamic analysis of sea ice variability. *J. Phys. Oceanogr.*, **10**, 2100-2120.

52. Frankignoul, C. and R. W. Reynolds, 1983: Testing a dynamical model for midlatitude sea surface temperature anomalies, *J. Phys. Oceanogr.*, **13**, 1131-1145.

53. Herterich K. and K. Hasselmann, 1987: Extraction of mixed layer advection velocities, diffusion coefficients, feedback factors, and atmospheric forcing parameters from the statistical analysis of the North Pacific SST anomaly fields. *J. Phys. Oceanogr.*, **17**, 2145–2156.

54. Saravanan, R. and J. C. McWilliams, 1997: Stochasticity and spatial resonance in interdecadal climate fluctuations. *J. Climate,* **10,** 2299–2320.

55. Deser, C. and M.L. Blackmon, 1993: Surface climate variations over the North Atlantic Ocean during winter: 1900-1989. *J. Climate*, **6**, 1743-1753.

56. Sutton, R. T. and M.R. Allen, 1997: Decadal predictability of North Atlantic sea surface temperature and climate, *Nature*, **388**, 563-567.

57. Alvarez-Garcia, F., M. Latif, and A. Biastoch, 2008: On multidecadal and quasi-decadal North Atlantic variability. *J. Climate*, **21**, 3433–3452.

58. White, W.B. and R. Peterson, 1996: An Antarctic circumpolar wave in surface pressure, wind, temperature, and sea ice extent. *Nature*, **380**, 699-702.

59. Weisse, R., U. Mikolajewicz, A. Sterl, and S. S. Drijfhout, 1999: Stochastically forced variability in the Antarctic Circumpolar Current, *J. Geophys. Res.*, **104**(C5), 11,049–11,064.

60. Frankignoul, C., P. Muller, E. Zorita, 1997: A simple model of the decadal response of the ocean to stochastic wind forcing. *J. Phys. Oceanogr.*, **27**, 1533-1546.

61. Schneider, N., A. J. Miller and D. W. Pierce, 2002: Anatomy of North Pacific decadal variability. *J. Climate*, **15**, 586-605.

62. Latif, M., and T.P. Barnett, 1994: Causes of decadal climate variability over the North Pacific and North America. *Science,* **266**, 634-637.

63. Gu, D. and S. G. H. Philander, 1997: Interdecadal Climate Fluctuations that depend on Exchanges between the Tropics and Extratropics, *Science*, **275**, 805-807.

64. Jacobs, G. A., H. E. Hurlburt, J. C. Kindle, E. J. Metzger, J. L. Mitchell, W. J. Teague, and A. J. Wallcraft, 1994: Decade-scale trans-Pacific propagation and warming effects of an El Niño anomaly. *Nature*, **370**, 360 – 363.

65. Dommenget, D. and M. Latif, 2008: On the generation of hyper climate modes. *Geophys. Res. Lett.*, **35**, L02706, doi:10.1029/2007GL031087.

66. Mikolajewicz, U. and E. Maier-Reimer, 1990: Internal secular variability in an ocean general circulation model. *Climate Dynamics*, **4**, 145-156.

67. Weisse, R., U. Mikolajewicz, and E. Maier-Reimer, 1994: Decadal variability of the North Atlantic in an ocean general circulation model, *J. Geophys. Res.*, **99**(C6), 12,411–12,421.

68. Delworth, T.L., and R.J. Greatbatch, 2000: Multidecadal thermohaline circulation variability driven by atmospheric surface flux forcing. *J. Climate,* **13**, 1481-1495.

69. Griffies, S. M., and E. Tziperman, 1995: A linear thermohaline oscillator driven by stochastic atmospheric forcing. *J. Climate*, **8**, 2440-2453

70. Stommel, H. M., 1961: Thermohaline convection with two stable regimes of flow. *Tellus*, **13**, 224–230.

71. Timmermann, A., M. Latif, R. Voss, and A. Grötzner, 1998: Northern Hemisphere interdecadal variability: A coupled air-sea mode. *J. Climate,* **11**, 1906-1931.

72. Eden, C. and R. J. Greatbatch, 2003: A damped decadal oscillation in the North Atlantic Ocean Climate System. *J. Climate*, **16**, 4043–4060.

73. Minobe S., A. Kuwano-Yoshida, N. Komori, S.-P. Xie, and R. J. Small, 2008: Influence of the Gulf Stream on the troposphere. *Nature*, **452**: 206-209.

74. Scaife, A. A., J. R. Knight, G. K. Vallis, and C. K. Folland, 2005: A stratospheric influence on the winter NAO and North Atlantic surface climate. *Geophys. Res. Lett.*, **32**, L18715.

75. Hansen, J. E., and co-authors, 2005: Efficacy of climate forcings. *J. Geophys. Res.* **110**, D18104, doi:10.1029/2005JD005776.

