WCC-3 Decadal Climate Variability Session:

Towards Prediction of Decadal Climate Variability and Change

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1. Introduction

The effects of anthropogenically-forced climate change are expected to continue through the 21st century and beyond. However, on a time scale of a few years to a few decades ahead, future regional changes in weather patterns and climate, and the corresponding impacts, will also be strongly influenced by natural unforced climate variations. This is supported by an extensive list of observed examples of sustained (decadal-scale) climate variations with significant impacts on society, including the US 1930s "dust bowl" droughts (e.g. Seager et al., 2008); rainfall in India (e.g. Mehta and Lau, 1997); rainfall in China (e.g. Hameed et al., 1983); floods in the Nile river (e.g. Kondrashov et al., 2005); droughts in the Nordeste region of Brazil (e.g. Mehta, 1998); the current drought in south-western US (Barnett et al., 2008); Sahel drought of the 1970s and 80s (e.g. Lu and Delworth, 2005); variability in Atlantic hurricane activity (e.g. Goldenberg et al., 2001; Zhang and Delworth, 2006); Arctic warming in 1930-40s (Semenov and Bengtsson, 2003; Johannessen et al., 2004); the mid-1970s climate shift in the Pacific (e.g. Meehl et al., 2009a); rapid warming in European winter temperatures from the 1960s to the 1990s (Scaife et al., 2005); variations of the Caspian Sea level (Rodionov, 1994); and others.

The decadal time scale is widely recognised as a key planning horizon for governments, businesses, and other societal entities (Vera et al., 2009). Its importance is recognised by IPCC, which will include results from an experiment specifically designed to provide decadal climate projections in its Fifth Assessment report (Taylor et al, 2008). It is also recognized through a number of national initiatives aimed at providing future climate information for decadal and (in some cases) longer time scales (Meehl et al., 2009b).

While important, decadal prediction remains a major challenge in climate science. On decadal time scales, regional anthropogenically-forced changes can be expected, but will typically be smaller than internal variability. There is emerging evidence, however, that some aspects of internal variability could be predictable for a decade or longer in advance (Meehl et al., 2009b). The evidence comes from idealised predictability studies (e.g. Collins et al., 2006a), and also from pioneering efforts at initialised decadal projections using global coupled ocean-atmosphere climate models (AOGCMs - Smith et al., 2007; Keenlyside et al., 2008; Pohlmann et al., 2009). These studies address the possibility of achieving skill in multiyear means of global or large-scale-regional surface temperature. The challenge is to develop from these efforts to the type of information needed for impacts and regional risk assessments. In many applications, the requirement could involve provision of plausible daily time series (e.g. to predict impacts on river flow, crops, etc.), as well as longer term averages.

Modelling systems for decadal prediction need to be designed to capture: (a) the commitment to future climate change arising from incomplete adjustment to past changes in external forcing (e.g. Meehl et al., 2005); (b) the effects of future changes in anthropogenic forcing (e.g. Lee et al., 2006; Stott and Kettleborough, 2002), noting that the effects of explosive volcanic eruptions are also potentially important (Shiogama et al., 2009), but cannot be predicted in advance; and (c) potential predictability of internal variability arising from initialisation of slowly-varying components of the climate system (Hurrell et al., 2009a). In addition to major enhancements of observational networks (Trenberth, 2008), particularly in the oceans, this will require further developments in initialisation techniques. Given inevitable uncertainties arising from the effects of initialisation, and modelling and forcing errors, more ambitious strategies will be needed for the design of ensemble climate model projections, in order to understand and quantify decadal predictability and how it may be affected by forced climate change.

The goal of this paper is to demonstrate the opportunities and challenges associated with improved understanding and predictions of climate on decadal time scales. . Two complementary white papers on various aspects of decadal variability and prediction, prepared for the OceanObs meeting in 2009, are Hurrell et al (2009a) and Latif et al. (2009).

2. Variability and predictability of decadal climate

2.1 Characteristics of observed decadal climate variability

2.1.1 Introduction

The purpose of this section is to synthesize in brief the essence of the current state of observed decadal climate variability (DCV) characteristics and some examples of DCV impacts on climate on land. In sections 2.1 and 2.2 we concentrate on aspects of DCV arising either from internal climate variability or from natural external forcing. In section 3 we consider potential predictability from these sources, and also from the influence of anthropogenic external forcing.

Many statistical analysis studies have isolated large-scale, coherent patterns of decadal variability in land- and sea-surface temperatures (SSTs), and rainfall on land. Radiative forcing associated with the 11- and 22-year sunspot cycles and lunar tidal forcing at the 18.6-year period have been cited to explain some of these patterns, and in some cases physical mechanisms have been proposed (e.g. Meehl et al. 2008; Hasumi et al., 2008). In addition, there is a large collection of patterns associated with unforced internal variability of the climate system, discussed in section 2.1.2 below. Occasionally, abrupt transitions from one climate state to another climate state spanning one or more decades are also referred to as DCV. There is also the possibility (also discussed briefly in section 2.1.2) that some aspects of DCV could also modulate internal variability on shorter time scales (e.g. the frequencies and intensities of El Niño-La Niña events). All these aspects of DCV phenomena are potential sources of decadal climate predictability (see section 2.3).

2.1.2 Major DCV phenomena and their association with climate variability on land

The North Atlantic Oscillation and the Atlantic Multidecadal Oscillation

Sir Gilbert Walker of the India Meteorological Department first discovered a north-south atmospheric pressure "seesaw" he termed the North Atlantic Oscillation (NAO) in the late 1920s (Walker and Bliss, 1932). This north-south pattern oscillates at a variety of time scales, among them decadal and longer periods (Hurrell, 1995; Hurrell and van Loon, 1997). In the last 10-15 years, the Arctic and Antarctic Oscillations (AO and AAO, respectively; Thompson and Wallace, 2000) have been associated with climate variability over the two respective high-latitude regions. The NAO is believed to be the North Atlantic component of the AO.

The Atlantic Multidecadal Oscillation (AMO) (e.g. Delworth and Mann, 2000; Knight et al., 2005) is a broad hemispheric pattern of multidecadal variability in surface temperature, centred on the North Atlantic basin (Fig. 1). Paleoclimate proxies and instrument-measured SST observations show that the AMO undergoes multidecadal variability (e.g. Fig. 1). Observations and coupled climate model simulations show that the AMO is associated with rainfall variations in central Africa, southern Africa, and the Indian subcontinent (e.g. Zhang and Delworth, 2006). Observations also show that the AMO is associated with variations in Atlantic hurricane activity via its influence on vertical wind shear in the tropical Atlantic region; and on summer temperatures in North America and Europe (e.g. Zhang and Delworth, 2006). Influences of the AMO on the Indo-Pacific Oceans have also been hypothesized. The relationship, if any, between the AMO and the NAO is not clear.

