DISTINGUISHING THE ROLES OF NATURAL AND ANTHROPOGENICALLY FORCED DECADAL CLIMATE VARIABILITY

Implications for Prediction

BY U.S. CLIVAR DECADAL PREDICTABILITY WORKING GROUP: AMY SOLOMON, LISA GODDARD, ARUN KUMAR, JAMES CARTON, CLARA DESER, ICHIRO FUKUMORI, ARTHUR M. GREENE, GABRIELE HEGERL, BEN KIRTMAN, YOCHANAN KUSHNIR, MATTHEW NEWMAN, DOUG SMITH, DAN VIMONT, TOM DELWORTH, GERALD A. MEEHL, AND TIMOTHY STOCKDALE

To assess decadal forecasts it is necessary to identify to what extent regional changes are due to natural climate variations, and are thus transitory, and to what extent they are due to anthropogenic forcing, and are likely to continue.

MOTIVATION. An ambitious effort to produce experimental near-term decadal forecasts has begun, motivated by the possibility that the climate models used for climate change projections can capture not only the impact of the changing atmospheric composition but also the evolution of slow natural variations of the climate system when initialized with ocean observations. In the cases where initialization improves the forecast, addressing the question of how much of that improvement is due to the natural versus the forced climate components is important to understanding the benefits of the initialization. Untangling the natural and forced components of the climate is necessary because the response to external forcing may project onto or comingle with natural climate variability. As the science of decadal prediction is in its infancy, one would like to assess and understand the following:

1) the expectations for added regional climate information and skill achievable from initialized decadal predictions;
2) what physical processes or modes of variability are important for the decadal predictability and prediction problem, and whether their relevance may evolve and change with time;
3) what elements of the observing system are important for initializing and verifying decadal predictions; and
4) in terms of attribution, to what extent are regional changes in the current climate due to natural climate variations and thus transitory, and to what extent are they due to anthropogenic forcing and thus likely to continue.

As with the preceding decade, the climate evolution in the near term will be a combination of forced climate change and natural variability. As an example, consider the prolonged drought conditions of the American West since the late 1990s. Most of the twenty-first-century climate change projections used in the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (AR4) suggest that this region will become drier as precipitation decreases and evaporative demand increases with future warmer temperatures (Seager et al. 2007). However, since dry conditions in this part of the world are also associated with *natural* interannual-to-decadal variability in sea surface temperatures in both the Atlantic and the Pacific basins (e.g. McCabe et al. 2004; Seager et al. 2005; Schubert et al. 2009) and appear to have occurred before the twentieth century (see Jansen et al. 2007), how much of the recent drought can be attributed to natural variability and how much can be attributed to ongoing climate change? An answer to this question could greatly aid western water resource managers in developing informed adaptation strategies.

The purpose of this paper is to describe existing methodologies to separate decadal natural variability from anthropogenically forced variability, the degree to which those efforts have succeeded, and the ways in which the methods are limited or challenged by existing data. Note that the separation of decadal natural variability from anthropogenically forced variability goes beyond what has already been accomplished in previous studies that focused primarily on the detection of a long-term anthropogenic signal (Hegerl et al. 2007b) because on decadal time scales anthropogenic effects may be nonmonotonic, regionally dependent, and/or convolved with natural variability.

The World Climate Research Programme (WCRP) is coordinating a set of decadal prediction experiments (Taylor et al. 2008; Meehl et al. 2009a) that are being conducted by modeling centers around the world. It must be clearly emphasized that these are preliminary experiments to assess the current feasibility of decadal predictions. The approaches for separating natural and forced variability discussed in this paper, presented with their benefits and limitations, are intended to serve as a starting point from which these decadal prediction experiments can be assessed and from which the processes and potential predictability of decadal variations can be better understood.

PHYSICAL PROCESSES INVOLVED WITH DECADAL TIME SCALES IN THE CLIMATE SYSTEM. To assess naturally occurring decadal variability in the climate system and the ability of models to simulate and forecast it, one must identify the relevant physical processes. Most studies point to oceanic mechanisms as central to climate memory, particularly those related to reservoirs of ocean heat or slowly evolving circulation and their interaction with the atmospheric variability. For example, in midlatitudes sea surface temperatures (SSTs) are well described by the stochastic climate model paradigm (Frankignoul and Hasselmann 1977), where random atmospheric surface forcing with a "white noise" spectrum, or equivalent power at all frequencies, is integrated by the ocean mixed layer to produce a "red noise" spectrum, in which power is amplified at lower frequencies [see Deser et al. (2010a) for a review]. Additionally, a number of ocean processes (e.g., overturning and gyre circulations, the triggering of Rossby waves, and advection of temperature/salinity anomalies by the mean currents) are potential candidates that may provide additional predictability by influencing atmospheric and thus terrestrial variability.

AFFILIATIONS: Solomon and Newman—University of Colorado, and NOAA/Earth System Research Laboratory, Boulder, Colorado; Goddard and Greene—NOAA/International Research Institute for Climate and Society, Palisades, New York; Kumar—NOAA/Climate Prediction Center, Camp Springs, Maryland; Carton—University of Maryland, College Park, College Park, Maryland; Deser and Meehl—National Center for Atmospheric Research, Boulder, Colorado; Fukumori—NASA Jet Propulsion Laboratory, Pasadena, California; Hegerl—University of Edinburgh, Edinburgh, United Kingdom; Kirtman—University of Miami, Miami, Florida, and Center for Ocean–Land–Atmosphere Studies, Calverton, Maryland; Kushnir—Lamont-Doherty Earth Observatory Columbia University, New York, New York; Smith—Met Office Hadley Centre, Exeter, United Kingdom; Vimont—University of Wisconsin—Madison, Madison, Wisconsin; Delworth—NOAA/Geophysical Fluid Dynamics Laboratory, Princeton, New Jersey; Stockdale—European Centre for Medium-Range Weather Forecasts, Reading, United Kingdom

CORRESPONDING AUTHOR: Amy Solomon, NOAA/ESRL/PSD, 325 Broadway, R/PSD1, Boulder, CO 80305–3328
E-mail: amy.solomon@noaa.gov

The abstract for this article can be found in this issue, following the table of contents.
DOI:10.1175/2010BAMS2962.1

In final form 7 October 2010

One example of potentially predictable natural climate variability is that produced by wind-forced extratropical ocean Rossby waves that propagate across an ocean basin and create thermocline anomalies near the western boundary. These signals in the ocean are then communicated to the surface through wintertime heat fluxes and wind stress. Schneider and Miller (2001) demonstrate that such a process in the North Pacific can yield predictable wintertime SST anomalies in the Kuroshio–Oyashio Extension at lead times of up to 3 years. Decadal timescale variability in patterns of Pacific basin SSTs associated with the interdecadal Pacific oscillation (IPO; Power et al. 1999) has been connected to wind-forced ocean Rossby waves near 25°N and 25°S that are central to a mechanism that produces the IPO (White et al. 2003; Meehl and Hu 2006; McGregor et al. 2007, 2008). The IPO has subsequently been used as the basis for decadal predictions of Pacific SSTs and associated precipitation over North America and Australia in a perfect model study using a large ensemble of climate model simulations (Meehl et al. 2010). Another example of a source of predictability may come from the shallow wind-driven meridional overturning ocean circulations called subtropical cells (STCs), which connect the subtropical atmosphere to the equatorial region through the ocean in both the Atlantic and Pacific basins [see Schott et al. (2004) for a review]. STCs have been hypothesized to play a role in decadal climate variability by the advection of salinity/temperature anomalies along STC pathways to the equator (Gu and Philander 1997; Yeager and Large 2004) or by changes in STC strength, which controls the amount of cold water that upwells at the equator, both in models (Kleeman et al. 1999; Solomon et al. 2003) and observations (McPhaden and Zhang 2002).

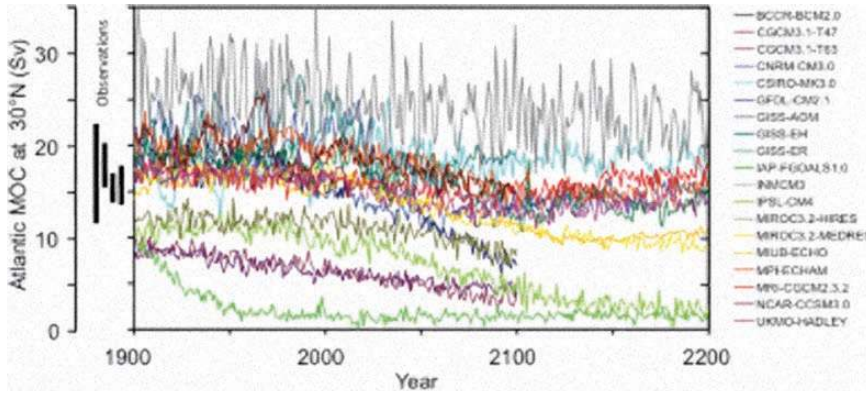

Fig. 1. Strength of the AMOC at 30°N in a variety of 19 AR4 coupled models forced with observed greenhouse gas and aerosol forcing until 1999 and the Special Report on Emissions Scenarios (SRES) A1B scenario of greenhouse gas forcing after 1999. Bars on the left show various observational estimates. From Meehl et al. (2007).

