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Decadal Prediction: Can it be skillful?

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Capsule: A new field called "decadal prediction" will use initialized climate models to produce time-evolving predictions of regional climate that will bridge ENSO forecasting and future climate change projections.

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Abstract: A new field of study, “decadal prediction”, is emerging in climate science. Decadal prediction lies between seasonal/interannual forecasting and longer term climate change projections, and focuses on time-evolving regional climate conditions over the next 10-30 years. Numerous assessments of climate information user needs have identified this timescale as being important to infrastructure planners, water resource managers, and many others. It is central to the information portfolio required to adapt effectively to and through climatic changes. At least three factors influence time-evolving regional climate at the decadal timescale: 1) climate change commitment (further warming as the coupled climate system comes into adjustment with increases of greenhouse gases that have already occurred), 2) external forcing, particularly from future increases of greenhouse gases and recovery of the ozone hole, and 3) internally-generated variability. Some decadal prediction skill has been demonstrated to arise from the first two of these factors, and there is evidence that initialized coupled climate models can capture mechanisms of internally-generated decadal climate variations, thus increasing predictive skill globally and particularly regionally. Several methods have been proposed for initializing global coupled climate models for decadal predictions, all of which involve global time-evolving three-dimensional ocean data, including temperature and salinity. An experimental framework to address decadal predictability/prediction is described in this paper and has been incorporated into the coordinated CMIP5 experiments, some of which will be assessed for the IPCC AR5. These experiments will likely guide work in this emerging field over the next five years.

1. Introduction: Need for decadal predictions

Prolonged drought in the American Southwest, increased hurricane activity in the tropical Atlantic since the late 1990s, changing fisheries regimes, extreme events like the 2003 European heat wave, as well as the need to adapt to time-evolving climate change and increasing temperatures have raised concern among policy and decision makers about climate change in the near term, i.e., out to 10 to 30 years, referred to as the "decadal" timescale. Impacts due to these conditions have significant social, economic and environmental implications and are consistent with the climate change projections of some models (Seager et al, 2007; Knutson and Tuleya, 2004; Meehl et al., 2007). Some aspects of observed changes have been attributed to naturally occurring decadal variability (Goldenberg et al, 2001; McCabe et al, 2004; Zhang and Delworth, 2006; Meehl et al., 2008b). Anthropogenically forced climate change, intrinsic climate variability, and natural external forcings (e.g. major volcanic eruptions or possibly the solar cycle) act together to produce the time-evolving climate. Given no future information on the third, the first two must thus be addressed to provide the best information on climate shifts over the coming decade or two.

The prospect of decadal prediction and its recognized importance has led, in part, to the initiation, in several countries, of climate services intended to bridge the gap between the seasonal-to-interannual (SI) climate information provided by the National Meteorological and Hydrological Services and the broad scale, longer time horizon information considered by the IPCC assessments. In the United States, the National Oceanic and

Atmospheric Administration (NOAA), in partnership with other agencies, is discussing formation of a National Climate Service that would, among other things, serve the near-term climate change information needs of the Regional Integrated Sciences and Assessments (RISAs[1]), the Regional Climate Centers (RCCs[2]), and the newly established National Integrated Drought Information System (NIDIS[3]). In Germany, the Climate Service Centre (CSC), funded by the German ministry for education and research (BMBF) for an initial period of about five years, will start (likely early in 2009) a program for climate prediction over the next few decades[4]. In the United Kingdom, the UK Climate Impacts Programme (UKCIP[5]), established in 1997, provides climate model projections of 21st century climate for use in national assessments of climate impacts and adaptation strategies. UKCIP will soon publish new probabilistic scenarios based on ensembles of climate model projections for a series of 30 year periods covering 2010-39 to 2070-99. In Italy, the Euromediterranean Center for Climate Change (www.cmcc.it) has been established with the mission to develop earth system models for climate scenarios. It is focusing on the near term period (2010-2040) with high resolution global models, using an approach that includes realistic initial conditions and emission scenarios.

In addition, partnerships developed through boundary organizations such as the RISAs, the IRI and others will need to be engaged to test and evaluate the benefits and limits of decadal-scale knowledge in appropriate decision-making environments.

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[1] http://www.climate.noaa.gov/cpo_pa/risa
[2] http://www.ncdc.noaa.gov/oa/climate/regionalclimatecenters.html
[3] http://www.drought.gov
[4] http://www.clisap.de/
[5] http://www.ukcip.org.uk/

The ability to provide meaningful decadal predictions using dynamical models has yet to be firmly established, but pioneering efforts at initialized coupled ocean-atmosphere 10-year predictions have begun (Smith et al, 2007; Keenlyside et al, 2008; Pohlmann et al, 2008). Later in this paper we describe an initiative by the climate science community (as part of the Coupled Model Intercomparison Project phase 5, CMIP5) to carefully examine the ability of dynamical models to simulate and predict decadal variability, to test the benefits and limitations of different initialization schemes, and ultimately to quantify the potential contributions of decadal climate outlooks over and above the projections typically considered in previous IPCC assessments which have focused mostly on the forced response. In addition, decadal prediction will likely involve higher resolution climate models for better simulation of regional climate and extremes since coupled models available today are barely capable of representing intense events like tropical cyclones (Gualdi et al., 2008). Model initialization could potentially yield higher skill just by assimilating persistent anomalies (e.g. in upper ocean heat content) even if they lack the ability to accurately simulate internal variability. Initialization may also enable more realistic simulation of the slow oceanic changes associated with decadal variability. Results from CMIP5 would be relevant to more coordinated future climate predictions where a number of timescales could be predicted, including the decadal (e.g. Shukla et al., 2009; Hurrell et al., 2008).

2. Background

The current practice for providing climate change information over the next several decades is to look at those time periods in ensemble averages of forced climate change simulations using various future emission scenarios that typically are run to 2100 (Fig. 1). Using this technique, it can be seen that some regional climate change information on decadal timescales already can be obtained mainly from two sources: 1) climate change commitment (e.g. Wetherald et al., 2001; Meehl et al., 2005; Wigley, 2005), and 2) the forcing from increasing greenhouse gases (e.g. Lee et al., 2006; Stott and Kettleborough, 2002). Climate change commitment arises because at any point in time the slower-warming oceans are lagging behind the land areas. Thus the oceans provide thermal inertia for the climate system. The timescale of this lag for the upper ocean is decades, and for the deep ocean 1000 years or more. This implies that even if greenhouse gas concentrations were stabilized today, the climate system would continue to warm at a rate of about 0.1C per decade for the next several decades for a total of about 0.6C after 100 years (Meehl et al., 2007). There also would be additional climate change due to further anticipated increases in greenhouse gases.

The pattern and magnitude of surface temperature change is similar for three different emission scenarios for the period 2011-2030 (Fig. 1) because the climate system response is comparable over the next few decades no matter which scenario is followed (Meehl et al., 2007). Only in the second half of the 21^{st} century does the climate response depend significantly on which emission pathway is followed. Therefore, barring a large volcanic eruption that could cool the system for a few years, a decadal prediction system already has some potential built-in skill simply from climate change commitment and forcing

(Lee et al., 2006), though model simulations of the forced response themselves contain significant uncertainties, even for the next 10-30 years (e.g. Hawkins and Sutton, 2008a).

Climate change projections from coupled models do exhibit decadal variability; however, they have been started from randomly selected pre-industrial states, so the inherent variability in projections is not synchronized with observations. Furthermore, such variability is typically averaged out using multi-member ensembles from individual models, or multi-model ensembles, so that only the forced response remains (Meehl et al., 2007). Climate variability results in a range of possible outcomes spanned by the models about the mean forced response. For the next few decades, however, the actual time-evolving climate is of interest. Presumably, better climate change information could be obtained if the models could track the time evolution of the inherent decadal variability in combination with the forced response. Even an ability to capture no more than the decay of existing “anomalies” towards the mean forced response would be an improvement over traditional climate projections, where the change over the next 20-30 years relative to the recent past typically takes no account of whether that recent past has been “above” or “below” what might have been expected. Initializing climate predictions, testing performance over recent decades and understanding the present state of the climate are all linked. Initialized predictions should better quantify the uncertainty range in the near future around the mean signal.

Recent studies suggest that much of the observed inherent decadal variability, particularly that in the Atlantic, arises from slow variations in the ocean circulation, and that this variability may be predictable if the ocean state could be properly initialized (e.g. Collins et al, 2006). Predictability of decadal oceanic modes could lead to regional prediction skill in some areas over and above that arising from commitment and forcing. Previous research has demonstrated that modes of climate variability influence mean and extreme climate over large parts of the globe through teleconnections (see, for example, Mantua et al., 1997; Knight et al., 2006; Kenyon and Hegerl, 2008; Seager et al., 2005). For example, the Pacific Decadal Variability index correlates at 0.8 with the number of unusually warm or cold daily temperatures over parts of North America in the Northern Hemispheric cold season (e.g., Kenyon and Hegerl, 2008); and up to 0.6 with an index of intense precipitation. If the initial state of the coupled climate system could be captured, especially the decadal mechanisms that reside primarily in the oceans, and if their time evolution could be predicted by models started from that state, then decadal variations in regional climate, including the behavior of extremes, could be better predicted.