76. IPCC, 2007: Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H. L. Miller (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 996 pp.

77. Lee, T. C. K., F. Zwiers, X. Zhang, and M. Tsao, 2006: Evidence of decadal climate prediction skill resulting from changes in anthropogenic forcing. *J. Climate*, **19,** 5305-5318.

78. Hibbard, K. A., G. A. Meehl, P. Cox, and P. Friedlingstein, 2007: A strategy for climate change stabilization experiments. *EOS*, **88**, 217, 219, 221.

79. Ammann, C. M., and P. Naveau, 2010: A statistical volcanic forcing-scenario generator for climate simulations. *J. Geophys. Res.,* in press, doi:10.1029/2009JD012550.

80. Collins, W. D., and co-authors, 2006: The formulation and atmospheric simulation of the Community Atmosphere System Model Version 3 (CAM3). *J. Climate*, **19**, 2144-2161.

81. Griffies, S. M., and K. Bryan, 1997: Predictability of North Atlantic multidecadal climate variability. *Science*, **275**, 181-184.

82. Collins, M., and co-authors, 2006. Interannual to Decadal Climate Predictability: A Multi-Perfect-Model-Ensemble Study. *J. Climate*, **19**, 1195–1203. doi:10.1175/JCLI3654.1.

83. Griffies, S. M., and co-authors, 2010: Problems and prospects in large-scale ocean circulation models. In these proceedings (Vol. 2).

84. Bryan, F. O., G. Danabasoglu, N. Nakashiki, Y. Yoshida, D. H. Kim, J. Tsutsui, and S. C. Doney, 2006: Response of North Atlantic thermohaline circulation and ventilation to increasing carbon dioxide in CCSM3. *J. Climate*, **19**, 2382-2397.

85. Danabasoglu, G., 2008: On multi-decadal variability of the Atlantic meridional overturning circulation in the Community Climate System Model version 3 (CCSM3). *J. Climate*, **21**, 5524-5544, doi:10.1175/2008JCLI2019.1.

86. Lean, J. L., and D. H. Rind, 2009: How will Earth's surface temperature change in future decades? *Geophys. Res. Lett.,* **36**, L15708, doi:10.1029/2009GL038932, 2009.

87. Enfield, D. B., and L. Cid-Serrano, 2006: Projecting the risk of future climate shifts. *Int. J. of Climatology*, **26**, 885-895.

88. Trenberth, K. E., J. T. Fasullo, and J. Kiehl, 2009: Earth's global energy budget. *Bull. Amer. Meteor. Soc.*, **90**, No. 3, 311-324.

89. Gulev, S. K., and co-authors, 2010: Surface energy and CO2 fluxes and sea ice. In these proceedings (Vol. 1).

90. Send, U., and co-authors, 2010: OceanSITES. In these proceedings (Vol. 2).

91. Smith, D. M., and co-authors, 2007: Improved surface temperature prediction for the coming decade from a global climate model. *Science,* **317,** 796-799.

92. Trenberth, K. E., 2008: Observational needs for climate prediction and adaptation. *WMO Bulletin*, **57** (1) 17-21.

93. Shukla, J., 2010: A Revolution in Climate Prediction is both necessary and possible. *Bull. Amer. Meteor. Soc.*, in press.

94. Delworth, T. L., and co-authors, 2006: GFDL's CM2 Global Coupled Climate Models - Part 1: Formulation and Simulation Characteristics. *J. Climate,* **19**, 643-674.

95. Domingues, C. M., J. A. Church, N. J. White, P. J. Gleckler, S. E. Wijffels, P. M. Barker, and J. R. Dunn, 2008: Improved estimates of upper-ocean warming and multi-decadal sea-level rise. *Nature*, **453**, doi:10.1038/nature07080.

96. Freeland, H., and co-authors, 2010: Argo – A decade of progress. In these proceedings (Vol. 2).

97. Keenlyside, N., M. Latif, J. Junclaus, L. Kornblueh, and E. Roeckner, 2008: Advancing decadal climate scale prediction in the North Atlantic. *Nature,* **453**, 84-88.

98. Pohlmann H, J. H. Jungclaus, A. Köhl, D. Stammer, and J. Marotzke, 2009: Initializing Decadal Climate Predictions with the GECCO Oceanic Synthesis: Effects on the North Atlantic. *J. Climate*, in press.

99. Zhang, S., M. J. Harrison, A. Rosati, and A. Wittenberg, 2007: System design and evaluation of coupled ensemble data assimilation for global oceanic climate studies. *Mon. Wea. Rev.,* **135(10)**, 3541-3564.