A potentially large source of predictability of natural climate variability on decadal time scales may also come from fluctuations in the Atlantic meridional overturning circulation (AMOC) (e.g., see Delworth and Mann 2000; Knight et al. 2005; Dijkstra et al. 2006; Zhang and Delworth 2006). This circulation plays a key role in climate by transporting warm upper-ocean water northward in the Atlantic and releasing that heat to the atmosphere; the cooled water sinks and returns southward at depths below 1000 m. The Atlantic shows evidence of multidecadal climate variations generally referred to as the Atlantic multidecadal oscillation (AMO; Enfield et al. 2001), with a basin-scale signature in SST. It has been hypothesized that the multidecadal fluctuations in SST may be related to AMOC fluctuations. AMO-like SST fluctuations are found in many coupled models (e.g., Latif et al. 2006), and while different models seem to produce fluctuations for different reasons and with different time scales (see Fig. 1), all seem to involve a link to the AMOC. The presence of feedbacks linking AMOC, SST, and the atmospheric circulation opens up potential for predictability of decadal climate variability over land associated with predictability of AMOC variations (see Knight et al. 2006).

A principal assertion behind the decadal prediction experiments is that initialization of decadal-scale ocean processes, such as those mentioned above, will provide additional predictability beyond that due to the radiative forcing from increasing greenhouse gases. The extent to which this is true using the current generation of GCMs and data assimilation systems has yet to be determined, although hindcast experiments appear promising (e.g., Smith et al. 2007). As described in the next section, several approaches have been proposed to separate natural from externally forced variability in order to highlight the added value of ocean initialization on predictions of the future or to help better understand or describe past trends and variability. To date, no superior approach exists; all have benefits and limitations.

APPROACHES TO SEPARATE NATURAL INTERNAL VARIABILITY FROM ANTHROPOGENICALLY FORCED DECADAL VARIATIONS.

Analysis of initialized decadal prediction studies. Natural and forced variability may be separated to a certain extent by comparing parallel sets of initialized and uninitialized hindcast experiments made with the same climate model (Smith et al. 2007; Keenlyside et al. 2008; Pohlmann et al. 2009). If all external forcing (i.e., from anthropogenic greenhouse gases and aerosols, solar irradiance, and volcanic eruptions) is identical, then differences between the two sets of hindcasts arise purely from initialization. Since natural internal variability can only be predicted by starting from its correct phase, improved skill in initialized over uninitialized hindcasts may indicate skillful prediction of some aspects of natural variability. However, improved skill in initialized hindcasts may also arise from removing biases that exist in uninitialized climate models forced by observed changes in external forcing and that may be smaller at the start of initialized decadal predictions. This source of additional skill is potentially important for improving predictions of climate change commitment or short-term response to volcanic eruptions, but it would need to be taken into account in any attempt to separate natural and forced variability.

There are also other issues to be considered when analyzing decadal hindcasts. Climate models cannot be initialized perfectly with incomplete observations. This usually leads to an initialization shock, during which the model rapidly adjusts to imbalances introduced by imperfect initialization, causing a degradation of forecast skill that could mask any signals from natural variability. It is also possible that unrealistic model responses to imperfectly estimated initial conditions (Acero-Schertzer et al. 1997; Ji et al. 2000; Masina et al. 2001) could lead to apparent hindcast skill that could be incorrectly attributed to natural variability. For example, in initialized hindcasts of the mid-1990s warming of the North Atlantic subpolar gyre, J. Robson et al. (2009, unpublished manuscript) found that skill was due to errors in assimilated density anomalies. Furthermore, initializing and assessing decadal hindcasts is severely hampered by the sparseness of historical subsurface ocean observations. For example, natural variations of the Atlantic AMOC are predictable in idealized model experiments (Collins et al. 2006), but our ability to confirm such predictability in reality is compromised by the lack of historical ocean observations. Ultimately these issues must be overcome in order to capitalize on the predictability from the natural variability to improve decadal forecasts.

Analysis of model ensemble means and variance. A large ensemble of climate simulations can be used to separate the model response to external forcing from the variations that are internal to the system. The former is referred to as external variability, while the latter is referred to as internal or the natural climate variability. The approach described closely follows a similar approach used in seasonal climate predictions, where seasonal atmospheric variability is decomposed into external variability because of SST and internal variability due to atmospheric processes alone (e.g. Kumar and Hoerling 1995; Rowell et al. 1995).

For coupled general circulation models (CGCMs) used in climate change projections, in which the ocean has not been initialized, the mean over an ensemble of CGCM simulations is the least biased estimate of the response of the model to the specified time evolution of external forcings (e.g., CO_2, solar variability, volcanic aerosols). The departure in each climate simulation from the ensemble mean then provides an estimate of the model's internal variability due to natural fluctuations. This approach can be applied to any time average extending from seasonal to annual to decadal. However, for longer time averages, the removal of weather or climate noise by ensemble averaging is more effective.

For large enough ensembles with specified external forcing, this approach also allows for the investigation of how external forcing may project onto dominant modes of internal variability. In one example, a 40-member ensemble of CGCM integrations with changing atmospheric composition and ozone recovery for the period 2005–60 was compared to a long (10,000 yr) unforced control run of the atmospheric model component with a specified repeating annual cycle of sea surface temperatures and sea ice conditions (Deser et al. 2011). The ensemble mean atmospheric circulation trend, interpreted as the forced response, exhibits a statistically significant weakening of the Southern Hemisphere polar vortex during austral summer (positive sea level pressure trends at high latitudes and negative ones at middle latitudes; Fig. 2, left panel). The spread of the response among the individual ensemble members, or intraensemble noise, is also characterized by an annular pattern reminiscent of the forced response (Fig. 2, middle panel). Further, the pattern of the noise closely resembles the leading EOF from the unforced atmospheric model control run (Fig. 2, right panel). This study illustrates that the pattern of the forced response may have similar structure to the natural variability in the model, as also noted by Meehl et al. (2009b) for the climate shift that occurred in the Pacific in the mid-1970s. These results further demonstrate that externally forced multidecadal trends of some variables can be subject to large uncertainties owing to noise, thus requiring analysis of very large ensembles.

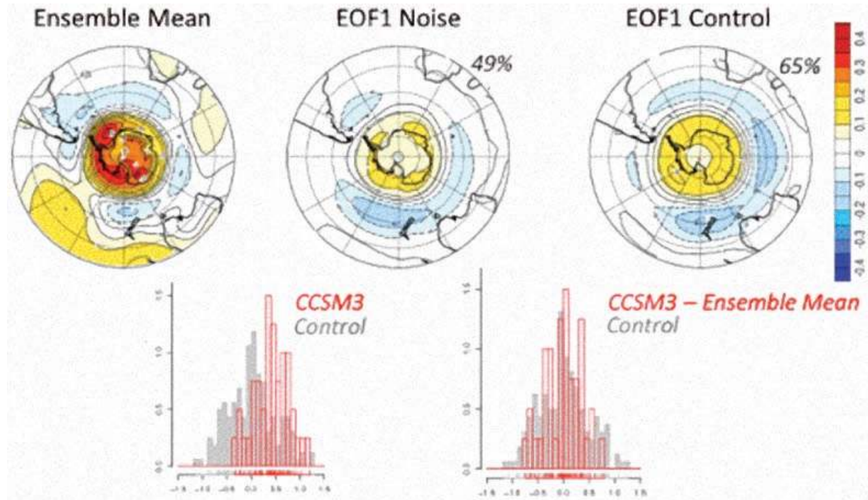

Fig. 2. Projected November–February sea level pressure trends during 2005–60 over the Southern Hemisphere. (top left) Forced 40-member coupled model ensemble mean. (top middle) Leading EOF of the deviation of each coupled model ensemble member's trend from the coupled model ensemble mean trend. (top right) Leading EOF of a 178-member ensemble of 56-yr trends from a 10,000-yr atmospheric model control integration. (bottom left) PDF of the trends in the index of the southern annular mode from each coupled model ensemble member (red bars) and from each atmospheric control member (gray). (bottom right) As at bottom left, but the coupled model ensemble mean trend has been removed from each individual coupled model ensemble member. From Deser et al. (2011).