The Tropical Atlantic SST Gradient Oscillation

The tropical Atlantic SST gradient (TAG for brevity) across the equator is known to vary at 12-13 years period (e.g. Mehta and Delworth, 1995; Chang et al., 1997; Mehta, 1998; Sutton et al., 2000). Variability of many atmosphere and ocean variables are associated with the TAG variability, such as winds in the lower troposphere; heat transferred between the Atlantic Ocean and the overlying atmosphere; cloudiness; rainfall in northeast Brazil and west Africa; Atlantic hurricanes; and water vapour influx and rainfall in the southern, central, and mid-western U.S. (e.g. Hastenrath, 1990; Mehta, 1998; Hurrell et al., 2006).

The North Pacific Oscillation, the Pacific Decadal Oscillation, and the Interdecadal Pacific Oscillation

Sir Gilbert Walker also discovered a phenomenon he termed the North Pacific Oscillation (NPO) in the late 1920s (Walker, 1925). The NPO is a seesaw in atmospheric pressure between sub-polar and sub-tropical latitudes in the North Pacific region. Subsequently, when long-term SST data in the Pacific Ocean became available in the 1990s, a number of researchers found that the dominant pattern of SST variability in the extratropical North Pacific varied at time scales of one or more decades and that this SST pattern was associated with the NPO in the atmosphere. This SST pattern is called the Pacific Decadal Oscillation (PDO; Mantua et al., 1997). The Interdecadal Pacific Oscillation (IPO; Power et al., 1999) is a Pacific-wide SST pattern covering both hemispheres, showing a similar pattern of variability to the PDO in the North Pacific (Folland et al., 2002). The IPO is characterized by year-to-year and longer-term, predominantly decadal-to-multidecadal, variability of the Pacific Ocean SSTs, with opposite phases between the tropical-subtropical Pacific Ocean and the mid-latitude Pacific Ocean in both hemispheres (Fig. 2).

Among the phenomena associated with the NPO-PDO-IPO (e.g. Mantua et al., 1997) are winds in the lower troposphere; heat transferred between the Pacific Ocean and the overlying atmosphere; cloudiness; Pacific typhoons; and periods of prolonged dryness and wetness in the western U.S. and the Missouri River Basin in the U.S. Major changes in northeast Pacific marine ecosystems have been correlated with phase changes in the PDO such as the mid-1970s climate shift in the Pacific (Meehl et al., 2009a); warm eras have seen enhanced coastal ocean biological productivity in Alaska and inhibited productivity off the west coast of the contiguous United States, while cold PDO eras have seen the opposite north-south pattern of marine ecosystem productivity. PDO phases are also associated with variations in salmon catch in the Pacific, especially in Alaska. The number of forest fires, tree growth rates, and streamflow in the Columbia River in the Pacific Northwest of the U.S. are also associated with PDO phases.

Decadal modulation of higher frequency phenomena

There is evidence that shorter term phenomena, such as El Niño-Southern Oscillation (ENSO) events, heavy rainfall events, and occurrences of tropical cyclones, undergo significant decadal modulation. In particular, the frequency, intensity, spatial pattern, and predictability of interannual El Niño-Southern Oscillation (ENSO) events have been found to undergo decadal-multidecadal variability (e.g. Gu and Philander, 1995; Kestin et al., 1998; Torrence and Webster, 1999; White and Cayan, 2000). Predictability of ENSO impacts on Australian climate was found to be modulated by the IPO such that in the warm IPO phase, there is no robust relationship between year-to-year Australian climate variations and ENSO. In the cold IPO phase, year-to-year ENSO variability is closely associated with year-to-year variability in rainfall, surface temperature, river flow and the domestic wheat crop yield in Australia (e.g. Power et al., 1999; Arblaster et al., 2002). ENSO impacts on North American climate were also found to be modulated by the NPO (e.g. Gershunov and Barnett, 1998; Minobe and Mantua, 1999).

2.2 Simulation of decadal climate variability

Since the success in the late 1980s of coupled ocean-atmosphere models in simulating ENSO-like variability, a variety of uncoupled and coupled ocean-atmosphere models have been used since the late 1980s-early 1990s to simulate observed decadal climate variability. State-of-the-art model are now able to simulate the key features of the most prominent observed modes of decadal variability. On a global and even continental scale, decadal temperature variability of coupled climate models has been shown to be realistic (Hegerl et al., 2007). However, precipitation variance in many latitude bands may be underestimated by climate models on average by about a factor of two (Zhang et al., 2007a), although the comparative sparsity of observed precipitation data limits the extent to which a firm conclusion can be drawn.

In the Atlantic sector, most climate models are able to simulate multi-decadal variations in SST similar to the observed AMO (Latif et al. 2006). These variations are generally associated with fluctuations in the Atlantic meridional overturning circulation (AMOC). However, the mechanisms for the variability differ among models, and there is a wide range of simulated periods and strengths, and even the oscillatory nature remains controversial. Models are able to reproduce many of the climate impacts in regions outside the North Atlantic (Knight et al., 2005), including the variations of the North American and Western European summertime climate (Sutton and Hodson 2005), and Northern Hemisphere averaged surface temperature (Zhang et al., 2007b).

In the Pacific, models also simulate decadal variations with a strong resemblance in their pattern to observations (e.g., Meehl and Hu, 2006). As with the Atlantic, the mechanisms of simulated variability differ among models. Several candidate mechanisms exist: (1) amplitude modulation of interannual El Niño and La Niña events (e.g. Jin, 2001), (2) uncoupled atmospheric variability reddened in its spectral characteristics by the large upper ocean heat capacity (Pierce et al., 2001), and (3) large-scale coupled ocean-atmosphere interactions (e.g. White and Cayan, 1998; Meehl and Hu, 2006; Power and Colman, 2006). Impacts over land regions are also simulated by models (e.g., Meehl and Hu, 2006)

Although there are some similarities between observed and simulated DCV, results are highly model-dependent. Also, observed time series of ocean surface and sub-surface variables, especially in the Pacific and Indian Oceans, are relatively short and their quality is also in doubt. Therefore, assessments of decadal spectral peaks and spatial patterns in the available observations are inconclusive, making their comparisons with multi-century model runs also inconclusive. A large part of the model uncertainty arises because of the insufficient understanding of fundamental ocean-atmosphere interactions believed to be important in DCV..

2.3 Potential predictability at decadal timescales

The relatively long oscillation period of DCV gave rise to the expectation that the state of these oscillations may be predictable with some skill many years to a decade or so in advance. This expectation led to attempts for over two centuries using sunspot numbers and lunar tidal phase as a predictor in conceptual and statistical models. Although successful over short periods, these attempts eventually failed because of non-stationarity of decadal climate phenomena, and unstable correlations between sunspot numbers and climate variables. Nevertheless, the existence of coherent observed patterns in Pacific sea surface temperature, precipitation and circulation anomalies associated with peak solar years (van Loon et al., 2007), supported by plausible physical mechanisms (e.g. Shindell et al. 1999; Meehl et al., 2008) may indicate potential for some degree of predictability in the response to solar forcing.