100. Hurrell, J. W., G. A. Meehl, D. Bader, T. Delworth, B. Kirtman, and B.Wielicki, 2009: A Unified Modeling Approach to Climate System Prediction. *Bull. Amer. Meteorol. Soc.*, doi:10.1175/2009BAMS2752.1

101. Schneider E. K., B. Huang, Z. Zhu, D. G. DeWitt, J. L. Kinter III, B. P. Kirtman, and J. Shukla, 1999: Ocean data assimilation, initialization, and prediction of ENSO with a coupled GCM. *Mon. Wea. Rev.*, **127**, 1187–1207.

102. Murphy, J., and co-authors, 2009: Towards prediction of decadal climate variability and change. In: Proceedings of the World Climate Conference-3 (WCC-3), 31 August – 4 September 2009, Geneva, Switzerland: World Meteorological Organization, in press.

103. Pierce, D. W., T. P. Barnett, R. Tokmakian, A. Semtner, M. Maltrud, J. Lysne, and A. Craig, 2004: The ACPI project, element 1: initializing a coupled climate model from observed conditions. *Climatic Change*, **62**, 13-28.

104. Troccoli, A., and T. N. Palmer, 2007: Ensemble decadal predictions from analysed initial conditions. *Phil. Trans. Roy. Soc. A*, 365, 2179-2191.

105. Stan, C., and B. P. Kirtman, 2008: The influence of atmospheric noise and uncertainty in ocean initial conditions on the limit of predictability in a coupled GCM. *J. Climate*, **21**, doi 10.1175/2007JCLI2071.1

106. Palmer, T. N., F.J Doblas-Reyes, R Hagedorn, and A Weisheimer, 2005: Probabilistic prediction of climate using multi-model ensembles: from basics to applications. *Philos. Trans. R. Soc. Lond.,* **360**, 1991–1998.

107. Kirtman, B. P., and D. Min, 2009: Multi-model ensemble ENSO prediction with CCSM and CFS. *Mon. Wea. Rev*., in press.

108. Palmer, T. N., F. J. Doblas-Reyes, A. Weisheimer, and M. J. Rodwell, 2008: Toward seamless prediction: Calibration of climate change projections using seasonal forecast. *Bull. Amer. Metero. Soc*., **89**, 459-470.

109. Doblas-Reyes, F. J., R. Hagedorn, and T. N. Palmer, 2005: The rationale behind the success of multi-model ensembles in seasonal forecasting - II. Calibration and combination. *Tellus A,* **57**, 234–252, doi:10.1111/j.1600-0870.2005.00104.x

110. Hagedorn, R. F. J. Doblas-Reyes, and T. N. Palmer, 2005: The rationale behind the success of multi-model ensembles in seasonal forecasting - I. Basic concept. *Tellus A*, **57**, 219–233, doi:10.1111/j.1600-0870.2005.00103.x

111. Palmer, T. N., and coauthors, 2004: Development of a European multi-model ensemble system for seasonal-to-interannual prediction (DEMETER), *Bull. Amer. Meteor. Soc*., **85,** 853-872.

112. Palmer, T. N., and co-authors, 2009: Towards the probabilistic earth system model. *J. Climate,* in press.

113. Gleckler, P. J., K. E. Taylor, and C. Doutriaux, 2008: Performance metrics for climate models, *J. Geophys. Res.*, **113**, D06104, doi:10.1029/2007JD008972.

114. Vera, C., and co-authors, 2009: Needs assessment for climate information on decadal time scales and longer. In: Proceedings of the World Climate Conference-3 (WCC-3), 31 August – 4 September 2009, Geneva, Switzerland: World Meteorological Organization, in press.

115. Hsu, W.-R., and A. H. Murphy, 1986: The attributes diagram: A geometric framework for assessing the quality of probability forecasts. *Int. J. Forecasting*, **2**, 285-293.

116. Cronin, M., and co-authors 2010: Monitoring ocean - atmosphere interactions in western boundary current extensions. In these proceedings (Vol. 2).

117. Calder, J., and co-authors, 2010: An integrated international approach to Arctic Ocean observations for society (A Legacy of the International Polar Year). In these proceedings (Vol. 2).

118. Gordon, A., and co-authors, 2010: "Interocean exchange of thermocline water: Indonesian throughflow; "Tassie" Leakage; Agulhas Leakage. In these proceedings (Vol. 2).

119. Taylor, K., R. J. Stouffer, and G. A. Meehl, 2009: A summary of the CMIP5 experiment design. See http://cmip.llnl.gov/cmip5/docs/Taylor_CMIP5_design.pdf.

120. Meehl, G. A., and K. A. Hibbard, 2007: A strategy for climate change stabilization experiments with AOGCMs and ESMs. WCRP Informal Report No. 3/2007, ICPO Publication No. 112, IGBP Report No. 57, World Climate Research Programme: Geneva, 35 pp.