This approach to separating the natural and externally forced variability, based on ensembles of climate simulations, is a conceptually simple methodology in its formulation. The approach, however, also has some limitations, including the fact that estimates of internal and externally forced variability are model dependent. On the other hand, based on an analysis of simulations from multiple CGCMs and a comparison of total variability against the observed estimates, some confidence in the model-based estimates can be gained. However, the approach, by construction, requires a large ensemble of simulations and can be computationally taxing. For example, existing model archives used in the third phase of the Coupled Model Intercomparison Project (CMIP3) generally do not have large enough ensembles from individual models for this approach to be viable.

Signal-to-noise maximizing EOFs. The signal-to-noise (S/N) maximizing EOF analysis is an effective method to distinguish between externally forced climate responses, which are common to all ensemble members, and natural internal climate variability. This approach can be used with small ensembles and can be used when the signal due to external forcing is on the order of, or weaker than, the internal variability in the model.

In signal-to-noise maximizing EOFs, the predictable patterns in ensemble prediction experiments are sought by calculating the dominant patterns (EOFs) of the covariance matrix of the ensemble-average output (e.g., Seager at al. 2008). In large ensembles, internal variability of each ensemble member largely cancels out in the ensemble mean, leaving the externally forced signal. In a small ensemble, say, of the size envisioned in the Fifth Assessment Report (AR5) decadal prediction experiments, the intra-ensemble noise due to energetic internal variability with coherent spatial structure will impact the EOFs of the ensemble mean and may make it difficult to distinguish between the patterns of signal and noise. To overcome this problem, a spatial prewhitening transformation is applied to the ensemble mean data to remove the spatial correlations from the noise structures and thus remove the impact of the climate noise on the ensemble mean (see Allen and Smith 1997; Venzke et al. 1999; Chang et al. 2000). This analysis is equivalent to identifying the predictable components that maximize the average signal-to-noise ratio (see DelSole and Tippett 2008).

Ting et al. (2009) applied S/N maximizing EOFs to twentieth-century SST variability over the North Atlantic basin to distinguish natural variability [in particular, Atlantic multidecadal variability (AMV)] from the externally forced signal in six small CMIP3 ensembles performed with several different CGCMs. The results exhibited a cleaner and better between-model agreement of the global forced signal than using a simple ensemble mean temperature. The estimate of the forced signal can then be subtracted to determine the pattern of internal interdecadal variability in the observed (and modeled) North Atlantic SST (see Fig. 3). This yields a much different impression of the magnitude of the AMV in the early twenty-first century than more subjective estimates of AMV [e.g., the departure from a linear trend, or from the global mean; see Enfield and Cid-Serrano (2010) or Ting et al. (2009) for a discussion].

While S/N EOF analysis can be useful for identifying a common signal in small ensembles of forced CGCM integrations, even in the presence of significant levels of climate noise, the method does have limitations in the context of decadal predictions. In particular, S/N maximizing EOFs would need an additional set of model simulations to separate information on the patterns of externally forced variability from any predictable or persistent patterns related to the initial conditions, as the initialized signal would also be part of the output common to all ensemble members.

Linear inverse models. Linear inverse modeling (LIM) is an empirical technique to fit a multivariate red-noise model to observations or model output. These models have been very successful in simulating ENSO variability and can reproduce the observed power spectrum on seasonal-to-interannual time scales of the dominant pattern of tropical SST variability (see Newman et al. 2009). Since LIM determines empirical, potentially nonorthogonal, dynamical modes, it is useful for identifying how these modes contribute to a physical phenomenon. For example, LIM has been used to show that the Pacific decadal oscillation (PDO; Mantua et al. 1997) may not be a single physical mode but a superposition of a number of processes with different dynamical origins (Newman et al. 2003; Schneider and Cornuelle 2005; Newman 2007). For example, LIM of Pacific basin SSTs finds that the "decadal ENSO" pattern with PDO signature in the North Pacific (Fig. 4c; e.g., Zhang et al. 1997; Deser et al. 2004) has a decay time that is far shorter than its period. As a result, little long-range forecast skill is associated with this eigenmode. Instead, predictability in this system on greater than interannual time scales comes from the two leading stationary eigenmodes: a leading eigenmode with a 100-yr trend (Fig. 4a) and a second eigenmode (Fig. 4b) that has a pattern somewhat similar to the multidecadal signal found by Deser et al. (2004) (see also D'Arrigo et al. 2005). The combined effects of these two eigenmodes alone dominate the patterns of Pacific SST trend in this dataset over both the entire century and the last 50 years. In addition, LIM is useful for identifying optimal initial conditions that produce the largest variability in a linearly stable stochastically forced system.

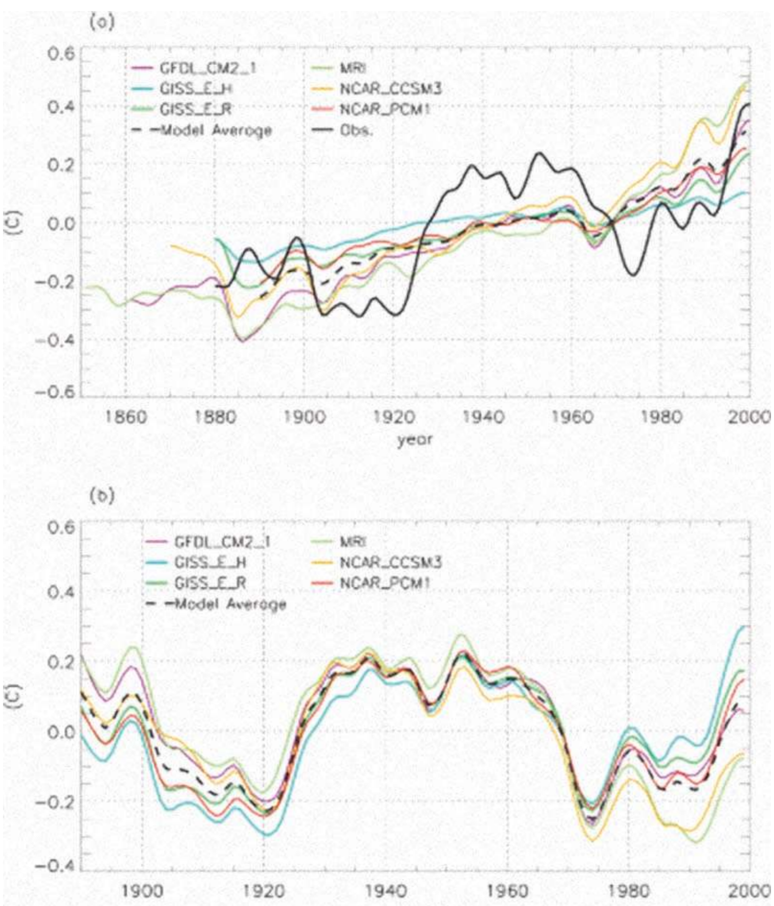

Fig. 3. (a) Projection of SST averaged in the North Atlantic basin onto the leading S/N maximizing principal component (PC) in each of the participating models [see list in figure and information in Ting et al. (2009)]. Each model PC is depicted by a different color, and the dashed line is the ensemble average. The observed SST average, suggesting a superposition of a forced trend and internal, multidecadal variability, is shown with the solid black line. (b) The observed AMO index constructed by subtracting from the observed North Atlantic SST average the model estimates of the forced North Atlantic SST shown in (a). The black dashed line shows the forced response average across all six participating models. From Ting et al. (2009).

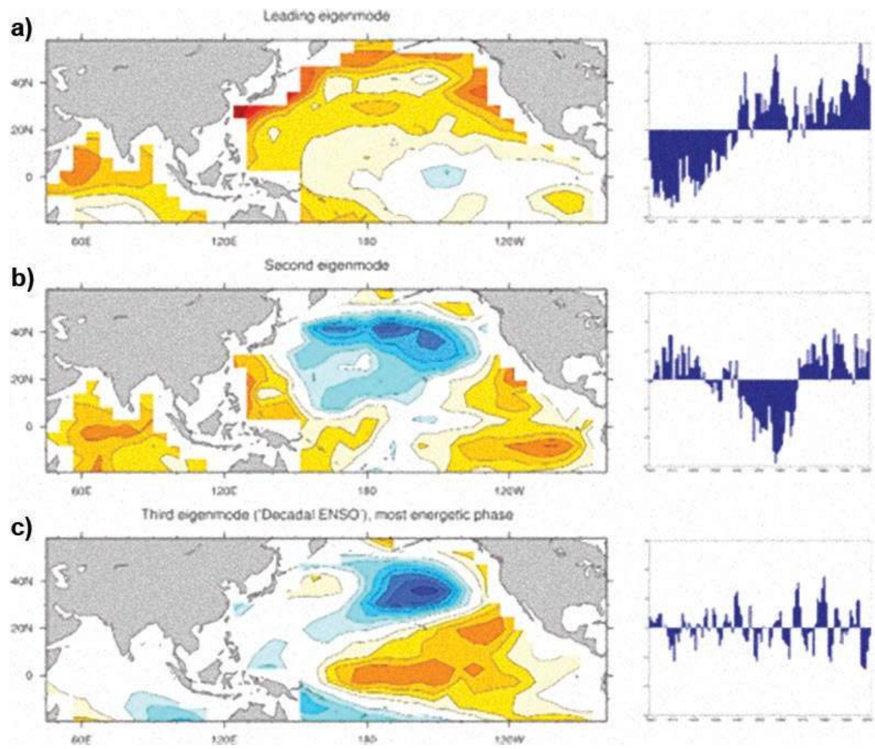

Fig. 4. (left) Leading empirical eigenmodes and (right) their corresponding time series from the LIM of annual-mean HadISST SST anomalies. The LIM is constructed as in Newman (2007), except that the EOF basis is determined over the entire Pacific domain (20°S–60°N); the leading 12 PCs are retained, explaining 92% of the variance in both the tropics and in the North Pacific, unlike in Newman (2007), where less than two-thirds of the North Pacific variance was retained. Contour interval is the same in all panels but is arbitrary. Red (blue) shading indicates positive (negative) values; zero contour is removed for clarity. (a) Leading eigenmode, stationary with decay time of 13 yr. (b) Second eigenmode, stationary with decay time of 6.4 yr. (c) Most energetic phase of third ("decadal ENSO") eigenmode, propagating with a period of 16 yr and decay time of 2.1 yr.