Projections of how anticipated changes in greenhouse gases and aerosols will influence climate over time scales of several decades to centuries (dec-cen) can be considered primarily "boundary condition problems" (Fig. 2). Such model-based projections seek to describe climate trends, not the details of individual days, seasons, or years. In contrast, daily weather forecasts and shorter-term, seasonal-to-interannual (SI) climate predictions (e.g., ENSO forecasts) can be thought of as "initial value problems", for which detailed knowledge of the observed current conditions are crucially needed to define the starting point (the initial conditions). Lorenz (1963) demonstrated how, even if one possessed a hypothetically perfect numerical model representing all the physical processes completely and without error, unavoidable uncertainties in the initial conditions will invariably grow and contaminate the numerical simulation of transient weather systems. This sensitivity to initial conditions (sometimes referred to as the “butterfly effect’) limits to about two weeks the time period over which even a perfect model could yield skillful weather forecasts. When considering El Niño, a quasi-oscillatory phenomenon that evolves more slowly than synoptic weather systems, skillful numerical forecasts of monthly mean or seasonal mean conditions (Shukla, 1984) can be made with a lead time of 6 – 12 months (Kirtman et al., 2002), although predictability varies on decadal timescales (e.g. Tang et al, 2008), and the ultimate predictability limits are not well established.

For many climate variables, decision-makers are interested in the 10 to 30 year time horizon (e.g. Pulwarty, 2003), a time period characterized by a forced climate change signal that is often weaker than or comparable to the magnitude of internally generated climate variations. If skillful decadal climate predictions are to be realized, the time scale for which initial conditions are shown to impact the predictions will need to be extended by roughly an order of magnitude beyond today’s El Niño forecasts. That is, decadal prediction involves having some predictable signal in the initial state that has been ignored in traditional dec-cen climate change simulations.

In the decadal time range, at the confluence between dec-cen and SI, there may be a “sweet spot” for enhanced signal-to-noise of climate change information. The relative uncertainty in global mean, decadal mean surface air temperature predictions initially decreases with lead time as the predictions transition from initial state dependence to the forced response (Fig. 3). At longer lead times the emissions scenario uncertainty generally becomes dominant (Hawkins and Sutton, 2008a).

Even if uncertainty is low in the decadal range relative to other periods, there remains the question of signal to noise, namely the extent to which predictable regional variations could rise above noise from uncertainties in the forced response, and also from unpredictable aspects of internal variability, on those time and space scales. On continental timescales, the observed response to external forcing has clearly emerged from decadal climate variability (Hegerl et al., 2007). However, on spatial scales smaller than sub-continental, it takes several decades for the forced signal to emerge (Karoly and Wu, 2005; Knutson et al., 1999). The situation becomes more difficult for other climate variables, such as precipitation, where presently even large-scale changes only marginally separate from internal climate variability (e.g. Zhang et al., 2007; Min et al., 2008).

Thus, there remain some unresolved questions regarding not only how to do decadal predictions, but also the quality and usefulness of the results. As we stand at the threshold of a new area of research, there are a variety of science questions that need to be addressed, and we turn to those next.

3. Observed and modeled decadal phenomena that could potentially contribute to prediction skill

a. CMIP3 models can already simulate the magnitude of observed decadal surface temperature variability over land

The potential for skillful decadal predictions depends largely on whether models simulate sufficient decadal climate variability both in terms of magnitude as well as structure. In that regard, the temperature variability of coupled climate models over global and continental space scales has been shown to be realistic, even on timescales of multiple decades (Fig. 4; Hegerl et al., 2007). Note that it is essential for comparisons between model simulated and observed variability to compare data that contain both the response to external forcing and internal climate variability.

For this purpose, 20th century simulations are particularly useful, since they should have similar contributions from external forcing as the observations. Comparison of reconstructed past temperature and models forced with appropriate external forcing in paleoclimate simulations also confirm that the current generation of climate models appear to be able to simulate low frequency temperature variability on spatial scales of continents and larger (Janssen et al., 2007), as well as on subcontinental scales (e.g. Karoly et al., 2005; Hegerl et al., 2007). Models also simulate many mechanisms of climate variability (e.g. improved simulations of El Niño) and show similar patterns of coupled variability as observed (Randall et al., 2007).

It is presently less well understood to what extent teleconnections arising from modes of variability are well simulated. Also, there is some evidence that models underestimate low-frequency precipitation variability, particularly in the tropics (Zhang et al., 2007), however, firm conclusions cannot be drawn due to limitations in observed data.

b. Examples of decadal timescale phenomena that could increase decadal prediction skill

Pacific

In the Pacific Ocean region, there are several candidate sources of decadal variability that, if captured in a decadal prediction, could contribute to enhanced prediction skill certainly over some regions of the Pacific Ocean and perhaps extend to other regions over land in the Pacific rim countries. One is externally forced by the 11 year solar cycle (van Loon et al., 2007). Another is internally generated and referred to as either the Pacific Decadal Oscillation (PDO, e.g. Mantua et al., 1997), or North Pacific Index (NPI; Deser et al., 2004). Both usually denote decadal variability in the North Pacific. The Interdecadal Pacific Oscillation (IPO, e.g. Power et al., 1999) has similar patterns of variability in the North Pacific, but also encompasses SST patterns across the entire Pacific Ocean region.   Since the PDO, NPI and IPO share elements in common with regards to the pattern of variability, they will be treated together below.

To address the first source of Pacific decadal variability noted above, it has been shown that the climate system, including the stratosphere and troposphere, responds to forcing from the roughly 11 year solar cycle (e.g. van Loon and Shea, 1999; van Loon and Labitzke, 1998 and many others). A number of mechanisms have been proposed to explain this response. Two of the most likely involve either stratospheric ozone being affected by solar forcing, with concomitant changes in temperature and winds starting in the stratosphere and extending into the troposphere (e.g. Shindell et al., 1999), with strengthened tropical precipitation (Balachandran et al., 1999) or a direct coupled ocean-atmospheric response to solar forcing that also enhances tropical precipitation that produces a La Niña-like pattern of SSTs in the Pacific with anomalously cold surface temperatures in the equatorial eastern Pacific as shown in Fig. 5 (e.g. van Loon et al., 2007). These mechanisms appear to work in the same sense and add together to produce an enhancement of the climatological mean precipitation in the Pacific region, stronger Hadley and Walker Circulations, intensified trade winds and upwelling, and cooler equatorial Pacific SSTs (Meehl et al., 2008a, b). Thus, by taking into account a climatological 11 year solar forcing, there could be some enhanced predictive skill for the tropical Pacific and associated teleconnections to midlatitude continental climate (Fig. 5; Meehl et al., 2008a).

With regards to another source of Pacific decadal variability that is related to internally generated variability in the Pacific region, as noted above the PDO/NPI/IPO are the most likely candidates known at this time to be able to provide some regional predictive skill. Both are usually characterized by a low pass filtered SST EOF pattern that has an "El Niño-like" character, with SST anomalies of one sign in the tropical central and eastern Pacific, northeastern and southeastern midlatitude Pacific, and opposite sign anomalies in the northwest and southwest Pacific (Fig. 6a) with decadal to multidecadal timescales of variability (Fig. 6b). The PDO and NPI focus on the part of this pattern in the North Pacific, and the IPO takes into account the entire Pacific-wide pattern. In the observations, there are a variety of other forcing mechanisms that could contribute to this pattern during the 20th century, but long control runs with global coupled models show that this pattern on the decadal timescale is internally generated by the models (Fig. 6c). This suggests that the similar low frequency pattern in the observations (pattern correlation of +0.63 between the observations in Fig. 6a and the model pattern in Fig. 6c; note that the observed pattern is noisy due to small number of samples) is internally generated as well.

Though it has been postulated that the PDO/NPI/IPO are simply products of amplitude modulation of interannual El Niño and La Niña events (e.g. Jin, 2001), arguments have been made that these decadal phenomena have deterministic mechanisms that are separate from ENSO and thus may be predictable beyond the ENSO timescale (e.g. White and Cayan, 1998; Meehl and Hu, 2006).