Much of DCV research in the modern era was based on the assumption that if decadal spectral peaks are stable, they can be potentially a source of multiyear to decadal climate predictability. However, while average decadal spectral peaks may be significant in multidecade to century long time series of rainfall and temperature on land, they may not be stable. Time series of instrument-measured SSTs are not long enough to assess stability of decadal spectral peaks. In spite of these problems, serious efforts in assessing potential predictability of the patterns described above and their impacts should be made using observations.

Several attempts have been made to assess decadal predictability of ocean circulations and temperature using coupled ocean-atmosphere models. In the Kuroshio-Oyashio Extension region in the northwest Pacific Ocean there appears to be some multiyear to decadal predictability of SSTs (e.g. Schneider and Miller, 2001). There is also evidence that integrated quantities such as the AMO or the strength of the AMOC may be predictable over decadal or longer time scales with some skill (e.g. Griffies and Bryan, 1997; Collins et al., 2006a), and that their association with (for example) rainfall in Africa and the Indian sub-continent (Zhang and Delworth, 2006) could allow some important aspects of climate over land to be predicted over a number of years. However, AOGCMs simulate spectral peaks in the North Atlantic which are highly-model dependent, therefore realization of this potential predictability remains a challenge in practice.

Based on analysis of AOGCM projections of future climate change, internal variability and the response to anthropogenic forcing are both important sources of potential predictability (Hawkins and Sutton, 2009a). At a regional level, however, their relative importance can be expected to vary. For example Boer (2009) finds that the forced response provides the largest component of uncertainty over the tropical oceans, while internal variability is more important over the mid- and high-latitude oceans. The extent of predictability due specifically to forced climate change will depends on how quickly the forced signal emerges from the background noise attributable to internal variability. For surface temperature the observed response has already emerged clearly from internal variability at continental scales (Hegerl et al., 2007), whereas for precipitation the separation between signal and noise is marginal (Zhang et al., 2007a; Min et al., 2008). At sub-continental or smaller scales it takes several decades for the forced change to emerge (Karoly and Wu, 2005; Knutson et al., 1999).

Prospects for climate prediction at decadal timescales therefore depends on prospects for obtaining skilful projections of aspects of interannual variability such as ENSO; natural decadal variability such as the patterns described in this paper; the response to natural forcings arising from variations in solar output, lunar tidal phase and volcanic eruptions; and human-induced climate changes including such as greenhouse gas- and aerosol- induced changes, and land use-cover changes. Moreover, there are interactions among the various timescales of natural variability, possible generation of harmonics by solar and lunar variability, and possible influence of a warming background climate on natural climate variability. These interactions and influences are largely unexplored. Nevertheless, there is some evidence that climate changes due to human-induced radiative forcing may provide some predictive skill, from the warming commitment arising from the delayed effects of human-induced radiative forcings experienced to date (e.g. Meehl et al., 2005), detection/attribution studies, and analysis of uncertainties in global climate model experiments (see above). It is possible that the global climate community will find some regions where predicted signal-to-background noise ratio is large enough to be useful for societal applications in the next five to 30 years or so, arising from abilities to project some aspects of internal climate variability as well as forced changes in responses to past and future emissions of CO_2, other greenhouse gases and aerosols..

3. Current decadal prediction activities

Prediction of decadal variations in climate is in its infancy. As discussed above, decadal climate variations originate from both internal processes and external forcing, the relative importance of which depends on the region and spatial scales considered. Thus, decadal prediction is a joint initial-boundary value problem. However, only recently was it considered as such. Earlier theoretical and essentially model-based studies investigated the initial value problem. These demonstrated that internal climate variations in the North Atlantic, North Pacific, and Southern Oceans may be predictable on decadal timescales (see, for example, Latif et al. (2006) for a review). Only a few of these studies made any attempt at the real prediction problem (e.g., Venzke et al., 2000; Eden et al., 2002). On the other hand, while the importance of external forcing on centennial timescales has long been recognised, its importance on the decadal timescale was not really considered until recently. For example, radiative forcing changes during the 20th century have been shown to give rise to decadal predictability in surface temperature not only at global, but also on regional scales (Lee et al., 2006; Laepple et al., 2008).

To date there have been five published studies following a joint initial-boundary value approach: two early studies investigating the impact of initialisation (Pierce et al., 2004; Troccoli and Palmer, 2007), followed by three extended hindcast experiments (Smith et al., 2007; Keenlyside et al., 2008; Pohlmann et al., 2009). In these studies, climate models were initialised from observational data, as in seasonal forecasting, and changes (natural and anthropogenic) in radiatively active gases were prescribed following observations (or scenarios), as in climate change experiments. The early studies found little additional predictability from initialization, over that due to changes in external radiative forcing, on global (Pierce et al. 2004) and regional scales (Troccoli and Palmer 2007). However, neither study considered more than two start dates.

The extended hindcast experiments, which considered at least nine different start dates, demonstrated enhanced skill from initialization on a global scale (Smith et al. 2007) and over the North Atlantic (Keenlyside et al. 2008; Pohlmann et al. 2009). Although having similar experimental setups, the initialization technique, data and models were different and gave rise to quite different results. Only Smith et al. (2007) demonstrated that initialization leads to better predictions for global mean temperature. However, a multi-model mean of only externally forced IPCC simulations appears in better agreement with observations (Fig. 3a), highlighting the need for decadal predictions to take into account modelling uncertainties. The other two studies demonstrated enhanced skill in the North Atlantic Sector, and for the Atlantic SST dipole index (Fig. 3b), all models appear to represent the multi-decadal variations better than the IPCC multi-model mean, which indicates a long-term downward trend that is likely associated with the weakening of the AMOC (e.g., Schmittner et al., 2005).

The mechanisms for predictability for the global mean and for the North Atlantic sector were different. In the first case, predictability arose from initialization of upper ocean heat content (Smith et al. 2007), and appears largely explained by a bias correction of the initial state (Laepple et al., 2008). In contrast, the skill in predicting North Atlantic SST was argued to originate from the initialisation of the Atlantic MOC, and hence was likely dynamical in origin. It may be speculated that differences among these systems come primarily from different initialization strategies, which is partly supported by the fact that Keenlyside et al. (2007) and Pohlmann et al. (2009) used essentially the same model. However, model differences cannot be discounted. Future ten-year projections from these systems also came to somewhat different outcomes (Fig. 3).

The decadal prediction studies to date have highlighted several issues (Meehl et al. 2009b). These include how best to initialise the ocean, how to minimise the influence of systematic model biases, how to measure the skill of hindcasts and how to represent the effects of initial state, modelling and forcing uncertainties (Hawkins and Sutton, 2009a). These issues are discussed in section 4.