Such initial conditions that would portend potential predictability have been identified for the North Atlantic (see Tziperman et al. 2008; Hawkins and Sutton 2009) and the tropical Pacific (see Penland and Sardeshmukh 1995).

As a consequence, the estimates of observed empirical modes from LIM can be used to assess the properties of empirical modes calculated from model output. Also, by comparing LIM simulations with external forcing to their corresponding control runs, one can gain some insight into how dynamical modes may be impacted by external forcing. For example, comparing empirical modes estimated from the output of twentieth-century simulations to empirical modes determined from both the corresponding control simulations and from observations indicates that external forcing substantially impacts the leading eigenmode (Fig. 5a). Moreover, the climate models might be underestimating the potential predictability of natural variability since in virtually all of the twentieth-century simulations, the second eigenmode is not only poorly captured but is also much less persistent than in the observed LIM, for reasons that are presently not understood (e.g., Newman 2007) (Fig. 5b).

Application of detection/attribution studies. Climate change detection and attribution studies aim to isolate the anthropogenically forced component of the evolving climate. They generally use information about the shape of the expected climate response to forcing (the "fingerprint") and are targeted to isolating the role of these fingerprints in observed climate change as clearly as possible from internal climate variability. Often, this is done using signal separation techniques, such as "optimal fingerprints" or best linear unbiased estimators (see review in Hegerl et al. 2007b). For detection and attribution, all relevant external influences on climate must be considered. The attribution methods then attempt, with uncertainty estimates, to identify the contribution of each external forcing factor to the observed change. The shape of the fingerprints is assumed known, and their magnitude is estimated, allowing the results to account for uncertainties, such as errors in a model's sensitivity to a particular forcing or in the magnitude of external forcings in general.

The results from detection and attribution methods, however, go further. The best-guess and uncertainty ranges of the greenhouse gas contribution in the observed temperature changes can be used directly to predict future changes (Stott and Kettleborough 2002) and have been used, among other methods, to provide uncertainty ranges for future climate change in the IPCC assessment (Knutti et al. 2008). Lee et al. (2006) demonstrated that over a large part of the twentieth century, the forced component, determined by optimal fingerprints, can produce skillful hindcasts of decadal global temperature variability.

The success of fingerprint methods in separating different factors influencing climate suggests that they may also be useful in separating the influence of initial conditions from those of external forcing, thus allowing us to trace where the initial conditions have made significant differences in hindcasts and how long this influence has lasted. The fifth phase of the CMIP (CMIP5) simulations will provide a useful test bed for such an extension of the detection and attribution method.

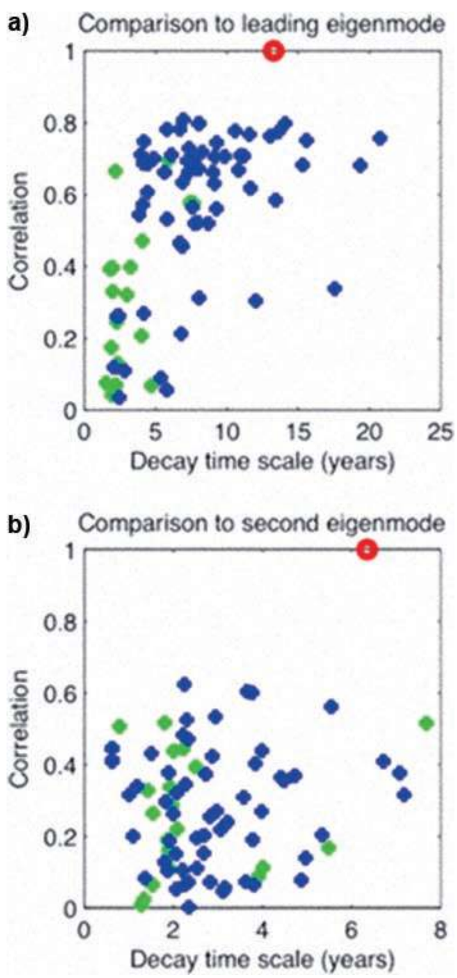

Fig. 5. Comparison of the (a) leading and (b) second observed eigenmodes with the corresponding eigenmodes based on each 100-yr ensemble member from the twentieth-century AR4 coupled GCMs (blue) and the associated control runs (green). Both plots show the decay time scale of each modeled eigenmode vs. its pattern correlation with the corresponding observed eigenmode. The red circle in each panel indicates the observed eigenmode.

However, when it comes to applying such approaches on regional scales and to variables other than temperature, a number of difficulties loom. One important shortcoming is that on smaller than continental scales, the uncertainty in forcings other than greenhouse gases is large; the exact time–space pattern of aerosols, land use change, and other forcings is often poorly known and poorly represented in models. This would hamper the ability to reliably attribute successes and failures in regional hindcasts to particular causes. When applying this approach to variables other than temperature, the difficulties increase. Only recently, for example, has the effect of anthropogenic forcing on precipitation been formally detected (Zhang et al. 2007). However, the multimodel fingerprint produces smaller changes in zonally averaged precipitation than observed, indicating that the understanding and simulation of precipitation variability is still limited.

CHALLENGES. *Interaction between natural and externally forced variability.* As discussed earlier, the response to external forcing may resemble the natural modes of variability on regional and hemispheric scales. This was seen to be the case in the modeling study of Meehl et al. (2009b), where natural and externally forced patterns of variability with similar structure contributed to the mid-1970s climate shift over the Pacific basin, from relatively cool to relatively warm conditions along the equator. Indeed, they argued that an anthropogenically forced shift would have occurred in the 1960s if it were not for the presence of large-amplitude natural variations that delayed the shift into the 1970s.

Just how external forcing interacts with natural modes of variability remains an important but unresolved issue. The process may be fundamentally linear with external forcing selecting certain natural internal modes because of their inherent time scales and spatial structures, or nonlinear where the impact of the external forcing on the modes of variability has a net effect on the long-term trend signal (e.g., see Branstator and Selten 2009). In the linear case, the forcing and the response may not have similar patterns because of the nonnormal growth of natural modes. In the nonlinear case, the external forcing may cause changes in the frequency of occurrence of climate modes with or without changing the spatial structure of the leading modes of variability (see Corti et al. 1999; Hsu and Zwiers 2001; Brandefelt

2006; Branstator and Selten 2009).

Observational uncertainties. Verification of the forced component of twentieth-century climate trends simulated in model experiments depends on the existence of accurate estimates of these trends in observations. Given the limited sampling in both space and time of the observations and proxy records, these verifications must be handled carefully. In particular, knowledge of the spatial patterns and magnitudes of climate trends over the oceans is hampered by the uneven and changing distribution of commercial shipping routes (Fig. 6) and other observational inputs as well as different approaches to merging analyses of the observations (Rayner et al. 2011).