There is also the issue of whether and/or how much external forcing has affected the time evolution of the PDO/IPO as depicted in Fig. 6a. For example, a significant shift occurred in the mid-1970s when the tropical Pacific SSTs transitioned from a relatively cool state to relatively warm conditions (e.g. Trenberth and Hurrell, 1994). Though this shift could have been entirely natural, there is evidence that the transition had a partial contribution from changes in external forcing from increases in anthropogenic greenhouse gases (Meehl et al., 2008c). Thus, predictive skill on the decadal timescale for the Pacific is most likely to be achieved by taking into account the interactions of external forcing (both anthropogenic and natural) and internally generated decadal variability (Motizuki et al., 2008).

Atlantic

Many coupled general circulation models (CGCMs) used in climate studies show multi-decadal oscillations in their Atlantic meridional overturning circulations (AMOCs) (e.g., Delworth et al. 1993; Dong and Sutton 2005; Danabasoglu 2008). These AMOC oscillations are mostly irregular and their periods range between 20 to more than 100 years among models. Other ocean fields also exhibit similar variability, including sea surface temperatures (SSTs) and northward heat transport.

Observational studies based on instrumental and proxy data also show distinct multi-decadal variability in SSTs with a broad hemispheric pattern in the Atlantic Ocean and with periods of about 40-70 years (e.g., Kushnir 1994; Delworth and Mann 2000). This multi-decadal variability is sometimes referred to as the Atlantic Multi-decadal Oscillation (AMO) or Atlantic Multi-decadal Variability (AMV), and it has been associated with multi-decadal variations of the North American and Western European summertime climate (Sutton and Hodson 2005), and Northern Hemisphere averaged surface temperature (Zhang et al., 2007). There is a broad resemblance between model-simulated and observed multi-decadal SST variability patterns in the North Atlantic that is usually associated with the AMOC (e.g., Delworth et al. 1993).

The variability of AMOC and possibly the associated climate changes may be predictable on decadal or longer time scales (Griffies and Bryan 1997), implying potential predictability for seasonal hurricane activity in the North Atlantic. The presence of such multi-decadal intrinsic variability also complicates climate studies investigating anthropogenic effects. Some recent modeling studies, however, suggest stronger ties of this AMOC variability with the North Atlantic Oscillation (NAO) (e.g., Eden and Jung, 2001; Dai et al. 2005; Dong and Sutton 2005; Danabasoglu 2008). The driving mechanism(s) of this AMOC oscillation, as well as whether it represents an atmosphere - ocean coupled mode or an ocean-alone mode, remain largely unresolved, showing differences among various climate models (Latif et al., 2006).

4. Science and data issues

a) Initialization

Initializing climate models offers the potential to predict internal variability in addition to externally-forced climate change on decadal timescales and is thought to be at the heart of the decadal predictability/prediction problem. Although idealized model experiments show considerable promise for predicting internal variability, particularly in the North Atlantic (Collins et al, 2006), 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. It is standard practice to remove such biases from SI 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 length of the experiments. An alternative approach, known as “anomaly initialization” (Schneider *et al*, 1999), has therefore been trialed (Barnett et al., 2004; Pierce et al., 2004; Smith *et al*, 2007, Keenlyside *et al*, 2008, Pohlmann *et al*, 2008). In this approach, models are initialized with observed anomalies added to the model climate, and the mean model climate state is subtracted to obtain forecast anomalies. The model climate is usually obtained from transient simulations of the 20th century, making this approach relatively expensive. These two approaches for dealing with model drift have been tested to some degree in SI forecasts. For example, ENSO hindcasts made using the NOAA Coupled Forecast System have been found to give similar skill using either approach. However, their relative merits have yet to be quantified on decadal timescales.

Decadal climate prediction aims to capitalize on the predictability of slowly-evolving patterns of heat in the ocean, which potentially control some aspects of climate variability on inter-annual to decadal timescales. Therefore, as noted above, initializing the ocean is of central importance. However, 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, 2008), making the development and testing of ocean initialization schemes difficult. A simple approach that avoids the difficulties with historical sub-surface ocean observations is to initialize models by assimilating only sea surface temperatures (Keenlyside *et al*, 2008), relying on ocean transport processes in the model to initialize 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 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. 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 fields from two of these have already been used to initialize models for decadal forecasts (Smith *et al*, 2007, Pohlmann *et al*, 2008), and there is evidence that analyzed currents can also be included in the initialization (Kirtman and Min, 2008, G. Danabasoglu and J. Tribbia, personal communication). In this way, modeling 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. 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 many more measurements of both temperature and salinity over the upper 2km of the world's oceans than were available historically, potentially offering a step change in our ability to initialize ocean heat and density anomalies.

In addition to ocean temperature and salinity, initialization 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. Initialization of these variables has not been attempted in decadal prediction studies to date, although the process of ocean initialization (and of atmospheric initialization in the case of Smith et al. 2007) may allow some aspects of the observed anomalous patterns to be captured in the initial conditions. However, explicit initialization could also be investigated, for example by using measurements of soil moisture from the planned SMOS (Soil Moisture & Ocean Salinity) satellite, or by initializing sea ice thickness with observations from the planned CryoSat-2 satellite.

b) Generation of ensemble forecasts

While the role of slowly-varying ocean anomalies provides a potential source of predictability in annual to decadal forecasts (e.g. Collins et al., 2006), the chaotic nature of the governing dynamical processes, together with the strong influence of ocean-atmosphere coupling on low frequency climate variability, implies that the forecast evolution is bound to be sensitive to uncertainties in both the atmospheric and oceanic initial conditions. The decadal prediction problem therefore requires strategies for sampling the spread of possible outcomes consistent with initial state uncertainties. These can be represented using ensembles of coupled model forecasts distinguished by perturbations to the applied initial conditions.

Early decadal prediction studies (see also section 4d) have used simple methods to generate these perturbations. Smith et al (2007) created four member hindcast ensembles involving the use of assimilated analyses of ocean and atmospheric observations taken from consecutive days immediately preceding the hindcast start date. These were then combined with ensembles started from previous seasons to improve the sampling of uncertainties in low frequency variability. Keenlyside et al (2008) performed three-member hindcast ensembles, with each member started from simulations of 20th century climate into which analyses of observed SST anomalies had been assimilated. These techniques are sufficient to generate a significant spread of possible outcomes. For example confidence limits on hindcasts of annually averaged global temperature, diagnosed from the ensemble spread, can give a reasonably good indication of actual hindcast errors (see Smith et al 2007, and Supporting Online Material therein). However it is likely that more sophisticated approaches could achieve a better characterization of the growth of forecast uncertainties associated with initial state errors. Even with the advent of the worldwide ARGO ocean observing system there is still a wide spread in analysed ocean states in particular (see http://www.clivar.org/organization/gsop/synthesis/synthesis.php), and this uncertainty will need to be more fully considered in future decadal predictions.

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 (e.g. Kleeman et al. 2003). An example of an optimal perturbation is shown in Fig. 7 for the Atlantic domain in the HadCM3 coupled model (Hawkins and Sutton, 2008b), showing that the far North Atlantic is the most sensitive region to small anomalies in this model, and is thus the optimal region both for perturbations to sample forecast uncertainties, and for targeted observations to help constrain its predictions. 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. Given that different approaches all have potential strengths and limitations, it remains an open research question to identify the best methods for representing initial state uncertainties in decadal predictions.

Modelling errors 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 that uncertainties arising from forced climate change are likely to contribute significantly to the total uncertainty in predictions for the next few decades (Fig. 3, Hawkins and Sutton, 2008a), it is 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 GCMs 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), has improved attribution results, for example, for precipitation thus suggesting increased skill (e.g., Zhang et al., 2007), and has been used extensively to provide quantitative uncertainty estimates in multi-decadal climate change projections (e.g. Tebaldi and Knutti, 2007; Meehl et al., 2007). An alternative approach based on systematic perturbation of uncertain parameters in a single model has also been studied in the context of long-term climate prediction (e.g. Murphy et al., 2007). A third approach 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 (e.g. Berner et al., 2008). The European

Union ENSEMBLES project has undertaken an initial comparison of these three methods of sampling modelling uncertainties in seasonal and annual hindcasts (Doblas-Reyes et al., 2009), and this study is currently being extended to a set of decadal hindcasts initialized during the period 1960-2005.

c) Predictability and predictions

The potential predictability of decadal climate anomalies has been studied by decomposing uncertainties in multi-model projections of climate change into components arising from the forced response and internal variability (see section 2). The results suggest that both internal variability and the forced response are important sources of potential predictability in global scale projections (Figure 3), while at a regional level their relative importance varies significantly (Boer 2008). The relative contribution to total uncertainty from the forced response tends to be largest over parts of the tropical oceans, while the contribution from the decadal component of internal variability is larger over the middle and high latitude oceans than elsewhere.

The extent to which these idealized predictability studies will match up with experience from prediction studies remains an open question. Early attempts at initialized decadal hindcasts (see section 4d) show wide variations in skill at a regional level, and in the impact of initialization relative to the signal arising from forced changes. Given that the predictable component of climate anomalies on annual to decadal time scales may typically be modest compared to the unpredictable component, it is important that a large dataset of hindcasts is built up to provide robust estimates of skill.