The recent recognition that decadal climate prediction is important is being strongly reflected in activity of the research community. The ENSEMBLES project (http://www.ensembles-eu.org) is already conducting a coordinated multi-model decadal hindcast study, and there are further new projects developing in Europe, the US and Japan. In addition, the new Coupled Model Intercomparison Project phase 5 (CMIP5) protocol for coordinated climate change experiments to be performed over the next five years includes an experimental design that focuses on decadal predictability and prediction. The goal is to provide a research framework for exploring the question of how predictable is climate one to three decades in advance, and how skilful decadal predictions out to about the year 2035 might be. A general description is given by Meehl et al. (2009b), and detailed requirements for the project are described by Taylor et al. (2008). CMIP5 emerged from extensive discussions in and beyond the CLIVAR and WGCM communities, and builds on the decadal prediction protocols of the European ENSEMBLES project. Only a brief overview is given here.

There are two core experiments for the decadal prediction part of CMIP5 that are considered essential to a meaningful decadal predictability/prediction exercise, and a number of tier 1 experiments that add additional insight into the science questions involved with decadal prediction (Fig. 4). The first core experiment is to make a series of 10-year hindcasts with initial observed climate states every 5 years starting near 1960. How to create the initial climate states is left to the discretion of the modelling groups. These 10-year hindcasts should allow estimates of both the theoretical limits of decadal predictability and our present ability to make decadal predictions. The second core experiment extends the integrations starting from 1960, 1980 and 2005 to 30 years, and explores predictability and prediction over time scales more likely to be significantly influenced by anthropogenic external forcing from changing concentrations of greenhouse gases and aerosols. In both core experiments, volcanic aerosol and solar cycle variability is prescribed during each integration using actual values for the past, and assuming a climatological 11 year solar cycle and no eruptions in the future. These forcings allow an assessment of the predictability and prediction of the internal variability of the climate system, and a clean comparison with observations, and also with uninitialised CMIP5 20th century runs started from pre-industrial control simulations. This CMIP5 activity is intended both to set up a framework for coordinated multi-model experiments to address various science questions involved with decadal predictability and prediction, and also to provide the foundation for the simulations to be assessed as part of the IPCC 5th Assessment Report (AR5).

The CMIP5 experimental protocol for global climate model projections is also being used as a basis for a coordinated regional climate downscaling experiment (CORDEX) for AR5 and beyond, the framework for which is being developed by a WCRP Task Force for Regional Downscaling (see http://wcrp.ipsl.jussieu.fr/SF_RCMTerms.html). The initial focus of CORDEX will be on downscaling of 21st century projections from global simulations of long term climate change. However an experiment to perform downscaling of initialised global model projections for 2005-2035, in regions where these are found to possess skill, will also be included in the CORDEX initiative. This reflects the fact that decadal prediction research is at an early stage, hence results from decadal prediction experiments must be carefully evaluated in the AR5 process so that results from CMIP5 are not misused.

4. Scientific challenges for future prediction systems

(a) Initialisation

Initialising climate models offers the potential to predict internal variability in addition to externally-forced climate change, and is thought to be at the heart of the decadal prediction problem. Although idealized model experiments show considerable promise for predicting internal variability, particularly in the North Atlantic (Collins et al, 2006a), there are technical obstacles that must be overcome if such potential predictability is to be achieved in reality. A fundamental problem is that climate models are unable to simulate the observed climate perfectly. When initialized with observations, models therefore drift towards their preferred imperfect climatology, leading to biases in the forecasts. Such biases are routinely removed from seasonal forecasts by an *a posteriori* empirical correction computed from a series of hindcasts (Stockdale, 1997). This strategy is potentially less applicable for decadal prediction, because the smaller magnitude of the predictable signal is more likely to be masked by inaccuracies in the bias correction computed from a comparatively short period, and because nonlinearities will inevitably grow with the length of the forecasts. An alternative approach, known as “anomaly initialisation” (Schneider *et al*, 1999), has therefore been tried (Pierce et al., 2004; Smith et al, 2007, Keenlyside et al, 2008, Pohlmann et al, 2009). In this approach, models are initialised with observed anomalies added to the model climate, and the mean model climate state is subtracted to obtain forecast anomalies. However, the relative merits of these approaches have yet to be quantified (Anderson et al., 2009).

Historically the sub-surface ocean has been very sparsely observed, and some of the data appear to be significantly biased (Domingues *et al*, 2008; Ishii and Kimoto, 2009). This makes the development and testing of ocean initialisation schemes difficult, reflected in differences between ocean reanalyses produced to date (Stammer, 2006). Furthermore, dynamical models can react to the assimilation of incomplete observations in undesirable ways (Acero-Schertzer *et al*., 1997; Ji *et al*., 2000; Masina *et al*., 2001), producing unrealistic analyses and poor forecasts. A simple approach that avoids the difficulties with historical sub-surface ocean observations is to initialise models by assimilating only sea surface temperatures (Keenlyside *et al*, 2008), relying on ocean transport processes in the model to initialise the sub-surface ocean indirectly. At NCAR and MPI, an alternative approach is being tested in which sub-surface ocean temperature and salinity can be diagnosed from an ocean model forced by atmospheric reanalysis data based on observations, and then nudged into a coupled model to produce initial conditions for forecasts (P. Gent and D. Matei, personal communication). However, the direct use of sub-surface ocean observations would be expected to improve forecast skill, as has been demonstrated for seasonal forecasts (Balmaseda and Anderson, 2009). Several reanalyses of historical ocean observations have been constructed, and are being evaluated through the CLIVAR Global Synthesis and Observations Panel (GSOP) intercomparison project. Temperature and salinity fields from two of these have already been used to initialise models for decadal forecasts (Smith *et al*, 2007, Pohlmann *et al*, 2009), and there is evidence that analysed currents can also be included in the initialisation (Baehr, 2009; Kirtman and Min, 2009; G. Danabasoglu and J. Tribbia, personal communication). In this way, modelling groups without data assimilation schemes can perform initialized climate predictions. Ultimately, however, fully-coupled data assimilation schemes, that take advantage of covariances between ocean and atmosphere variables to generate an optimal estimate of the climate system, would seem to potentially offer the most forecast skill, and are being developed by some groups (Sugiura *et al*, 2008; A. Rosati, M. Kimoto, A. Navarra; personal communications).

Studies of historical periods are important in order to assess the likely skill of forecasts over a range of different climate states. However, recent and planned improvements to the observational network promise significant improvements in future forecast skill. Perhaps the most important of these is the recent deployment of a global array of profiling floats by the ARGO programme (see http://www.argo.ucsd.edu/). 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 initialise and predict ocean heat and density anomalies. These measurements, for instance, are likely critical in order to make useful predictions of the Atlantic MOC. Another important recent contribution is the altimetry data (http://www.aviso.oceanobs.com) that, in addition to its own merits, holds great promise in conjunction with ARGO.