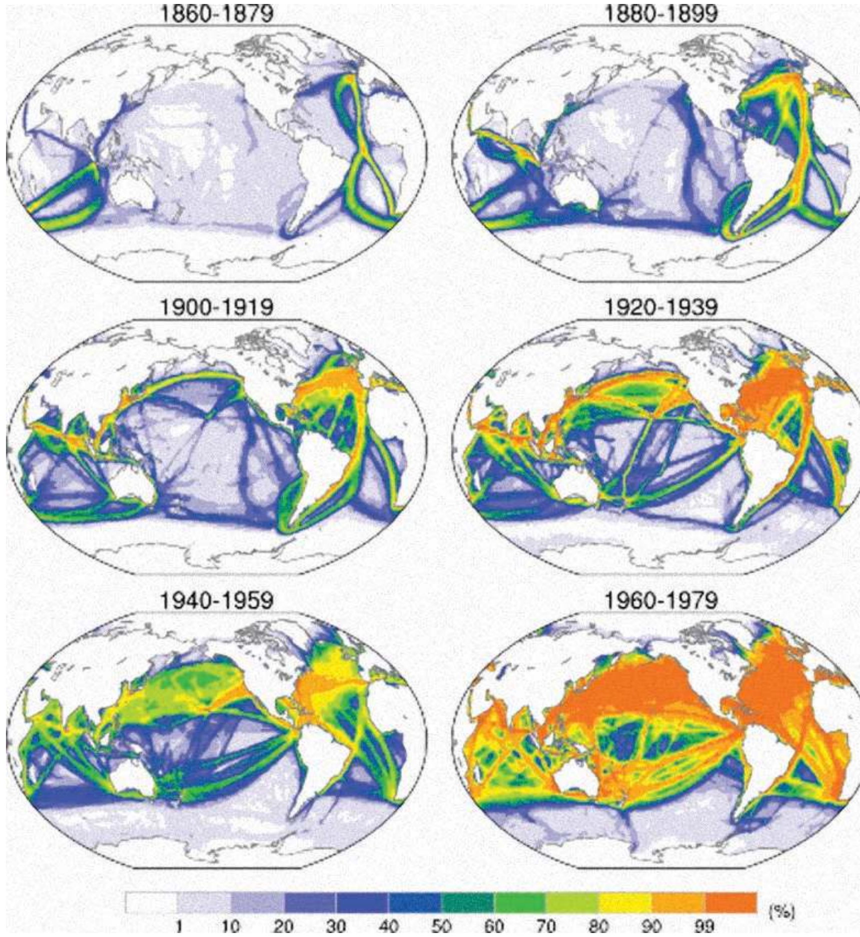

Fig. 6. Distribution of surface marine observations from the International Comprehensive Ocean–Atmosphere Data Set (ICOADS), shown as the percent of months with at least one observation per 2° lat × 2° lon grid box during the 20-yr period indicated. Adapted from Deser et al. (2010a).

An example of the impact of observational uncertainties on the interpretation of twentieth-century SST trends is shown in Fig. 7 based on an uninterpolated dataset [version 2 of the Hadley Centre SST dataset (HadSST2); Rayner et al. 2006] and two optimally interpolated reconstructions [the Hadley Centre Sea Ice and SST dataset (HadISST; Rayner et al. 2003) and version three of the National Oceanic and Atmospheric Administration's (NOAA's) extended reconstructed SST (ERSSTv3; Smith et al. 2008)]. Although trends from the three datasets share many features in common, such as a strengthening of the equatorial Pacific zonal temperature gradient (Karnauskas et al. 2009), there are also differences. Most notably, the eastern equatorial Pacific shows cooling in HadISST and warming in HadSST2 and ERSSTv3 (see also Vecchi et al. 2008). However, independently measured but related variables, such as nighttime marine air temperatures, provide some evidence that the eastern Pacific trends represented in the HadSST2 and ERSSTv3 datasets may be the more realistic ones (Deser et al. 2010b). These observational sampling issues underscore the challenge of providing a robust target for model validation of twentieth-century surface marine climate trends and perhaps the need to consider a suite of complementary measures for poorly sampled variables and/or regions.

A limitation of the instrumental record is that it spans at most a few realizations of decadal variability. Paleoclimate records—derived from tree rings, corals, lake sediments, or other "proxies"—have been used to extend this record to hundreds of years or more and are generally believed to be free of anthropogenic influence prior to the industrial age (Brook 2009; Jansen et al. 2007), thus constituting a potential means of model verification. Particular proxy types are generally restricted to specific ecological domains and spatial coverage can be patchy, but there has been a recent emphasis on the reconstruction of complete climate fields (Luterbacher et al. 2001; Cook and Krusic 2004; Mann et al. 2007; Riedwyl et al. 2009; Cook et al. 2010; Neukom et al. 2011). Because paleodata constitute the sole records of Earth's pre-instrumental climate, such reconstructions merit attention as a potential means of model verification with respect to both unforced and naturally forced climate fluctuations (Jansen et al. 2007; Hegerl et al. 2007b).

Additional challenges are faced in the assessment of ocean processes below the surface, even for the recent past. The available analyses of ocean observations span a wide range of products aimed at climate studies as well as ocean "nowcasting" and short-term forecasting applications. The ocean analysis products differ in the underlying models and estimation methods, as well as the suite of observations that are assimilated. Many of the analysis products span multiple decades from the 1980s to the present, with some also reaching back to the 1950s, and provide a convenient means for retrospective studies of climate variability; however, the relative accuracy and fidelity of the analyses depend in part on the specific variables used and are active areas of study. While many of the ocean syntheses employ estimation methods based on those first developed in weather forecasting, some employ so-called smoothing methods that estimate the source of the model inaccuracies corrected by combining with data [see review by Balmaseda et al. (2010)]. The assimilation of Argo data in these analyses may remove biases in the upper ocean and allow for the initialization of ocean circulations and transports (e.g., see Forget et al. 2007); however, such records are limited to after 2000.

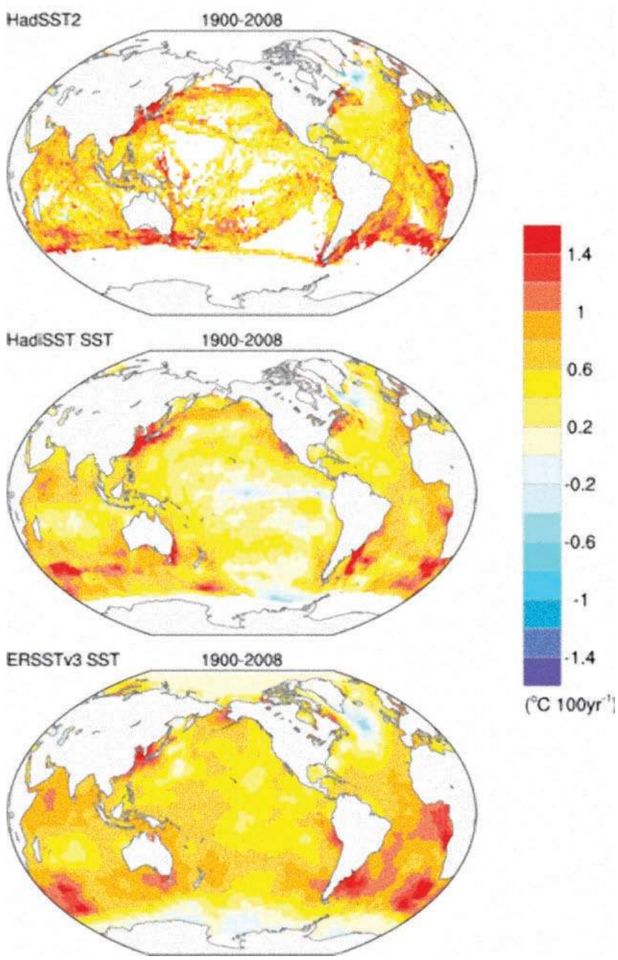

Fig. 7. Twentieth-century SST trends [°C (100 yr)$^{-1}$] from the (top) uninterpolated HadSST2, (middle) reconstructed HadISST, and (bottom) reconstructed ERSSTv3 datasets, based on monthly anomalies during 1900–2008. A minimum of 3 months per decade in each decade was required to compute a trend from the HadSST2 dataset. Adapted from Deser et al. (2010b).

Modeling uncertainties. The spatial structure and dominant time scales of natural variations differ across models (see discussion of Fig. 5). Additionally, coupled climate models produce a range of responses, in space and time, to anthropogenic radiative forcing (Fig. 8). Such differences in model estimates of internal variability and response to external forcing limit our understanding for the potential of the decadal climate predictions.

As an example, the historical changes and future response of the tropical Pacific mean state have been subjects of debate. Different proposed mechanisms disagree on the expected sign of change in the zonal SST gradient in the tropical Pacific (Knutson and Manabe 1995; Meehl and Washington 1996; Cane et al. 1997; Clement and Seager 1999) in response to anthropogenic forcing. The observational record does little to clarify the situation, as trends in different observed SST records differ in even their sign (see Fig. 7). Models that simulate the largest El Niño–like response have the least realistic simulations of ENSO variability, while models with the most realistic simulations of ENSO project little change in the Pacific zonal SST gradient (Collins 2005). These differences in tropical Pacific interannual variability and change have implications for Pacific decadal variability through their impact on large-scale changes in the atmospheric circulation (e.g., Alexander et al. 2002; Vimont 2005).

