A UNIFIED MODELING APPROACH TO CLIMATE SYSTEM PREDICTION

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Demand for more accurate predictions of regional climate necessitates a unified modeling approach explicitly recognizing that many processes are common to predictions across time scales.

The global coupled atmosphere–ocean–land–cryosphere system exhibits a wide range of physical and dynamical phenomena with associated physical, biological, and chemical feedbacks that collectively result in a continuum of temporal and spatial variability. The traditional boundaries between weather and climate are, therefore, somewhat artificial. The large-scale climate, for instance, determines the environment for microscale (1 km or less) and mesoscale (from several kilometers to several hundred kilometers) processes that govern weather and local climate, and these small-scale processes likely have significant impacts on the evolution of the large-scale circulation (Fig. 1; derived from Meehl et al. 2001).

The accurate representation of this continuum of variability in numerical models is, consequently, a challenging but essential goal. Fundamental barriers to advancing weather and climate prediction on time scales from days to years, as well as long-standing systematic errors in weather and climate models, are partly attributable to our limited understanding of and capability for simulating the complex, multiscale interactions intrinsic to atmospheric, oceanic, and cryospheric fluid motions.

The purpose of this paper is to identify some of the research questions and

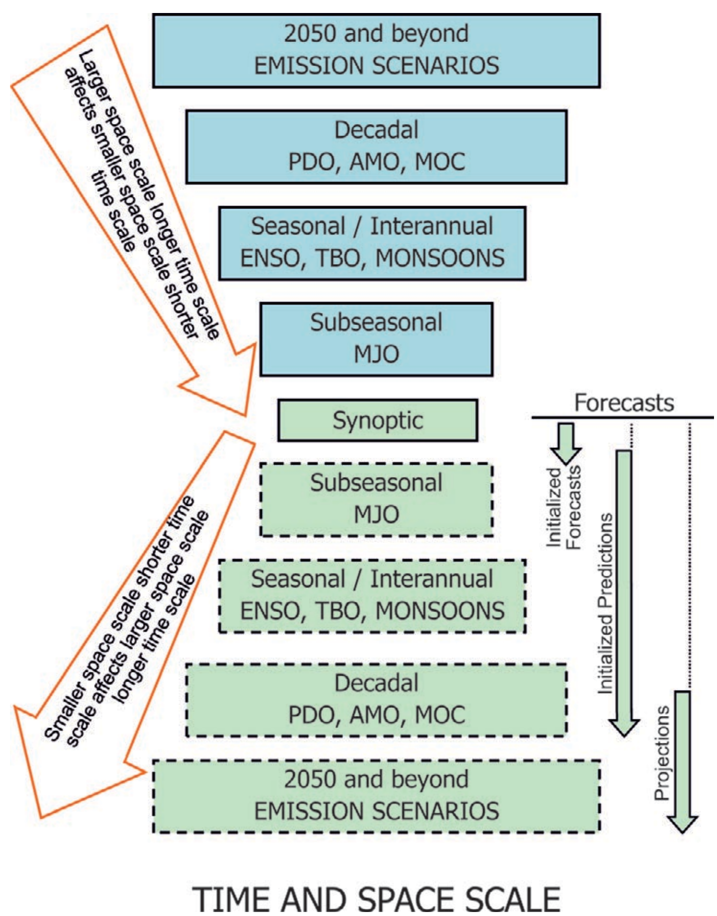

FIG. 1. Schematic illustrating interactions between various time and space scales in the climate system. (left) Space scales and (right) possible forecasts are indicated. Though "synoptic" is the smallest time scale, these interactions could continue to infinitely short time scales and small space scales.

challenges that are raised by the movement toward a more unified modeling framework that provides for the hierarchical treatment of forecast and climate phenomena that span a wide range of space and time scales. This has sometimes been referred to as the "seamless prediction" of weather and climate (WCRP 2005; Palmer et al. 2008; Shapiro et al. 2009, manuscript submitted to *BAMS*; Brunet et al. 2009, manuscript submitted to *BAMS*). The central unifying theme is that all climate system predictions, regardless of time scale, share processes and mechanisms that consequently could benefit from the initialization of coupled general circulation models with best estimates of the observed state of the climate (e.g., Smith et al. 2007; Keenlyside et al. 2008; Pohlmann et al. 2009). However, what is the best method of initialization, given the biases in models that make observations possibly incompatible with the model climate state, and how can predictions best be performed and verified?