Even then, hindcast studies performed over a limited number of past decades will inevitably give results which depend on the characteristics of observed decadal variability during the relevant period. For example, Smith et al (2007) found that initializing their climate model with observed ocean anomalies (compared with parallel simulations without initialization) gave a particularly large improvement in regional skill over the Indian and Australasian sectors of the Southern oceans, based on hindcasts started from dates covering 1982-2001. This was largely because the disparity between observed upper ocean temperature anomalies, and those simulated in the uninitialized hindcasts, happened to be large in this region over these particular decades. However, the largest disparities could occur in other parts of the world during alternative periods, so there is no guarantee that regional variations in skill diagnosed from past cases will be a robust guide to future performance. Pohlmann et al. (2008) come to equivalent conclusions.

For projecting a decade or two ahead, the role of uncertainties in anthropogenic emissions of forcing agents is likely to be relatively small in general (e.g. Figure 3), although there could be exceptions in regions where uncertainties in the forcing due to spatially heterogeneous agents, such as tropospheric aerosols (Schulz et al., 2006), are largest. Another issue concerns the impact of future variations in natural forcing, such as the solar cycle and explosive volcanic eruptions (Shiogama *et al*, 2008). In a real forecasting situation the solar cycle and eruptions cannot be predicted, so there is a strong case for assuming no past knowledge of those forcings in hindcast studies (a “no cheating” strategy). The hindcast studies published to date (section 4d) all follow this principle. If in practice there is an eruption during a forecast period, then a subset of hindcasts based on the “no cheating” strategy will give some guidance on likely forecast skill. However, if there is no eruption during the forecast period, then past skill statistics based on a “no cheating” strategy will be less informative, because any hindcasts for which the observed verification data was affected by a post-initialisation eruption will give a misleadingly pessimistic estimate of skill. On the other hand, hindcast skill estimates assuming prior knowledge of solar activity and past eruptions could be too optimistic, since a source of large forced anomalies (the response to which is likely to be relatively predictable (e.g. Soden et al., 2002)) would be present in the hindcast dataset, but not in the forecast. Another factor is that past knowledge of solar variability and eruptions is now assumed in most historical climate change simulations (see Table 10.1 of Meehl et al., 2007), so there is a case for following the same strategy in initialized decadal hindcasts from a resource perspective, since this allows existing historical climate simulations (at least for modeling groups possessing these) to be used as a “no initialization” baseline for the assessment of hindcast skill.

d) **Examples of decadal predictions**

There were three recent efforts at decadal prediction, all following a similar strategy: Initialise a global climate model from observations and run it forward ten years, while accounting for changes in external forcing (natural and anthropogenic). In the first work (Smith et al., 2007), the Hadley centre model was initialized using analyzed anomalies of surface and subsurface ocean temperature and salinity observations, and anomalies of atmospheric winds, temperatures and surface pressure from ECMWF reanalyses. The results showed that global mean temperature could be predicted out to a decade in advance (Figure 8a), with more skill than obtained when only external radiative forcing (boundary condition) changes are accounted for (Fig. 8). Beyond the first year, this skill enhancement resulted mainly from initialisation of the upper ocean heat content. There was also skill enhancement in predictions of multiyear averages of surface temperature in some regions, including the Indian Ocean and parts of the Southern Ocean.

In the second study (Keenlyside et al., 2008), the Max Planck Institute for Meteorology (MPI) climate model (ECHAM5/MPI-OM) was initialized using only SST observations (described above). Although simple, the scheme was able to initialise low frequency variations in the ocean circulation, particularly the Atlantic meridional overturning circulation (MOC). SST variations associated with the Atlantic MOC could be predicted a decade in advance, but due to an overly strong MOC signal, their strength was overestimated (Figure 8b). Skill in predicting ten year mean surface temperature variations over parts of the North Atlantic Sector, including Europe and North America, and the Tropical Pacific was demonstrated, greater than that obtained from the specification of external radiative forcing alone. Ten year averaged global surface temperature variations were also predictable (Figure 8a), but with marginally less skill than obtained from radiative forcing only.

In both studies forecasts were made for the next ten years (Figure 8b), and in both cases, natural internal variability was found to temporarily offset anthropogenic global warming. The offset was largest in Keenlyside et al. (2008), whose results suggest a temporary lull in global warming for the next decade, but the simplicity of the scheme employed needs to be kept in mind. The results of both studies highlight the impact of internal variability on the evolution of surface temperature, globally and regionally, over the next decade and warrant further investigation.

The third study (Pohlmann et al., 2008) aimed at improving the forecast skill of climate predictions through the use of ocean synthesis data as initial conditions of a coupled climate model. For this purpose, the MPI climate model was initialized with oceanic synthesis fields available from the German contribution to Estimating the Circulation and Climate of the Ocean (GECCO) project. The use of an anomaly-coupling scheme during the initialization avoids the main problems with drift in the climate predictions. The coupled model is thus continuously forced to follow the density anomalies of the GECCO synthesis over the period 1952-2001. Hindcast experiments were initialized from this experiment at constant intervals. The results show predictive skill through the initialization up to the decadal time scale particularly over the North Atlantic. Viewed over all timescales analyzed here (annual, 5-year, and 10-year mean), greater skill for the North Atlantic sea surface temperature (SST) is obtained in the hindcast experiments than either damped persistence or a trend forecast. The hindcast Atlantic Meridional Overturning Circulation follows closely that of the GECCO oceanic synthesis. Hindcasts of global-mean temperature do not obtain greater skill than either damped persistence or a trend forecast, owing to the SST errors in the GECCO synthesis, outside the North Atlantic. An ensemble of forecast experiments is performed subsequently over the period 2002-2011. North Atlantic SST from the forecast experiment agrees well with observation until the year 2007 and is higher than simulated without the oceanic initialization, averaged over the forecast period. The results confirm that in decadal climate predictions, both the initial and the boundary conditions must be accounted for.

5. Decadal prediction evaluation

An important advantage of decadal over centennial predictions is that the likely skill can potentially be quantified in tests of past cases, or “hindcast” experiments. In these, the model is used to “forecast” a historical period, but only using data that would have been available prior to this period (though this is not quite an independent test since these data generally are used to develop, test and tune the model). The accuracy of the model can then be assessed by comparing with what actually happened. A large set of such hindcasts is typically made in order to obtain a robust estimate of the likely skill and reliability of actual forecasts.

There are many different measures of skill, although no one measure can capture all aspects of forecast quality. For experimental forecasts with limited numbers of hindcasts, such as in the case of decadal predictions, estimates of forecast quality encounter many limitations, and care is needed when interpreting the results. For example, the correlation between forecast and observed anomalies can be a useful and easily interpretable measure of the ability to predict the phase of natural cycles such as ENSO. However, on decadal timescales very high anomaly correlations can be achieved simply by predicting the warming trend in response to increased greenhouse gases, giving little guidance on any ability to predict natural internal variability beyond the forced response. Even if one were to investigate the relative skill of two different forecasts, such as comparing initialized forecasts with radiatively-forced forecasts, improved forecast quality due to the initial conditions does not necessarily indicate that the initial conditions provide predictability of natural decadal variability. The improvement may just have come about by the initial conditions better quantifying the ocean's thermal state, and thus bias correcting the radiatively-forced projections. The rate of change between two points in time, or over two distinct periods, may provide additional information on the contribution of ocean dynamics to low-frequency climate variability and change. Beyond these simple diagnostics, detection and attribution techniques that use ideas from signal-processing (Hegerl et al., 2007) may help to separate the influence of forcing and initial conditions in the presence of climate variability. Assessing the statistical significance of any differences is also an important aspect of such comparisons, and care is needed to ensure that uncertainties arising from finite ensemble sizes, finite hindcast sets and correlation of errors are properly accounted for.

Some examples of different skill measures are provided in recent examples of decadal predictions. Smith et al. (2007) used root mean square error of their decadal hindcasts as their skill measure and showed that global average anomalies of annual mean surface temperature were predicted with significantly higher skill by initialized forecasts than by uninitialized, radiatively-forced forecasts. Keenlyside et al (2008) used correlations of time series of initialized hindcasts with observations and of climate model projections with radiative forcing changes only for several different average surface temperature series. For the global mean surface temperature, both the initialized hindcasts and the climate model projections show very high correlations with observations due to the large trend in global mean temperature over the period considered. In fact, the correlation of the twentieth century radiatively-forced projections with observations is greater than that of the hindcasts, but only marginally at the 5% significance level.