Different climate model responses to radiative forcing may lead to differences in the slowly varying base state of the oceans. Differences in the ocean base state, in turn, may alter the character of natural variability by changing the advective time scale of

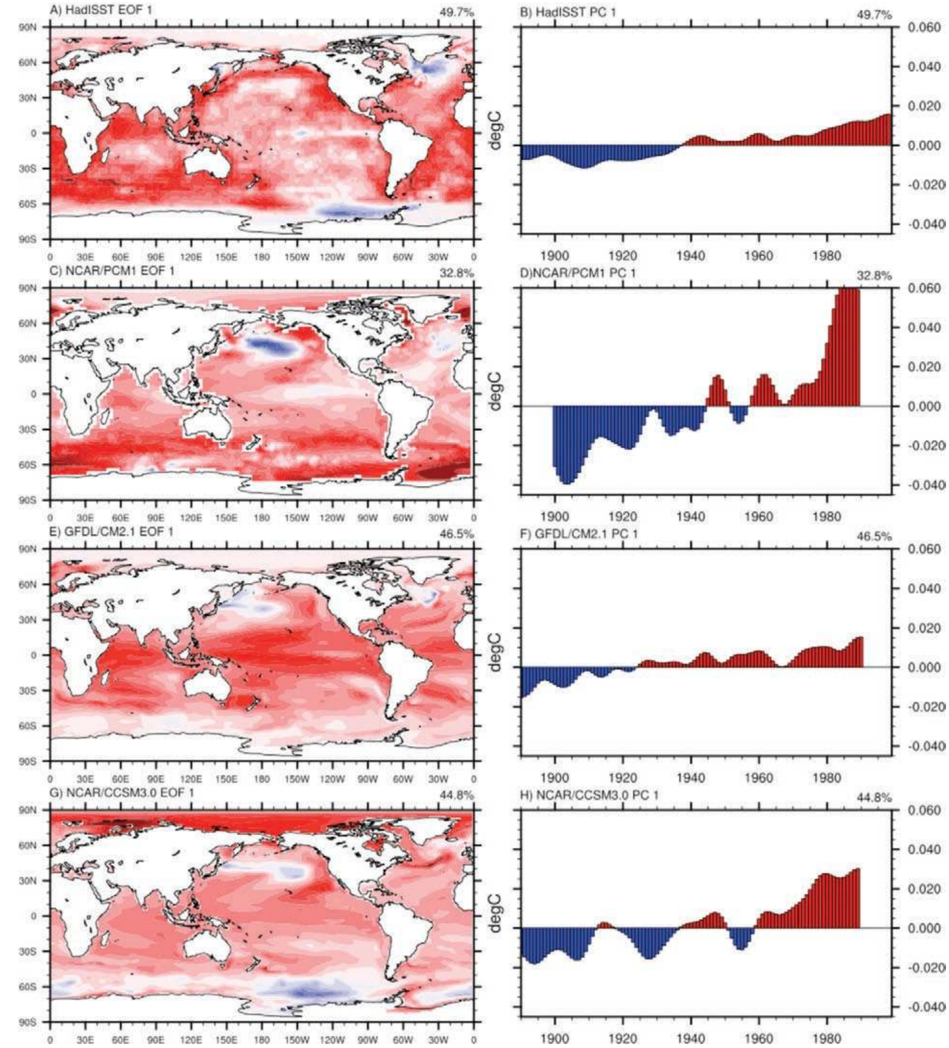

Fig. 8. First EOF and associated principal component (PC) of annual-mean sea surface temperature from observations and three twentieth-century simulations for years 1890–1999: (a),(b) HadISST dataset (Rayner et al. 2003); (c),(d) National Center for Atmospheric Research (NCAR)– U.S. Department of Energy Parallel Climate Model, version 1 (PCM1; www.cgd.ucar.edu/pcm/); (e),(f) The Geophysical Fluid Dynamics Laboratory (GFDL) climate model, version 2.1 (CM2.1; Delworth et al. 2006); (g),(h) The NCAR Community Climate System Model, version 3.0 (CCSM3.0; www.ccsm.ucar.edu/models/ccsm3.0). All data have been smoothed with a 10-yr low-pass Lanczos filter using 21 weights. EOF patterns are normalized. PCs are in units of degrees Celsius. The percent in the upper right of each figure indicates the amount of variance explained by each pattern. Note that the PC time series from the climate model simulations show fluctuations with larger amplitude than observations, all of which fluctuate on different time scales.

density/salinity anomalies and pathways between the extratropics and tropics. Thus, the ability of models to reproduce the observed spatial patterns of forced variability is important to realizing the full benefits of ocean initialization of natural variability; however, validation of the forced patterns of variability is not straightforward, given the observational uncertainty present in identifying even the natural, internal patterns of low-frequency variability.

DEVELOPING A FRAMEWORK TO ASSESS DECADAL PREDICTIONS. Given that over the course of the next 10–30 years the magnitude of natural decadal variations may rival that of anthropogenically forced climate change on regional scales, initialized decadal predictions have the potential to provide important information for climate-related management and adaptation decisions. Such predictions are presently one of the grand challenges for the climate community. Long experience in weather and climate forecasting has shown that forecasts are of little utility without a priori assessment of forecast skill and reliability. This will be no less true for decadal forecasts if they are to be useful. However, even crudely estimating skill for a forecast system requires some understanding of the sources for potential skill, especially when expected skill depends upon the initial conditions themselves, and the expected evolution of forecast spread, which is one measure of uncertainty.

For decadal predictions, understanding of the sources for potential skill requires identifying those physical phenomena—and their model equivalents or lack thereof—that may provide additional predictability on decadal time scales. This includes an assessment of the physical processes through which

Table 1. Comparison of methods to separate natural and forced decadal variability described in the paper. Note that all methods are still subject to conflation of natural and forced patterns.

Property method	Requires large ensembles	Distinguishes natural and externally forced trends	Isolates dynamical modes of natural variability	Identifies skill due to initialization
Analysis of ensemble means and variance (ANOVA)	Yes	Identifies change in statistics due to external forcing by comparing forced and unforced runs	No	Can identify skill due to initialization and external forcing
Optimal fingerprinting	Yes, to identify fingerprints of response to external forcing	No	No	Potentially
S/N maximizing EOF	Less sensitive to number of ensemble members than ANOVA	Identifies change in statistics due to external forcing by comparing forced and unforced runs	No	No
Linear inverse models	No	Identifies change in statistics due to external forcing by comparing forced and unforced runs	Identifies empirical modes	Yes
Initialized hindcasts	Potentially	Potentially		Yes

anthropogenic forcing interacts with or projects upon natural variability. However, it is important to note that the rate at which forecast experience will accumulate on the decadal time scale is necessarily much slower than the rate at which it accumulates for weather forecasting. Given this, a physical framework is necessary to provide a consistent assessment of the different decadal prediction experiments planned for the AR5.

The main conclusion drawn from the body of work reviewed in this paper is that distinguishing between natural and externally forced variations is a difficult problem that is nevertheless key to any assessment of decadal predictability and decadal prediction skill. Note that all the techniques are limited by some assumption intrinsic to their analysis, such as the spatial characteristics of the anthropogenic signal, independence of noise from signal, or statistical stationarity. Benefits and limitations of techniques described in this paper are listed in Table 1. Also, all the techniques utilize either short and potentially inaccurate observational datasets and/or potentially biased but lengthier CGCM datasets. The analysis techniques discussed in the paper should be applied to the long control CGCM runs and both the twentieth-century simulations and twenty-first-century projections, which will serve as a critical test bed for analysis of the relationship between natural and anthropogenic variability. These strategies can also be applied to existing decadal prediction experiments and climate change projections in order to develop a series of metrics that can be used to assess the predictions to be done for the AR5. These metrics could help identify, to the extent possible with limited ensemble sizes, the impact of different initialization strategies, model biases, and errors in model physics on the response to external forcing and the predictable and unpredictable natural variations.

A reasonable starting point for these metrics is to focus on decadal variability due to ocean processes, as discussed earlier. This requires analyses that assess the spatial patterns and associated time scales of natural variations, and their potential change in structure and frequency due to external forcing. A starting point for such analyses could be to compare the existing climate change projections against their companion control runs. In addition, since externally forced SSTs play an important role in climate variations over land through atmospheric teleconnections, it is necessary to develop metrics that assess the spatial pattern of externally forced SST variability, as well as upper-ocean structure and variability. To quantify signal-to-noise ratios, it is necessary to develop metrics that can properly validate ensemble simulations and predictions. The development of these metrics will help guide the assessment of decadal forecasts and will provide a framework for identifying potential directions to improve our ability to make decadal predictions.

ACKNOWLEDGMENTS. The authors of this paper are members of the Decadal Predictability Working Group, sponsored by U.S. CLIVAR. We appreciate the support from the U.S. CLIVAR office. We thank two anonymous reviewers for their helpful and thoughtful suggestions.

REFERENCES

Acero-Schertzer, C. E., D. V. Hansen, and M. S. Swenson, 1997: Evaluation and diagnosis of surface currents in the National Centers for Environmental Prediction's ocean analyses. *J. Geophys. Res.,* **102,** 21 037–21 048.