Hurricane prediction, for example, has traditionally been regarded as a short-term weather prediction from an initialized atmospheric model. However, hurricanes generate a cold wake as they churn up the ocean and not only extract considerable amounts of heat through evaporative cooling but also mix heat down into the thermocline (e.g., Emanuel 2001, 2006; Trenberth and Fasullo 2007; Korty et al. 2008). Feedback from the cold wake is now thought to be important to improving the forecast accuracy of intensity and track, and the heat and freshwater fluxes could contribute to multidecadal variability in the Atlantic Ocean climate system (e.g., Hu and Meehl 2009). Hence, hurricane forecasting is a short-term coupled problem as well as a longer-term climate problem requiring not only an initialized atmospheric model but also the initialization of a model of the ocean and its heat content.

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SCALE INTERACTIONS AND CLIMATE SYSTEM PREDICTIONS.

Scale interactions, both spatial and temporal, are the dominant feature of all aspects of atmospheric and oceanic prediction. The hope is that predictions will improve as models begin to explicitly resolve processes on ever-finer spatial scales. Weather and climate predictions, consequently, have been major drivers for higher-resolution models requiring advanced numerical and physical techniques and for sophisticated computing systems.

State-of-the-art weather forecasting is carried out using atmospheric general circulation models (AGCMs) that have traditionally been forced with sea surface temperature (SST) anomalies observed at some initial time, but are then projected and damped toward climatological conditions as the integrations proceed out to typically 10–14 days. On these time scales, dynamical interactions of the atmosphere with other climate system components were generally thought to be unimportant and, therefore, have typically not been included.

For decadal-to-centennial predictions, the radiative forcings and coupled interactions and feedbacks among the climate system components are critical. Usually, these coupled model integrations are initialized from an arbitrary and relatively stable climate state obtained from a several-century control (without external forcing) integration. Such coupled "atmosphere–ocean general circulation models" ("AOGCMs") typically include components of the atmosphere, ocean, land surface, and sea ice.

These two time scales address two distinct scientific problems. For a weather forecast on the scale of days, deterministic time evolution of individual synoptic systems must be forecast as an initial value problem, and the effects of longer-term coupled processes, such as the meridional overturning circulation (MOC) in the ocean, are small. For seasonal climate time scales and beyond, statistics of the collections of weather systems are of interest and are crucial to the fidelity of the climate simulation and/or prediction, but the deterministic time evolution of the weather systems cannot be predicted.

For seasonal predictions, coupled air–sea interactions are especially important, but it is an open question whether the prediction of an El Niño event depends critically on aspects of the climate system that evolve on even longer time scales, such as the MOC or the state of the Pacific decadal oscillation (PDO). For even longer time scales, however, interactions of the atmosphere with not only the ocean but also the sea ice, land, snow cover, land ice, and freshwater reservoirs become very important. Biogeochemistry and interactive vegetation, and external effects, such as changes in solar activity, volcanic eruptions, and human influences, all influence the evolution of the climate system.

While the validity of the assumptions made in designing and conducting numerical experiments must be evaluated in the context of the problem being studied, a more unified approach explicitly recognizes the importance of processes and mechanisms shared across the time and space scales, and the potential benefit of the greater convergence of methods used in weather and climate forecasting, in particular with regard to the initialization of the climate system.

The El Niño–Southern Oscillation (ENSO) phenomenon, for example, can now be predicted with some skill with an initialized state of the atmosphere and at least an upper-ocean model of the tropical Pacific but profound gaps in our prediction abilities remain. Large systematic errors in the coupled models mean that i) the coupled model mean state does not agree with the observed mean state with sufficient fidelity; and ii) the space–time evolution of the simulated climate anomalies is not sufficiently realistic.

Historically, these two problems have been addressed from semiempirical perspectives. The first approach is to improve the individual physical parameterizations in the component models (e.g., Toniazzo et al. 2008), a specific example of which (Fig. 2) is the improvement in the simulation of ENSO by the Community Climate System Model (CCSM; Collins et al. 2006) after improvements to the parameterization of deep convection in the atmospheric model component (Neale et al. 2008). The second approach has centered on how best to use imperfect models to make predictions, for example, through calibration analysis (Rodwell and Palmer 2007; Palmer et al. 2008), by utilizing a multimodel ensemble, or through stochastic–dynamic parameterization (e.g., Palmer et al. 2009, manuscript submitted to *J. Climate*; see the "Single versus multiple model predictions" section).