One complication when measuring skill from hindcasts is that the coverage of sub-surface ocean observations has recently dramatically improved with the deployment of ARGO floats. Actual forecasts benefiting from ARGO data are therefore potentially significantly more skilful than hindcasts based on very sparse historical observations. Experiments are therefore currently underway to assess the impact of ARGO data on dcecadal forecasts. Another aspect also under investigation is whether skill depends on the initial state. For example, are forecasts initialized from an extreme phase of natural internal variability more skilful than average? This is the situation with seasonal-to-interannual climate forecasts dependant on ENSO, and is expected to also be the case with decadal predictions (Griffies et al, 2005; Dixon et al, 2008). Confidence in decadal forecasts requires both an assessment of model performance in hindcasts and an understanding of the physical mechanisms giving rise to any predicted changes in climate.

Ultimately, not just the quality but the value of decadal forecasts should be quantified – this is the societal or economic value of the prediction information to climate-related decisions or impacts studies. However, such estimates are meaningless if derived outside the context of the actual decision setting. Even in regions where it might be useful, there will be forecasts of opportunity when the information carries value together with other environmental and social indicators. The quality of the prediction information must first be assessed before prototype information can be developed and tested for value. In these cases, the consistency and probabilistic quality of the information must be measured. Of greatest interest to decision makers is the risk or likelihood of adverse or beneficial thresholds that affect management triggers.

6. CMIP5 coordinated decadal predictability/prediction experiment

The new CMIP5 protocol for coordinated climate change experiments to be performed over the next five years involves 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 skillful decadal predictions out to about the year 2035 might be. The detailed requirements for the project are described by Taylor et al. (2008; http://www-pcmdi.llnl.gov/). 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 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. 9). 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 modeling groups since how best to initialize models is one of the central unanswered questions involved with decadal prediction. These 10 year hindcasts should allow estimates of both the theoretical limits of decadal predictability and our present ability to make decadal predictions, accounting for both the regional decadal phenomena discussed earlier, and the climate change commitment from previous increases of GHGs. The minimum ensemble size from any given starting point is 3 members, although 10 or more ensemble members are desirable.

The second core experiment extends the integrations starting from 1960, 1980 and 2005 to 30 years, and explores predictability and prediction over time scales thought to be more influenced by external forcing from increasing GHGs. Depending on how the initial conditions are prepared, the experimental design for the 30 year integrations does not necessarily require long control runs of the coupled model, and thus opens the door for a wider class of models to be used in short-term climate prediction. 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 the standard CMIP5 20th century runs. They allow an estimate of the skill of decadal predictions when the forcing is known, which for the future means an estimate conditional on no major volcanic eruptions.

The tier 1 integrations include simulations that start from initial climate states representing each of the years in this century when the ocean data coverage is much better than in previous years due in particular to the ARGO float data. There is also the option to perform high atmospheric resolution time slice experiments where the historical SSTs are either derived from observations or models. Further runs can study the impact of volcanoes, and others can include interactive atmospheric chemistry to investigate the impact of various short lived species and pollutants on the predictions.

It is intended that this CMIP5 activity will not only set up a framework for coordinated multi-model experiments to address various science questions involved with decadal predictability/prediction, but also provide the foundation for the simulations to be assessed as part of the IPCC 5th Assessment Report (AR5).

7. Conclusions

Decadal prediction, a new field of study, focuses on time-evolving regional climate conditions over the next 10-30 years which is a time period of interest to infrastructure planners, water resource managers, and others. The decadal scale offers a critical bridge for informing adaptation strategies as climate varies and changes. However, since decadal prediction is so new, there are a number of outstanding scientific and technical questions that need to be addressed. One of the chief challenges is how to initialize the modeled climate system. Since decadal prediction lies between seasonal/interannual forecasting and longer term climate change projections, there is some knowledge from El Niño forecasting that can be applied to decadal prediction, and climate change commitment and forcing changes also provide some information as to how skillful decadal predictions might be. One of the interesting science questions involves whether an initial climate state, particularly an initial observed ocean state, can capture the proposed mechanisms that could contribute to enhanced regional prediction skill (e.g. AMOC and AMO in the Atlantic, PDO/IPO in the Pacific) to. Since an accurate observed initial climate state is thought to be important for decadal prediction skill, it is important to maintain a comprehensive global climate observing system with particular emphasis on the ocean.

There are questions regarding how to evaluate decadal prediction skill, what form decadal information would take, and the role such information would play in applications. An experimental framework to address decadal predictability/prediction over the next five years has been incorporated into the coordinated climate change experiments of CMIP5. Some of the results of these experiments will be assessed for the IPCC AR5, in addition to guiding research activity in decadal prediction to at least 2013.

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Figure Captions

Fig. 1: Near-term surface air temperature anomalies from CMIP3 multi-model projections, 2011-2030 minus 1980-99 (C), for the low (top), medium (middle) and high (bottom) emission scenarios from IPCC AR4 (Meehl et al., 2007).

Fig. 2: Schematic illustrating progression from initial value problems with daily weather forecasts at one end, and multi-decadal to century projections as a forced boundary condition problem at the other, with seasonal and decadal prediction in between (Dixon, personal communication)

Fig. 3: The relative importance of different sources of uncertainty in IPCC GCM projections of decadal mean surface air temperature in the 21st century is shown by the fractional uncertainty (i.e. the prediction uncertainty divided by the expected mean change, relative to the 1971-2000 mean). Model uncertainty is the dominant source of uncertainty for lead times up to 50 years, with internal variability being important for the first decade or so. Scenario uncertainty becomes important at multi-decadal lead times. (from Hawkins & Sutton, 2008a).

Fig. 4: Comparison of variability as a function of time scale for continental mean temperature for continental regions (°C^2 yr^{-1}) from the observed record (Hadley Centre/Climatic Research Unit gridded surface temperature data set, HadCRUT3) and from CMIP3 AOGCM simulations assessed for the IPCC AR4. Models include both anthropogenic and natural forcings. All power spectra are estimated using a Tukey-Hanning filter of width 97 years. The model spectra

displayed are the averages of the individual spectra estimated from individual ensemble members. Most models simulate variability on decadal time scales and longer that is consistent with observations. Exceptions where models are inconsistent with the observations (at the 10% significance level) are two models over South America, five models over Asia and two models over Australia. (Hegerl et al., 2007)

Fig. 5: a) The average anomalies of sea surface temperature in 11 solar peak years (°C), computed relative to all other years, December-January-February, from the NOAA Extended Reconstructed Sea Surface Temperature data set; b) The average tropical rainfall anomalies (GPCP gridded precipitation data set) in the solar peak years starting in the late 1970s (mm day^{-1}), January-February, in comparison to all other years. Dashed line is the 6 mm day^{-1} contour from the long term mean climatology; c) same as (a) except for the average anomalies of sea level pressure (Hadley Centre sea level pressure data set) in 11 solar peaks, hPa, December-January-February; Shading indicates significance at or above the 95% level, indicating the relative magnitude of the anomalies compared to the noise (Meehl et al., 2008a).

Fig. 6: a) The second EOF (the first EOF is the trend) of 13 year low pass filtered non-detrended observed SSTs for the period 1890-2006, b) PC time series for second EOF, c) The first EOF of 13 year low pass filtered SSTs from a 300 year period of an unforced model control run (Meehl et al., 2008b).

Fig. 7: An optimal perturbation for the Atlantic domain from the HadCM3 model, using a Linear Inverse Modelling approach (from Hawkins and Sutton 2008b). The panels

show integrated temperature (left) and salinity (right) from the surface to a depth of 1800m. The coloured regions indicate where the ocean is sensitive to small anomalies, and are thus the optimal regions for initial condition perturbations, and for targeted observations to improve forecast skill.

Fig. 8: Decadal prediction examples. Observed and hindcast values of (A) ten year mean global mean surface temperature and (B) an Atlantic sea surface temperature (SST) dipole index. The latter is a proxy for MOC fluctuations and is defined as the average SST difference for 60-10W,40-60N minus 50-0W, 40-60S. Hindcasts begin in 1982 (1955) in Smith et al. 2007 (Keenlyside et al. 2008), with a four (three) member forecast every season (five years); shading (error bars) indicates the ensemble range. The error bars centered on 2015 represent actual forecasts for the period 2005-2015. Hindcasts for Smith et al. 2007 (Keenlyside et al. 2008) are adjusted to have the observed means over the 1979-2001 (1955-2005) period. Note the different axis used in (A) for Keenlyside et al. 2008. Observations are from HadISST 1.1 and HadCRU3.

Fig. 9: Schematic of decadal predictability/prediction experiments as part of CMIP5 (from Taylor et al., 2008).