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

Allen, M. R., and L. A. Smith, 1997: Optimal filtering in singular spectrum analysis. *Phys. Lett.,* **234,** 419–428.

Balmaseda, M. A., and Coauthors, 2010: Initialization for seasonal and decadal forecasts. *Proceedings of OceanObs'09: Sustained Ocean Observations and Information for Society,* Vol. 2, ESA Publ. WPP-306, https://abstracts.congrex.com/scripts/jmevent/abstracts/FCXNL-09A02a-1652576-1-Formatted_CWP_Initialization_v4.pdf

Brandefelt, J., 2006: Atmospheric modes of variability in a changing climate. *J. Climate,* **19,** 5934–5943.

Branstator, G., and F. M. Selten, 2009: "Modes of variability" and climate change. *J. Climate,* **22,** 2639–2658.

Brook, E. J., 2009: Paleoclimate: Atmospheric carbon footprints? *Nature Geosci.,* **2,** 170–172.

Cane, M. A., A. C. Clement, A. Kaplan, Y. Kushnir, D. Pozdnyakov, R. Seager, S. E. Zebiak, and R. Murtugudde, 1997: Twentieth-century sea surface temperature trends. *Science,* **275,** 957–960.

Chang, P., R. Saravanan, L. Ji, and G. C. Hegerl, 2000: The effect of local sea surface temperatures on atmospheric circulation over the tropical Atlantic sector. *J. Climate,* **13,** 2195–2216.

Clement, A. C., and R. Seager, 1999: Climate and the tropical oceans. *J. Climate,* **12,** 3383–3401.

Collins, M., 2005: El Niño- or La Niña-like climate change? *Climate Dyn.,* **24,** 89–104.

——, and Coauthors, 2006: Interannual to decadal climate predictability in the North Atlantic: A multimodel-ensemble study. *J. Climate,* **19,** 1195–1203.

Cook, E. R. and P. J. Krusic, cited 2004: The North American Drought Atlas. Lamont-Doherty Earth Observatory and the National Science Foundation. [Available online at http://iridl.ldeo.columbia.edu/SOURCES/.LDEO/.TRL/.NADA2004/.pdsi-atlas.html.]

——, K. J. Anchukaitis, B. M. Buckley, R. D. D'Arrigo, G. C. Jacoby, and W. E. Wright, 2010: Asian monsoon failure and megadrought during the last millennium. *Science,* **328,** 486–489, doi:10.1126/science.1185188.

Corti, S., F. Molteni, and T. N. Palmer, 1999: Signature of recent climate change in frequencies of natural atmospheric circulation regimes. *Nature,* **398,** 799–802.

D'Arrigo, R., and Coauthors, 2005: Tropical–North Pacific climate linkages over the past four centuries. *J. Climate,* **18,** 5253–5265.

DelSole, T., and M. K. Tippett, 2008: Predictable components and singular vectors. *J. Atmos. Sci.,* **65,** 1666–1678.

Delworth, T. L., and M. E. Mann, 2000: Observed and simulated multidecadal variability in the Northern Hemisphere. *Climate Dyn.,* **16,** 661–676.

——, and Coauthors, 2006: GFDL's CM2 global coupled climate models. Part I: Formulation and simulation characteristics. *J. Climate,* **19,** 643–674.

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

——, M. A. Alexander, S.-P. Xie, and A. S. Phillips, 2010a: Sea surface temperature variability: Patterns and mechanisms. *Ann. Rev. Mar. Sci.,* **2,** 115–143, doi:10.1146/annurev-marine-120408-151453.

——, A. S. Phillips, and M. A. Alexander, 2010b: Twentieth-century tropical sea surface temperature trends revisited. *Geophys. Res. Lett.,* **37,** L10701, doi:10.1029/2010GL043321.

——, ——, V. Bourdette, and H. Teng, 2011: Uncertainty in climate change projections: The role of internal variability. *Climate Dyn.,* in press, doi:10.1007/s00382-010-0977-x.

Dijkstra, H. A., L. A. Te Raa, M. Schmeits, and J. Gerrit, 2006: On the physics of the Atlantic multidecadal oscillation. *Ocean Dyn.,* **56,** 36–50.

Enfield, D. B., A. M. Mestas-Nuñez, and P. J. Trimble, 2001: The Atlantic multidecadal oscillation and its relation to rainfall and river flows in the continental U.S., *Geophys. Res. Lett.,* **28** (10), 2077–2080, doi:10.1029/2000GL012745.

Enfield, D. S., and L. Cid-Serrano, 2010: Secular and multidecadal warmings in the North Atlantic and their relationships with major hurricane activity. *Int. J. Climatol.,* **30,** 174–184, doi:10.1002/joc.1881.

Forget, G., B. Ferron, and H. Mercier, 2007: Combining ARGO profiles with a general circulation model in the North Atlantic. Part I: Estimation of hydrographic and circulation anomalies from synthetic profiles, over a year. *Ocean Modell.,* **20,** 1–16.

Frankignoul, C., and K. Hasselmann, 1977: Stochastic climate models. Part II: Application to sea-surface temperature variability and thermocline variability. *Tellus,* **29,** 289–305.

Gu, D., and S. G. H. Philander, 1997: Interdecadal climate fluctuations that depend on exchanges between the tropics and extratropics. *Science,* **275,** 805–807.

Hawkins, E., and R. Sutton, 2009: Decadal predictability of the Atlantic Ocean in a coupled GCM: Forecast skill and optimal perturbations using linear inverse modeling. *J. Climate,* **22,** 3960–3978.

Hegerl, G. C., T. J. Crowley, M. Allen, W. T. Hyde, H. N. Pollack, J. Smerdon, and E. Zorita, 2007a: Detection of human influence on a new, validated 1500-year temperature reconstruction. *J. Climate,* **20,** 650–666.

——, and Coauthors, 2007b: Understanding and attributing climate change. *Climate Change 2007: The Physical Science Basis,* S. Solomon et al., Eds., Cambridge University Press, 663–745.

Hsu, C. J., and F. Zwiers, 2001: Climate change in recurrent regimes and modes of Northern Hemisphere atmospheric variability. *J. Geophys. Res.,* **106,** 20 145–20 159.

Jansen, E., and Coauthors, 2007: Palaeoclimate. *Climate Change 2007: The Physical Science Basis,* S. Solomon et al., Eds., Cambridge University Press, 433–497.

Ji, M., R. W. Reynolds, and D. W. Behringer, 2000: Use of TOPEX/Poseidon sea level data for ocean analyses and ENSO prediction: Some early results. *J. Climate,* **13,** 216–231.

Karnauskas, K. B., R. Seager, A. Kaplan, Y. Kushnir, and M. A. Cane, 2009: Observed strengthening of the zonal sea surface temperature gradient across the equatorial Pacific Ocean. *J. Climate,* **22,** 4316–4321.

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

Kleeman, R., J. P. McCreary, and B. A. Klinger, 1999: A mechanism for generating ENSO decadal variability. *Geophys. Res. Lett.,* **26,** 1743–1746.

Knight, J. R., R. J. Allan, C. K. Folland, M. Vellinga, and M. E. Mann, 2005: A signature of persistent natural thermohaline circulation cycles in observed climate. *Geophys. Res. Lett.,* **32,** L20708, doi:10.1029/2005GL024233.

——, C. K. Folland, and A. A. Scaife, 2006: Climate impacts of the Atlantic multidecadal oscillation. *Geophys. Res. Lett.,* **33,** L17706, doi:10.1029/2006GL026242.

Knutson, T. R., and S. Manabe, 1995: Time-mean response over the tropical Pacific to increased CO_2 in a coupled ocean–atmosphere model. *J. Climate,* **8,** 2181–2199.

Knutti, R., and Coauthors, 2008: A review of uncertainties in global temperature projections over the twenty-first century. *J. Climate,* **21,** 2651–2663.

Kumar, A., and M. P. Hoerling, 1995: Prospects and limitations of seasonal atmospheric GCM predictions. *Bull. Amer. Meteor. Soc.,* **76,** 335–345.

Latif, M., M. Collins, H. Pohlmann, and N. Keenlyside, 2006: A review of predictability studies of Atlantic sector climate on decadal time scales. *J. Climate,* **19,** 5971–5987.

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

Luterbacher, J., and Coauthors, 2001: Reconstruction of sea level pressure fields over the eastern North Atlantic and Europe back to 1500. *Climate Dyn.,* **18,** 545–561.

Mann, M. E., S. Rutherford, E. Wahl, and C. Ammann, 2007: Robustness of proxy-based climate field reconstruction methods. *J. Geophys. Res.,* **112,** D12109, doi:10.1029/2006JD008272.