In addition to ocean temperature and salinity, initialisation of other aspects of surface climate, notably sea-ice, snow cover, frozen soil, and soil moisture, may have potential to contribute to predictive skill beyond the seasonal time scale. Direct initialisation of these variables has not been attempted in decadal prediction studies to date, although the process of ocean initialisation (and of atmospheric initialisation in the case of Smith et al. 2007) may allow some aspects of the observed anomalous patterns to be captured in the initial conditions. Additionally, the technique used in the Global Soil Wetness Project (GSWP), whereby atmospheric forcing is used to initialise soil moisture, could be applied to the decadal prediction problem. Explicit initialisation could also be investigated, for example by using measurements of soil moisture from the planned SMOS (Soil Moisture & Ocean Salinity) satellite, or by initialising sea ice thickness with observations from the planned CryoSat-2 satellite.

(b) Improved climate models

Climate models have demonstrated great success in reproducing observed climate variability. Many regional and global scale modes of variability appear spontaneously in models based on first principles of physics. Nevertheless, studies of decadal climate predictions still identify climate model error as a key source of uncertainty (e.g. Hawkins and Sutton 2009a) and there are prominent examples of regional climate fluctuations which are not well reproduced in model simulations (Stenchikov et al 2006) or have inconsistent predictions in different climate models (Biasutti et al 2008). These errors mean that the promising early levels of forecast skill that have been identified in decadal forecasts are undoubtedly underestimates of what will be attained after further model development.

There is growing evidence that current models could gain much from quite modest increases in vertical and horizontal resolution. Most climate models place their upper boundary in the mid stratosphere (Karpechko et al 2008) but there are clear indications that this may sever important teleconnections between predictable tropical modes of climate variability such as the El Nino Southern Oscillation and extratropical climate (e.g. Ineson and Scaife 2008, Cagnazzo and Manzini 2009). Other sources of multiannual predictability such as the stratospheric Quasi-Biennial Oscillation are completely absent from most current models but nevertheless appear to offer surface climate predictability (Thompson et al 2002). Finally, while large-scale aspects of the response to increasing greenhouse gases can be captured in existing climate models, some of the regional details may be improved by better resolution of the stratosphere (Huebener et al 2006). All of these sources of predictability could be represented in decadal prediction models with relatively modest increases in vertical resolution and complexity (e.g. Scaife et al 2002).

A less well established but potentially important improvement in predictability could come from improved ocean-atmosphere coupling. While the influence of the tropical oceans on the atmosphere is well established, the role of extratropical ocean changes on the atmosphere is unclear (Kushnir et al. 2002). However, recent experiments suggest that at ocean eddy resolving resolution there may be a step change in the response of the atmosphere to the ocean. In the boundary layer, near surface winds are known to respond to sharp sea-surface temperature gradients that are beyond the resolution of current decadal prediction models (e.g. Maloney and Chelton 2006). Early tests with high resolution models suggest that this response also extends deep into the troposphere (Minobe et al. 2008). Finally high resolution models (Kravtsov et al 2008) suggest that there could be unrealised predictability for extratropical climate. As with vertical resolution, these studies suggest that horizontal resolution may only need to be increased by a factor of two beyond current levels to achieve these benefits.

(c) Ensembles and uncertainties

The importance of sampling uncertainties in the initial state is well established in seasonal prediction (e.g. Stockdale et al., 1998; Stan and Kirtman, 2008), but is yet to be fully investigated in decadal predictions. Early studies by Smith et al (2007) and Keenlyside et al (2008) did employ simple strategies to generate small ensembles of hindcasts with perturbed initial conditions, finding that these gave rise to a significant spread in the simulated outcomes (e.g. Fig. 3). However, more sophisticated methods will be needed to achieve a fully realistic representation of initial state errors (particularly in the ocean), and their effects on the growth of forecast uncertainties. One approach could be to identify a set of perturbations which optimally capture the fastest growing forecast errors, following methods such as breeding vectors (Toth and Kalnay, 1997; Vikhliaev et al., 2007) or singular vectors (Molteni et al., 1996). Such techniques are commonly used in ensemble weather forecasting, and are now being applied to longer term climate predictions (Kleeman et al. 2003; Hawkins and Sutton, 2009b). An alternative option could be the use of ensemble assimilation methods such as the ensemble Kalman filter (Evensen, 1994), in which analyses of observations are created by using the forecast model and observations to update an ensemble of previous analyses, accounting for analysis, model and observational errors. In prediction systems which assimilate analyses of observations created off-line, another alternative could be to perturb the analyses consistent with their errors, noting that these would arise both from the observations themselves, and from the analysis methods used to convert them into spatially complete fields.

Results from physical climate system models indicate that uncertainties in greenhouse gas emissions are likely to be a relatively minor contributor to the total uncertainty in projections for the next few decades (Meehl et al., 2007), although these results do not account for uncertainties in carbon cycle processes (Friedlingstein et al. 2006). These have potential to increase the spread of projected atmospheric CO_2 concentrations for the next few decades, while noting that the importance of carbon cycle uncertainties, like emissions uncertainties, is considerably larger for longer term projections. At a regional level, there are significant uncertainties in the expected forcing due to tropospheric aerosols (Schulz et al., 2006) and stratospheric ozone (Perlwitz et al., 2009), both of which have potential to affect predictions on the decadal time scale.

Errors in the modelling of dynamical and physical processes are known to be an important source of uncertainty in predictions of internal climate variability on seasonal time scales (e.g. Hagedorn et al., 2005), and of the response to externally forced climate change on multidecadal time scales (e.g. Meehl et al., 2007). Given the importance of both internal variability and forced change in determining future climate anomalies for the next few decades (Hawkins and Sutton, 2009a), it is likely to be important that ensemble forecasts are constructed to sample model as well as initial state uncertainties. The multi-model approach of constructing ensembles from different available AOGCMs has been shown to provide improved estimates of uncertainty in seasonal forecasts compared to single-model ensembles using only perturbed initial conditions (Hagedorn et al., 2005), and also to improve attribution of past changes to anthropogenic forcing (e.g., Zhang et al., 2007a), suggesting potential to improve signal to noise characteristics in decadal predictions. Multi-model ensembles have also been used extensively to provide quantitative uncertainty estimates in multi-decadal climate change projections (e.g. Tebaldi and Knutti, 2007; Meehl et al., 2007), as have perturbed physics ensembles, an alternative approach created by systematically sampling alternative combinations of values for uncertain parameters in a single model (e.g. Stainforth et al., 2005; Collins et al. 2006b; Murphy et al., 2007). A third proposed method consists of applying random rather then sustained perturbations to the model physics, through the introduction of terms designed to represent stochastic aspects of the parameterization of sub-grid scale processes. These stochastic-dynamic parameterization schemes have been applied to the seasonal forecast problem (e.g. Berner et al., 2008). The ENSEMBLES project has compared multi-model, perturbed physics and stochastic physics methods of sampling modelling uncertainties in seasonal and annual hindcasts, finding that the different methods give similar levels of skill on average (Doblas-Reyes et al., 2009).