Another relevant consideration is that current climate models have been limited to a relatively coarse resolution compared to that of numerical weather prediction (NWP) models. The coarse resolution limits the accurate simulation of atmospheric [e.g., the Madden–Julian oscillation (MJO) and synoptic weather systems] and oceanic (e.g., tropical instability waves) dynamics and, thus, their interactions with climate. A way forward is to better resolve the weather–climate link (e.g., Palmer et al. 2008), but the question remains: how best to represent the important missing elements of the simulation of day-to-day weather in climate models?

The typical assumption for subgrid-scale parameterization is to assume that the statistics of subgrid-scale processes can be parameterized in terms of the grid-scale variables. However, in many cases this assumption may be seriously flawed. An alternative strategy has been to reduce the grid size of the model and resolve more of the motions explicitly, as in NWP (e.g., Shapiro and Thorpe 2004); however, this approach has been limited, so far, by available computing power. The history of climate prediction has been marked by compromise between model resolution, the inclusion of additional processes, the length and number of simulations, and available computing resources. Global climate predictions would certainly benefit from running AOGCMs at resolutions near or at current NWP models (Shapiro et al. 2009, manuscript submitted to *BAMS*), but it has not yet been feasible to marshal the considerable computer resources necessary (e.g., Shukla et al. 2009).

IMPROVING CLIMATE MODELS. *Upscaling research.* The climate research community is beginning to use higher-resolution (~50 km) models for the decadal prediction problem (e.g., Meehl et al. 2009), but global modeling frameworks that resolve mesoscale processes are needed to improve our understanding of the multiscale interactions in the coupled system, identify those of greatest importance, and document their effects on climate. Ultimately, such basic research will help determine how to better represent small-scale processes in relatively coarse-resolution Earth system models (ESMs). We refer to the impacts of small-scale processes on larger scales as "upscaling."

There is a wide range of upscale interactions to be considered. Current parameterization schemes do not adequately handle the mesoscale organization of convection, which is a critical missing link in the scale interaction process (e.g., Moncrieff et al. 2007, 2009, manuscript submitted to *BAMS*). The limited representation of convection and cloud processes is likely a major factor in the inadequate simulation of tropical oscillations (Fig. 3). Cloud and convective processes also appear to play a role in the well-known double intertropical convergence zone (ITCZ) bias issue (e.g., Fig. 4, top), though coupled processes involving a systematically intense equatorial cold tongue in the ocean also likely contribute to this persistent systematic error (Randall et al. 2007).

Uncertainty in the representation of clouds (on all scales) is also a major influence in the response of the climate system to changes in radiative forcing. Improved simulation of cloud processes in the multiscale modeling framework (MMF; Randall et al. 2003), which embeds two-dimensional cloud-resolving physics within three-dimensional weather-scale physics, has shown improved MJO variability and reduced the bias in Kelvin wave propagation (Fig. 3; see Khairoutdinov et al. 2008).

Another scale interaction problem is the challenge in modeling the subtropical eastern boundary (STEB) regimes off the coasts of southwest Africa, Peru–Ecuador–Chile, and Baja–southern California. These