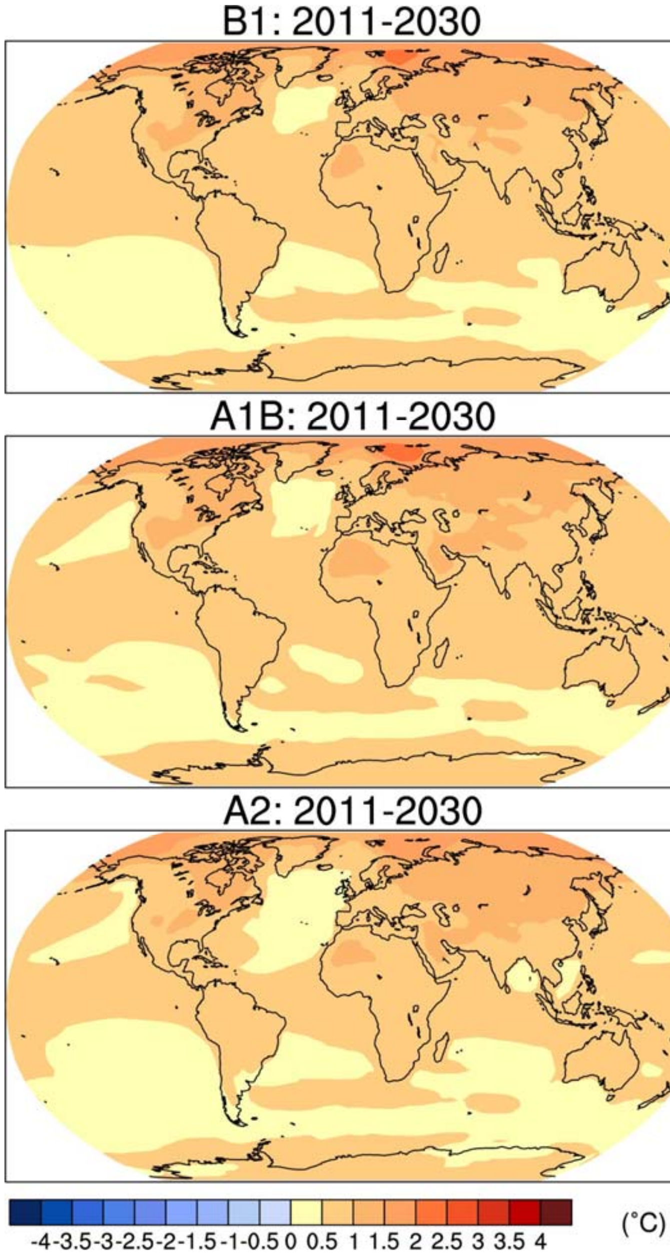

B1: 2011-2030
A1B: 2011-2030
A2: 2011-2030
-4 -3.5 -3 -2.5 -2 -1.5 -1 -0.5 0 0.5 1 1.5 2 2.5 3 3.5 4
(°C)

Fig. 1

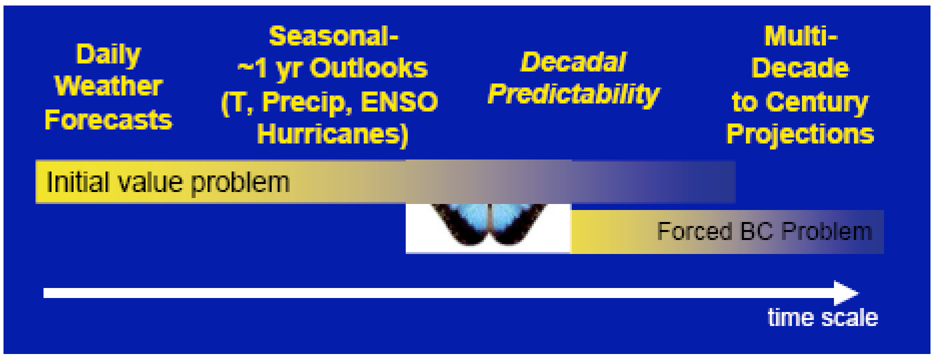

Daily
Weather
Forecasts
Seasonal-
~1 yr Outlooks
(T, Precip, ENSO
Hurricanes)
Decadal
Predictability
Multi-
Decade
to Century
Projections
Initial value problem
Forced BC Problem
time scale

Fig. 2

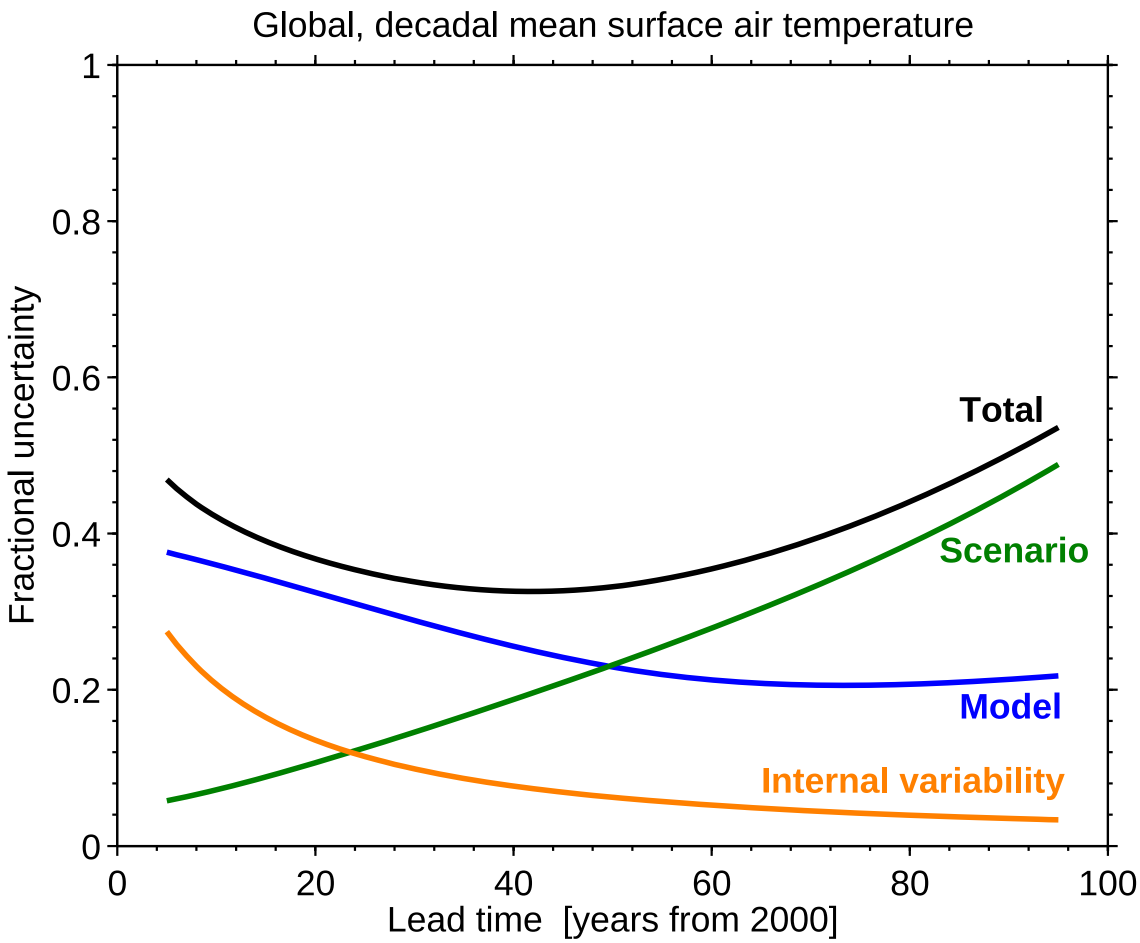

Global, decadal mean surface air temperature
Fractional uncertainty
0
0.2
0.4
0.6
0.8
1
0
20
40
60
80
100
Lead time [years from 2000]
Total
Scenario
Model
Internal variability