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

Masina, S., N. Pinardi, and A. Navarra, 2001: A global ocean temperature and altimeter data assimilation system for studies of climate variability. *Climate Dyn.,* **17,** 687–700.

McCabe, G., M. Palecki, and J. Betancourt, 2004: Pacific and Atlantic Ocean influences on multidecadal drought frequency in the United States. *Proc. Natl. Acad. Sci. USA,* **101,** 4136–4141.

McGregor, S., N. J. Holbrook, and S. B. Power, 2007: Interdecadal sea surface temperature variability in the equatorial Pacific Ocean. Part I: The role of off-equatorial wind stresses and oceanic Rossby waves. *J. Climate,* **20,** 2643–2658.

——, ——, and ——, 2008: Interdecadal sea surface temperature variability in the equatorial Pacific Ocean. Part II: The role of equatorial/off-equatorial wind stresses in a hybrid coupled model. *J. Climate,* **21,** 4242–4256.

McPhaden, M. J., and D. Zhang, 2002: Slowdown of the meridional overturning circulation in the upper Pacific Ocean. *Nature,* **415,** 603–608.

Meehl, G. A., and W. M. Washington, 1996: El Niño-like climate change in a model with increased atmospheric CO_2 concentrations. *Nature,* **382,** 56–60.

——, and A. Hu, 2006: Megadroughts in the Indian monsoon region and southwest North America and a mechanism for associated multidecadal Pacific sea surface temperature anomalies. *J. Climate,* **19,** 1605–1623.

——, and Coauthors, 2007: Global climate projections. *Climate Change 2007: The Physical Science Basis,* S. Solomon et al., Eds., Cambridge University Press, 747–845.

——, and Coauthors, 2009a: Decadal prediction: Can it be skillful? *Bull. Amer. Meteor. Soc.,* **90,** 1467–1485.

——, A. Hu, and B. D. Santer, 2009b: The mid-1970s climate shift in the Pacific and the relative roles of forced versus inherent decadal variability. *J. Climate,* **22,** 780–792.

——, ——, and C. Tebaldi, 2010: Decadal prediction in the Pacific region. *J. Climate,* **23,** 2959–2973.

Neukom, R., and Coauthors, 2011: Multiproxy summer and winter surface air temperature field reconstructions for southern South America covering the past centuries. *Clim. Dyn.,* in press, doi:10.1007/s00382-010-0793-3.

Newman, M., 2007: Interannual to decadal predictability of tropical and North Pacific sea surface temperatures. *J. Climate,* **20,** 2333–2356.

——, G. P. Compo, and M. A. Alexander, 2003: ENSO-forced variability of the Pacific decadal oscillation. *J. Climate,* **16,** 3853–3857.

——, P. D. Sardeshmukh, and C. Penland, 2009: How important is air–sea coupling in ENSO and MJO evolution? *J. Climate,* **22,** 2958–2977.

Penland, C., and P. D. Sardeshmukh, 1995: The optimal growth of tropical sea surface temperature anomalies. *J. Climate,* **8,** 1999–2024.

Pohlmann, H., J. Jungclaus, A. Köhl, D. Stammer, and J. Marotzke, 2009: Initializing decadal climate predictions with the GECCO oceanic synthesis: Effects on the North Atlantic. *J. Climate,* **22,** 3926–3938.

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

Rayner, N. A., D. E. Parker, E. B. Horton, C. K. Folland, L. V. Alexander, D. P. Rowell, E. C. Kent, and A. Kaplan, 2003: Global analyses of sea surface temperature, sea ice, and night marine air temperature since the late nineteenth century. *J. Geophys. Res.,* **108,** 4407, doi:10.1029/2002JD002670.

——, P. Brohan, D. E. Parker, C. F. Folland, J. J. Kennedy, M. Vanicek, T. Ansell, and S. F. B. Tett, 2006: Improved analyses of changes and uncertainties in sea surface temperature measured in situ since the mid-nineteenth century: The HadSST2 dataset. *J. Climate,* **19,** 446–469.

——, and Coauthors, 2011: Evaluating climate variability and change from modern and historical SST observations. *Proceedings of OceanObs'09: Sustained Ocean Observations and Information for Society,* Vol. 2, ESA Publication WPP-306, in press. [Available online at https://abstracts.congrex.com/scripts/jmevent/abstracts/FCXNL-09A02a-1662927-1-cwp2a15.pdf.]

Riedwyl, N., M. Küttel, J. Luterbacher, and H. Wanner, 2009: Comparison of climate field reconstruction techniques: Application to Europe. *Climate Dyn.,* **32,** 381–395.

Rowell, D. P., C. K. Folland, K. Maskell, and M. N. Ward, 1995: Variability of summer rainfall over tropical North Africa (1906–92): Observations and modeling. *Quart. J. Roy. Meteor. Soc.,* **121,** 669–704.

Schneider, N., and A. J. Miller, 2001: Predicting western North Pacific Ocean climate. *J. Climate,* **14,** 3997–4002.

——, and B. D. Cornuelle, 2005: The forcing of the Pacific decadal oscillation. *J. Climate,* **18,** 4355–4373.

Schott, F. A., J. P. McCreary, and G. C. Johnson, 2004: Shallow overturning circulations of the tropical subtropical oceans. *Earth Climate: The Ocean–Atmosphere Interaction, Geophys. Monogr.,* Vol. 147, Amer. Geophys. Union, 261–304.

Schubert, S., and Coauthors, 2009: A U.S. CLIVAR project to assess and compare the responses of global climate models to drought-related SST forcing patterns: Overview and results. *J. Climate,* **22,** 5251–5272.

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

——, and Coauthors, 2007: Model projections of an imminent transition to a more arid climate in southwestern North America. *Science,* **316,** 1181–1184.

——, Y. Kushnir, M. F. Ting, M. Cane, N. Naik, and J. Miller, 2008: Would advance knowledge of 1930s SSTs have allowed prediction of the Dust Bowl drought? *J. Climate,* **21,** 3261–3281.

Smith, D., S. Cusack, A. Colman, A. Folland, G. Harris, and J. Murphy, 2007: Improved surface temperature prediction for the coming decade from a global circulation model. *Science,* **317,** 796–799.

Smith, T. M., R. W. Reynolds, T. C. Peterson, and J. Lawrimore, 2008: Improvements to NOAA's historical merged land–ocean surface temperature analysis (1880–2006). *J. Climate,* **21,** 2283–2296.

Solomon, A., J. P. McCreary, R. Kleeman, and B. A. Klinger, 2003: Interactions between interannual tropical oscillations and decadal extratropical oscillations in an intermediate coupled model of the Pacific basin. *J. Climate,* **16,** 383–405.

Stott, P. A., and J. A. Kettleborough, 2002: Origins and estimates of uncertainty in predictions of twenty-first century temperature rise. *Nature,* **416,** 723–726.

Taylor, K. E., R. J. Stouffer, and G. A. Meehl, cited 2008: A summary of the CMIP5 experimental design. [Available online at www.clivar.org/organization/wgcm/references/Taylor_CMIP5.pdf.]

Ting, M. F., Y. Kushnir, R. Seager, and C. H. Li, 2009: Forced and internal twentieth-century SST trends in the North Atlantic. *J. Climate,* **22,** 1469–1481.

Tziperman, E., L. Zanna, and C. Penland, 2008: Nonnormal thermohaline circulation dynamics in a coupled ocean–atmosphere GCM. *J. Phys. Oceanogr.,* **38,** 588–604.

Vecchi, G. A., A. C. Clement, and B. J. Soden, 2008: Examining the tropical Pacific's response to global warming. *Eos, Trans. Amer. Geophys. Union,* **89,** doi:10.1029/2008EO090002.

Venzke, S., M. R. Allen, R. T. Sutton, and D. P. Rowell, 1999: The atmospheric response over the North Atlantic to decadal changes in sea surface temperature. *J. Climate,* **12,** 2562–2584.

Vimont, D. J., 2005: The contribution of the interannual ENSO cycle to the spatial pattern of decadal ENSO-like variability. *J. Climate,* **18,** 2080–2092.

White, W. B., Y. M. Tourre, M. Barlow, and M. Dettinger, 2003: A delayed action oscillator shared by biennial, interannual, and decadal signals in the Pacific basin. *J. Geophys. Res.,* **108,** 3070, doi:10.1029/2002JC001490.

Yeager, S. G., and W. G. Large, 2004: Late-winter generation of spiciness on subducted isopycnals. *J. Phys. Oceanogr.,* **34,** 1528–1547.

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

Zhang, X., F. W. Zwiers, G. C. Hegerl, H. Lambert, N. Gillett, S. Solomon, P. Stott, and T. Nozawa, 2007: Detection of human influence on twentieth-century precipitation trends. *Nature,* **448,** 461–465.

Zhang, Y., J. M. Wallace, and D. S. Battisti, 1997: ENSO-like interdecadal variability. *J. Climate,* **10,** 1004–1020.