(d) Hindcasts and evaluation

Decadal prediction systems can be tested in hindcast studies in which the systems are used to “forecast” historical periods, using only data which would have been available at the initialisation time. By comparing parallel initialised and non-initialised hindcast sets containing identical specifications of external forcing, the benefits of initialisation can in principle be assessed. However the scope for comprehensive verification is more limited than for seasonal prediction (e.g. Palmer et al., 2004), in the sense that only a small number of past cycles of decadal variability can feasibly be sampled. For example, it should not be assumed that specific regions in which initialisation of climate model projections is found to give additional skill in some hindcast set (the Indian Ocean and Australasian regions in the case of Smith et al (2007), or the North Atlantic region in Keenlyside et al (2008)) will also show added skill in future projections, because the observed ocean heat, salinity or circulation anomalies giving rise to enhanced predictability could occur in different parts of the world.

Explosive volcanic eruptions provide a further difficulty in the use of past cases to inform future prediction skill. Realistic hindcast studies (e.g. Fig. 3) assume no prior knowledge of past eruptions, and thus avoid generating excessively optimistic estimates of skill (since the response to large eruptions is likely to be a significant source of additional predictability (Soden et al., 2002)). However, the alternative hindcast strategy of assuming prior knowledge of eruptions allows their effects to be studied more comprehensively, which is useful if an eruption occurs in practice in the future. Another factor is that past knowledge of eruptions is now assumed in most historical climate change simulations (Meehl et al., 2007), so there is a case for following the same strategy in initialised decadal hindcasts from a resource perspective, since this allows existing historical climate simulations to be used as a “no initialisation” baseline for the assessment of hindcast skill.

The skill of future forecasts, and of hindcasts initialised from recent observations, may in general be better than that of hindcasts from earlier periods, due to improved initialisation of ocean anomalies likely to arise from the deployment of ARGO floats (section 4a). The growth in amplitude (since the 1970s) of the component of worldwide climate anomalies due to anthropogenic forcing provides an additional reason why future anomalies might be more predictable (at least in sign) than in the past. For example, Shiogama et al. (2007) found that a robust signal of forced climate change in projected temperature extremes for 2011-2030 could be identified using a 10 member ensemble sampling different realisations of internal variability, although larger ensembles might be needed for projections of precipitation extremes (Shiogama et al., 2008). Techniques used in the detection and attribution of such signals (Hegerl et. al., 2007) may help to distinguish between forced changes and internal variability in initialised ensemble projections carried out in future. Assessments of the statistical significance of hindcast skill will be helped by maximising the number of start dates and ensemble members in the hindcast datasets, given potentially modest levels of predictability and the influence of correlations between forecast errors from different cases (e.g. Smith et al., 2007).

Hindcast skill should be quantified using different verification scores, in order to assess different aspects of their quality. For example, a metric such as the anomaly correlation coefficient can be useful when interpreting the ability of systems to predict the phases of natural variability during a limited period characterised by an approximately constant climatological baseline, but will be of less value when assessing the added value of initialised projections superposed upon a significant anthropogenic warming trend occurring over several decades (Meehl et al., 2009b). Ensemble hindcasts should be assessed using measures of probabilistic skill, which depend on the ability of the prediction system to capture a realistic spread of possible outcomes, as well as measures of the skill of "best-estimate" forecast outcomes, such as that based on the ensemble mean (see, for example, Doblas_Reyes et al., 2009).

In addition to statistical assessments of hindcasts, evaluation of the physical mechanisms giving rise to skill will also be essential in order to inform the level of confidence which can be placed in future projections. Understanding and reducing systematic model errors will also be important. There may be scope to augment information derived from extended climate simulations (e.g. Randall et al., 2007) by adopting a “seamless” approach to prediction in which unified modelling hierarchies are deployed in predictions from days to decades ahead in order to target the reduction of biases common to all time scales (Hurrell et al., 2009b).

However, there is also scope to consider post-processing calibration techniques (e.g. Doblas-Reyes et al., 2005), in order to correct for persistent forecast biases which may be resistant to improvements in model performance. The use of metrics of model performance to weight different members of forecast ensembles has been investigated in seasonal prediction (Doblas-Reyes et al., 2005) and long term climate projections (e.g. Murphy et al. 2004; Tebaldi et al., 2005; Watterson, 2008), and can also be considered in decadal prediction, while acknowledging that the definition of appropriate metrics is a difficult task (Gleckler et al., 2008).

(e) Providing regional information for users

Sections 4a-d summarise the wide range of research and development issues relevant to the task of building modelling systems suitable for decadal prediction. Users will require projections at regional scales, including demand for information on the expected characteristics of seasonal, daily or even sub-daily time series (see, for example http://www.ukcip.org.uk) as well as the simple multiyear averages assessed in studies carried out to date. In responding to these needs, improved global models will be needed (section 4b), while a strong case can also be made for ensembles to quantify uncertainties in projections arising from imperfectly known initial conditions, the modelling of relevant physical processes and some aspects of the projected radiative forcing (section 4c).

Given the fledgling status of decadal prediction activities, and limitations imposed by finite computational resources, there will be a balance to be struck between development of systems which address all the above requirements (which should be aimed for, but may take considerable time), and providing projections using current models and systems. For example, existing global models can already capture some key aspects of low frequency climate variability (section 2), and their results can be used to derive skilful simulations of localised features of mean climate, daily time series and extremes through the use of regional climate models (e.g. Denis et al., 2002; Frei et al., 2003; Buonomo et al., 2007), although this depends on the extent of regional systematic biases simulated in the driving global models (e.g. Latif et al., 2001; Pan et al., 2001).

Careful evaluation will therefore be needed prior to the deployment of climate models to provide the detailed information needed by regional stakeholders and decision-makers. A minimum requirement is that a model (or ensemble of models) can be identified which is capable of capturing skilfully any secular regional trends expected as a result of externally forced climate change, while also simulating realistically the regional envelope of internal variability around that trend. Dynamical or statistical downscaling may play an important role in capturing the full extent of regional internal variability, in regions where a significant component of total variability arises from fine scale processes not resolved in the available global models (e.g. Laprise, 2003). Here, an important question will be the level of detail at which regional internal variability needs to be well captured to make a projection useful to users. Will it be sufficient simply to capture the amplitude of the variability on (say) seasonal to decadal time scales, or will it also be necessary to capture higher order aspects such as spells of hot, dry or wet days , or the risk of drought persisting over several seasons or years ?

Beyond these basic requirements, the ability to predict some aspects of internal variability about any long term trend, through initialised model projections, will be a highly desirable feature of any regional prediction system. However, it is not clear what level of skill (beyond that associated with projections of forced changes) is required by potential users of decadal predictions. In this respect, dialogue between climate prediction experts and groups working on regional impacts and applications will be critical, in order to reach a joint assessment of the case for providing useful but imperfect projections using modelling systems available at any given time, versus the benefits of waiting for improved (though probably still imperfect) projections likely to become available at some future date.