Fig. 3

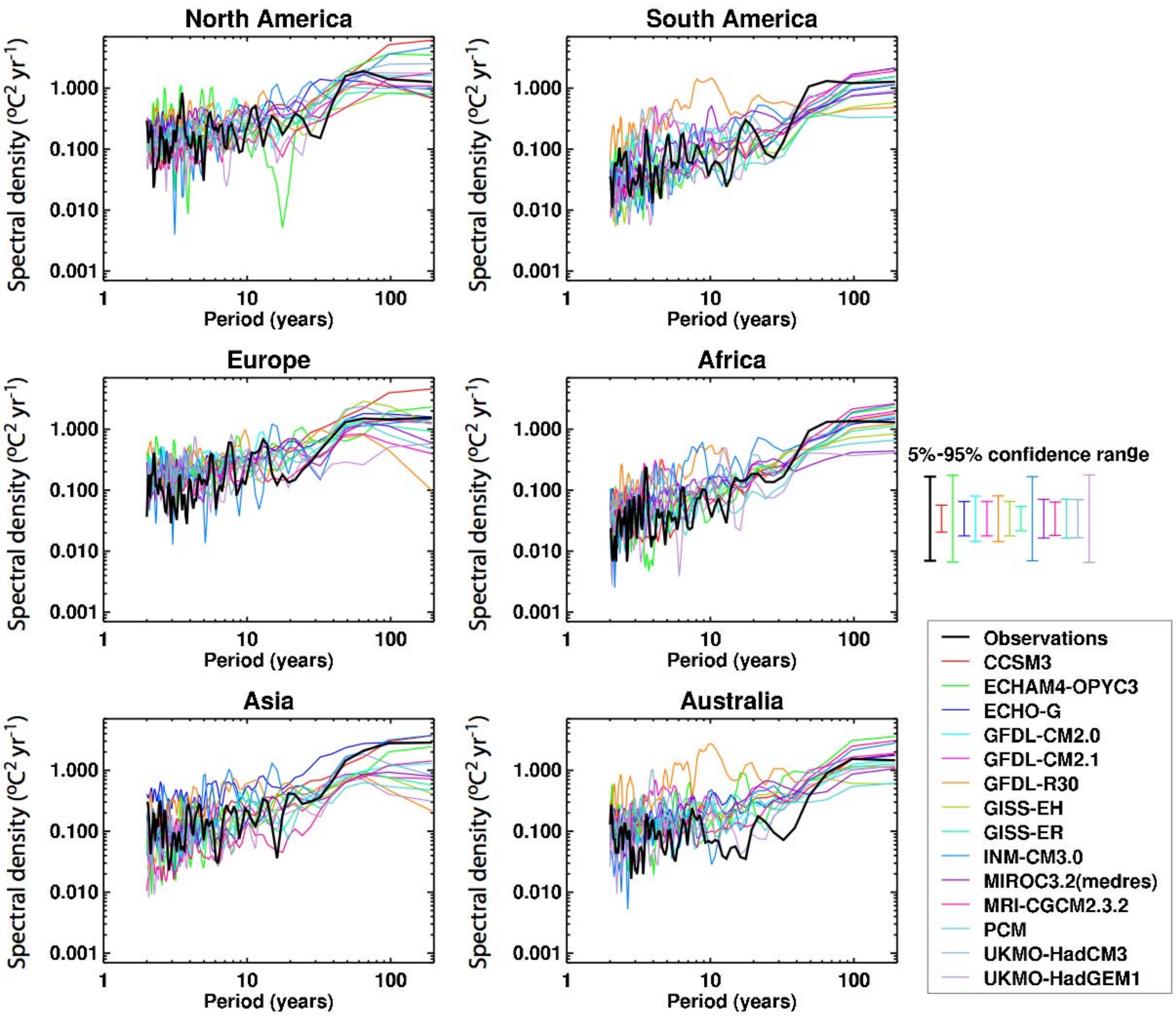
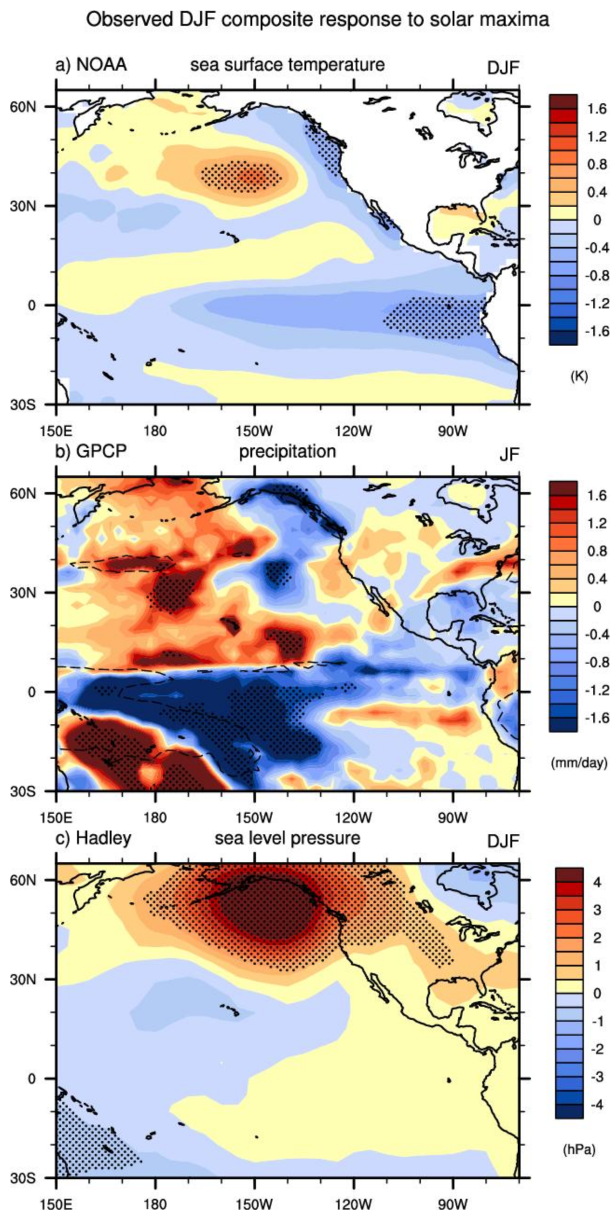

North America
South America
Europe
Africa
Asia
Australia
Spectral density (ºC² yr⁻¹)
Period (years)
5%-95% confidence range
Observations
CCSM3
ECHAM4-OPYC3
ECHO-G
GFDL-CM2.0
GFDL-CM2.1
GFDL-R30
GISS-EH
GISS-ER
INM-CM3.0
MIROC3.2(medres)
MRI-CGCM2.3.2
PCM
UKMO-HadCM3
UKMO-HadGEM1

Fig. 4



Observed DJF composite response to solar maxima
a) NOAA
sea surface temperature
DJF
(K)
b) GPCP
precipitation
JF
(mm/day)
c) Hadley
sea level pressure
DJF
(hPa)
60N
30N
0
30S
150E
180
150W
120W
90W

Fig. 5

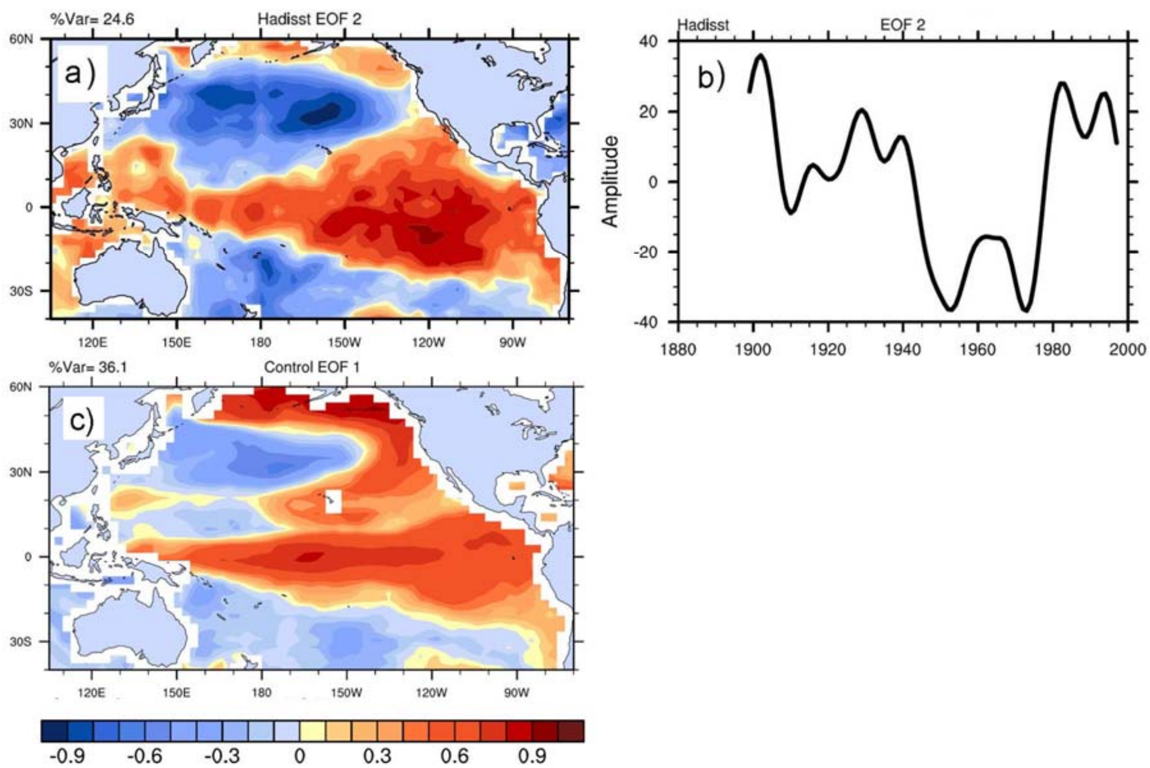

%Var= 24.6
Hadisst EOF 2
a)
60N
30N
0
30S
120E
150E
180
150W
120W
90W
Hadisst
EOF 2
b)
Amplitude
40
20
0
-20
-40
1880
1900
1920
1940
1960
1980
2000
%Var= 36.1
Control EOF 1
c)
-0.9
-0.6
-0.3
0
0.3
0.6
0.9

Fig. 6

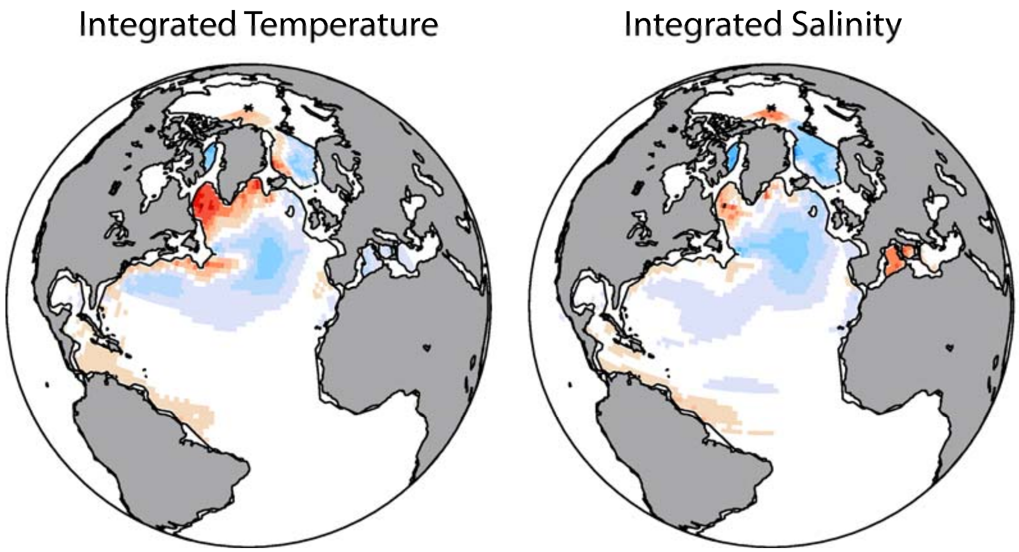


Fig. 7

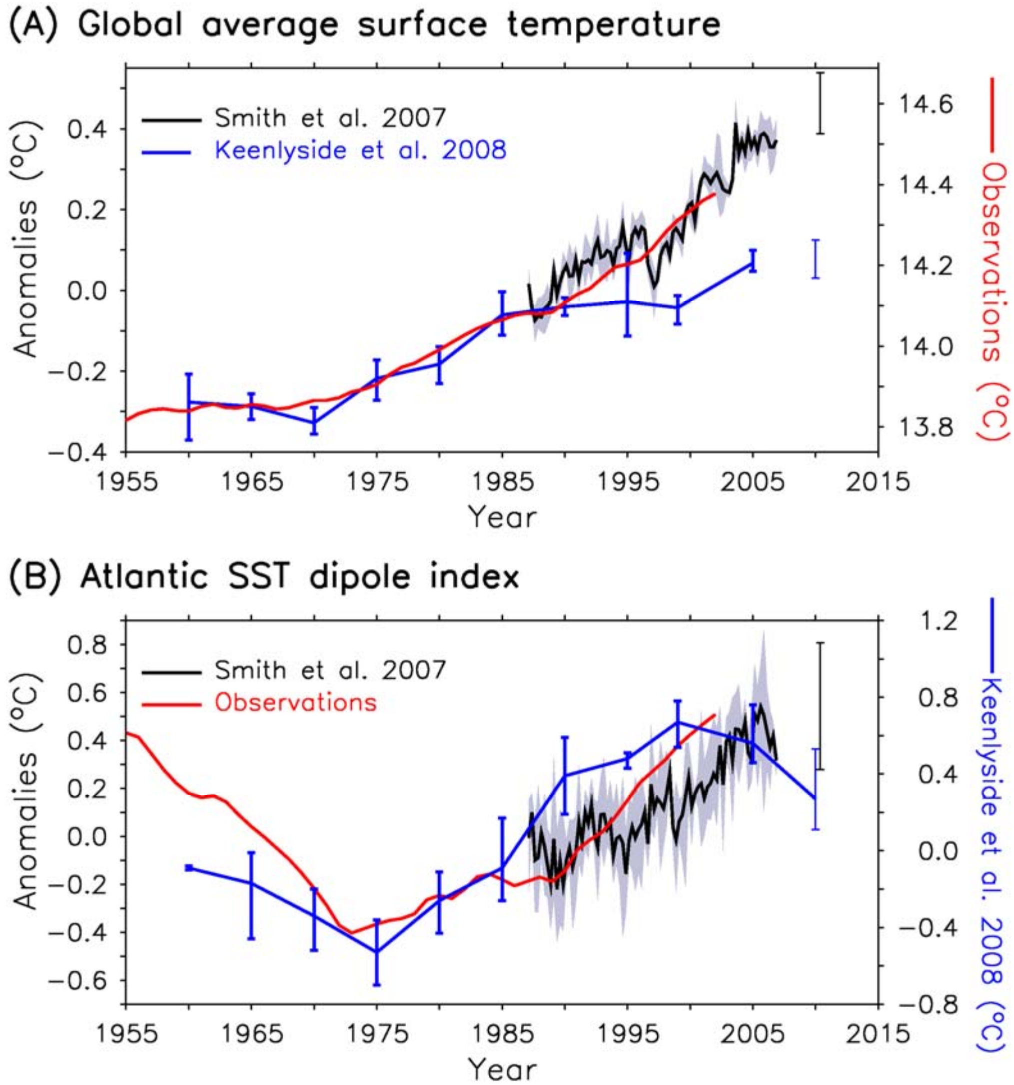

(A) Global average surface temperature
Smith et al. 2007
Keenlyside et al. 2008
Anomalies (°C)
Observations (°C)
0.4
0.2
0.0
−0.2
−0.4
14.6
14.4
14.2
14.0
13.8
1955
1965
1975
1985
1995
2005
2015
Year
(B) Atlantic SST dipole index
Smith et al. 2007
Observations
Anomalies (°C)
Keenlyside et al. 2008 (°C)
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6
1.2
0.8
0.4
0.0
−0.4
−0.8
1955
1965
1975
1985
1995
2005
2015
Year

Fig. 8

CMIP5 Decadal Predictability/Prediction Experiments

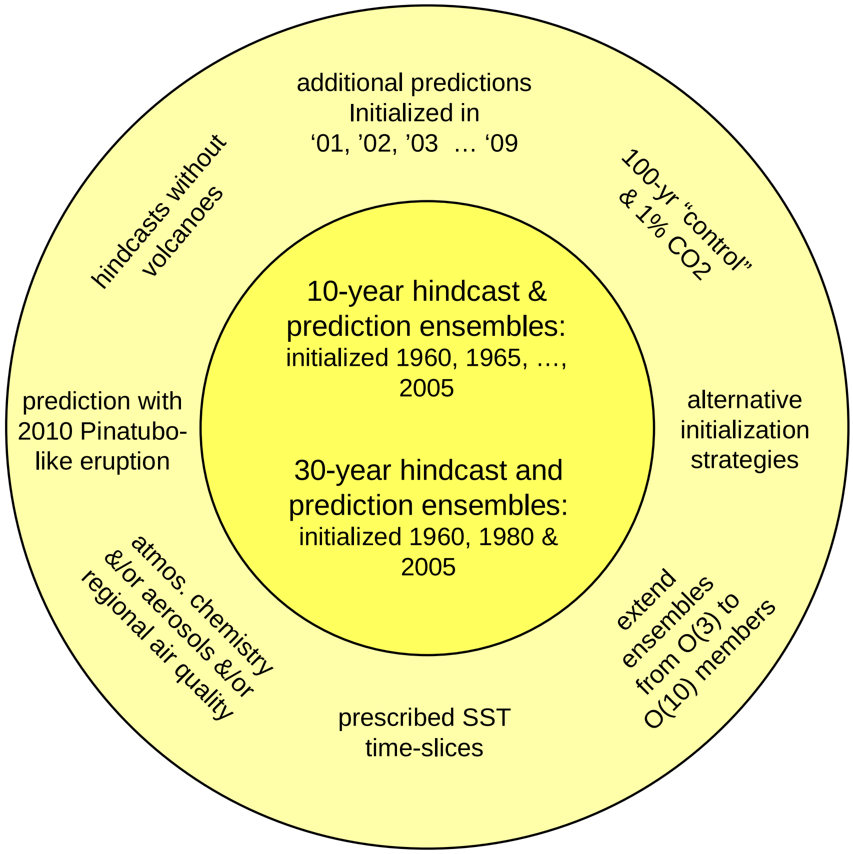


Fig. 9