5. Summary and recommendations

There is growing interest in the field of decadal climate prediction, supported by observational evidence of natural decadal climate variations with significant regional impacts, and evidence of potential skill from idealised predictability studies and pioneering attempts at predictions obtained by initialising climate models with observations. However, this new area of climate science is at an early stage, hence a number of significant challenges, listed below, need to be addressed if practical prediction systems are to be provided which are capable of providing credible projections at regional scales for use by impacts scientists, stakeholders and planners.

- A much better understanding is needed of the physics underlying the various patterns of decadal climate variability (see Section 2). Efforts need to be made to ensure that the important physical mechanisms are well-represented in the models used for decadal predictions..
- Initialisation of slowly-varying components of the climate system is essential, if low frequency aspects of internal climate variability are to be predicted. Recent improvements to the coverage of ocean observations (ARGO) need to be sustained, and methods of analysing and assimilating these observations into climate models need to be improved. The potential of satellite data to contribute to improved initialisation of the ocean, sea-ice, snow cover and soil moisture should also be investigated.
- The response to past and future anthropogenic forcing from greenhouse gases and aerosols is recognised as a significant source of predictability, and natural external forcing from recent volcanic eruptions and projected solar variations are also potentially important. Projections must therefore include the best possible specifications of expected future forcing.
- The development of climate models with better horizontal and vertical resolution is a priority, given their potential to improve the representation of coupled ocean-atmosphere variability and stratospheric effects on surface and tropospheric climate anomalies.
- High resolution projections are also needed to provide realistic information on detailed regional changes, extremes and time series required by users. These can

potentially be obtained either directly from global models, or more cheaply from dynamical or statistical downscaling of projections from lower resolution global models, if the latter can be shown to provide skill in projections at sub-continental scales.

- Given inevitable uncertainties in model projections, the development of ensemble techniques to achieve realistic sampling of the consequences of initial state and modelling errors is also important. Uncertainties in some regional aspects of external forcing (aerosols and ozone) may also be significant for decadal predictions in some regions.
- Hindcast studies of past cases are needed to assess the basis for skilful future forecasts, recognising that a large set of cases will be necessary to obtain statistically significant results, to sample (as far as possible) different phases of past realisations of decadal variability and to allow different sources of predictability to be quantified and understood.
- The issues listed above create competing resource requirements. Several coordinated international experiments (ENSEMBLES, CMIP5, CORDEX) are in progress, which will provide some of the information needed to address and prioritise these research challenges.

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Figures

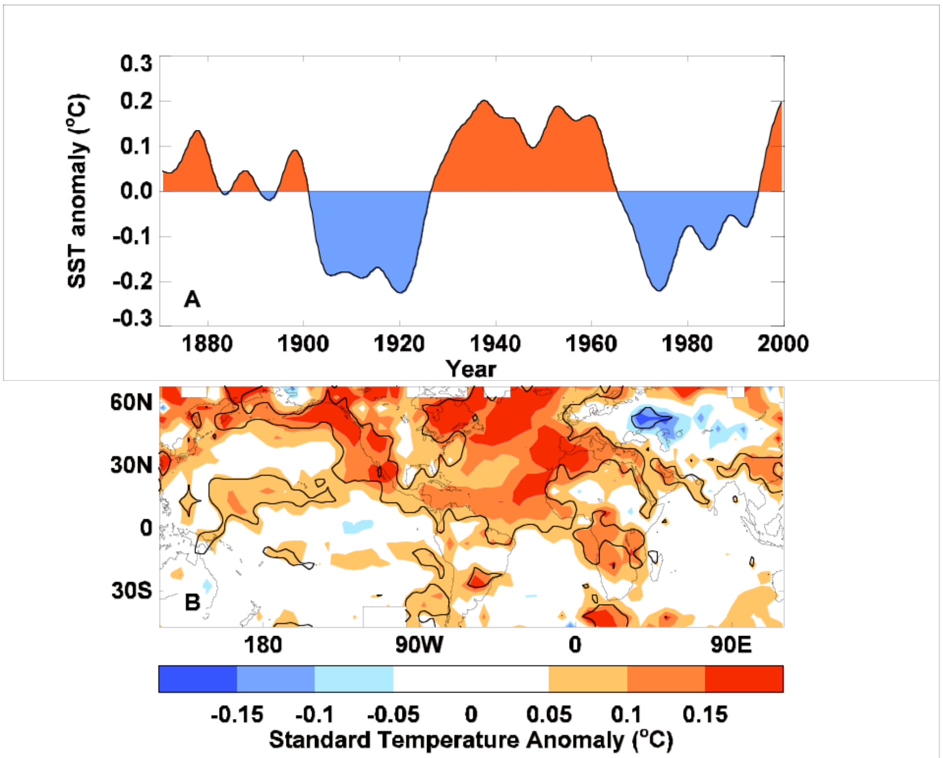
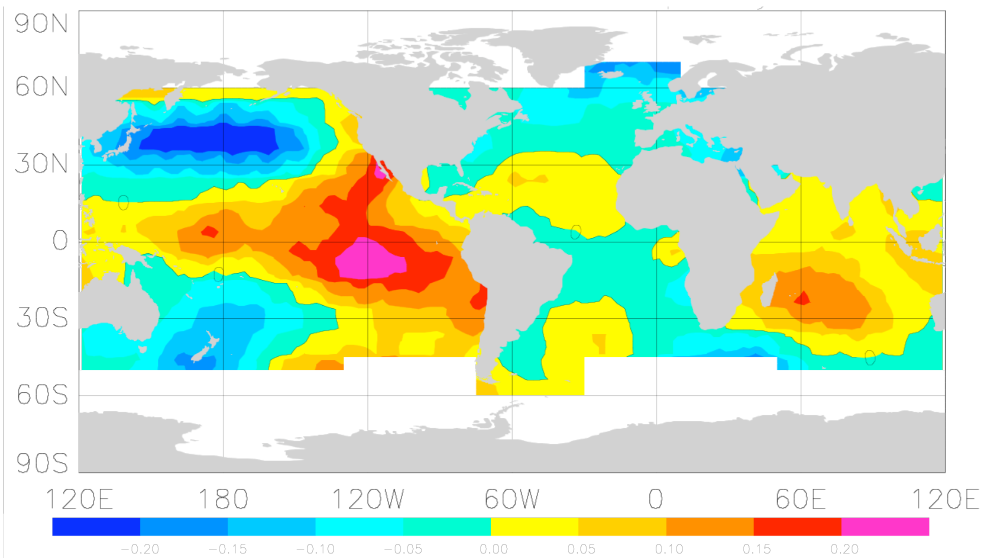


Figure 1. The Atlantic Multidecadal Oscillation. Time series of observed anomalies derived from detrended SST anomalies in the North Atlantic (upper, °C) and associated pattern of anomalous surface temperatures showing enhanced warming over the North Atlantic and Pacific basins. Further details in Knight et al (2005).



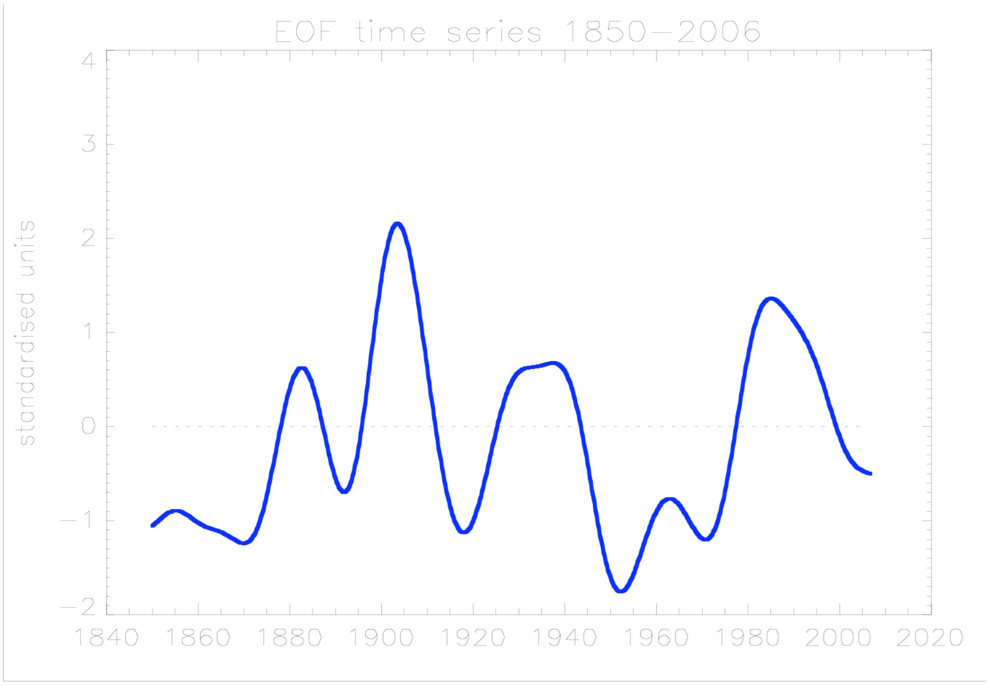


Figure 2. The Interdecadal Pacific Oscillation. Pattern of anomalous low-pass filtered sea surface temperature (upper) showing enhanced warming over the equatorial Pacific and cooling over the North and South Pacific ocean. Time series of observed IPO anomalies (lower). Further details in Parker et al. (2007).

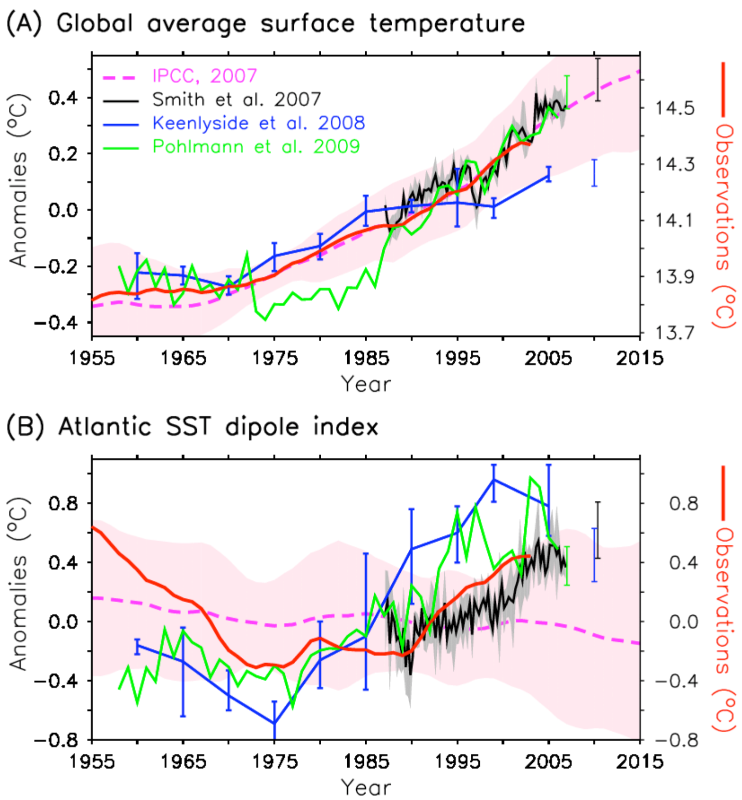


Figure 3: Observed and hindcast ten year mean (top) global surface temperature and (bottom) Atlantic SST dipole indices. The latter, a proxy for MOC fluctuations, is the

SST average difference 60-10W, 40-60N minus 30W-10E, 10-40S. Hindcasts for Smith et al. (2007) begin in 1982, with one per season and four ensemble members (spread shaded); Keenlyside et al. (2008) begin in 1955, with one every five years and three ensemble members (vertical bars); and Pohlmann et al. (2009) begin in1953, with one per year. The ensemble mean of 24 IPCC, 2007 models (CMIP3, 20C + A1B scenario simulations) are shown, smoothed with a 10-year running mean; pink shading indicates ±1.65 the standard deviation of the ensemble spread. Separate vertical bars centered on the predicted period show future forecasts. The Pohlmann et al. (2009) forecast has seven ensemble members. Smith et al. (2007), Keenlyside et al. (2008), and Pohlmann et al. (2009) 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, and have been smoothed with a 10-year running mean.

CMIP5 Decadal Predictability/Prediction Experiments

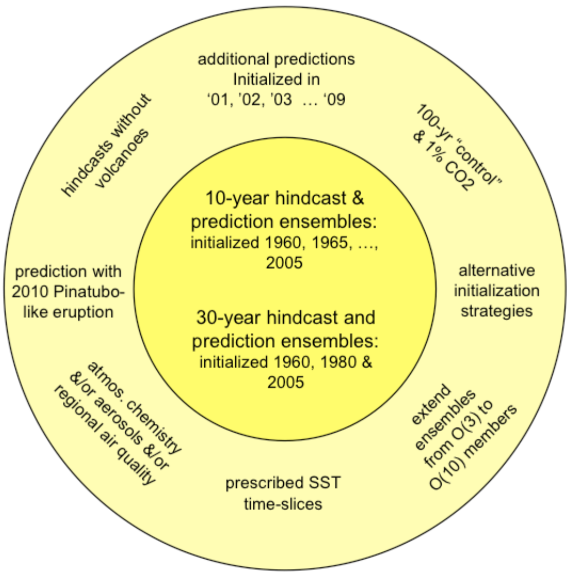


Figure 4: Schematic of decadal predictability/prediction experiments as part of CMIP5 (from Taylor et al., 2008).