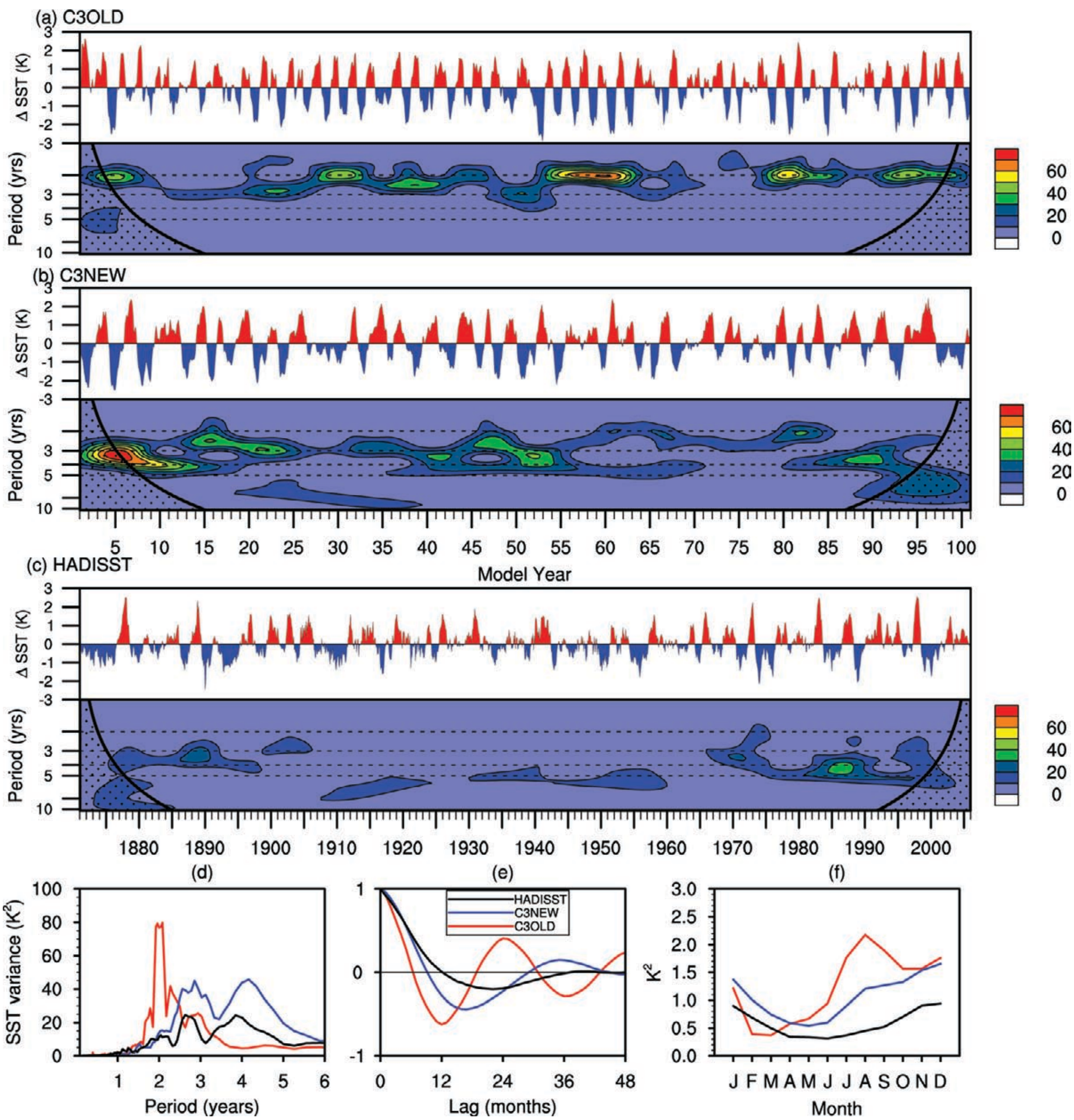

Fig. 2. Summary statistics of Niño-3.4 (5°N–5°S, 170°–120°W) monthly SST anomalies. Time series (K) and wavelet analysis (K^2 per unit frequency) for 100 simulated years from (a) CCSM3 (Collins et al. 2006), (b) after modifications to the CCSM3 parameterization for deep convection, and (c) the most recent 80 yr of the observed Hadley Centre Global Sea Ice and SST (HadISST) record, in addition to (d) power spectra, (e) autocorrelation, and (f) average variance for each calendar month, for all model runs. See Neale et al. (2008) for details.

regimes are marked by marine stratus, equatorward alongshore winds, and ocean upwelling. Large and Danabasoglu (2006) suggest that better resolution of these features produce not only a better simulation of the regional climate but also effects that propagate and strongly influence the large-scale climate system, reducing rainfall biases across the tropical oceans (Fig. 4, bottom).

Other examples of "hot spots" with significant upscaled effects include the monsoon regions of India and Tibet and Central and South America, where steep topographical gradients and mesoscale processes, such as low-level jets and mesoscale convective complexes, play an important role in the water and energy budgets locally and remotely (e.g., Webster 2006). Over the Maritime Continent, Lorenz and Jacob (2005) presented a study of two-way coupling using global and regional models and demonstrated large and positive impacts on the tropospheric temperature and large-scale circulation in the global climate simulation.

Clearly, addressing these errors is critical to climate prediction on all time scales. Therefore, there is a strong need to develop pilot projects to demonstrate the methodologies and impacts of multiscale interactions on the regional and global climate. While numerical models and techniques will be central to this effort, so too will be sophisticated theoretical and physical research to both understand and specify the critical interactions. Significant increases to computing resources to facilitate explicit simulation of smaller-scale processes and their interactions with the larger scale will be essential.

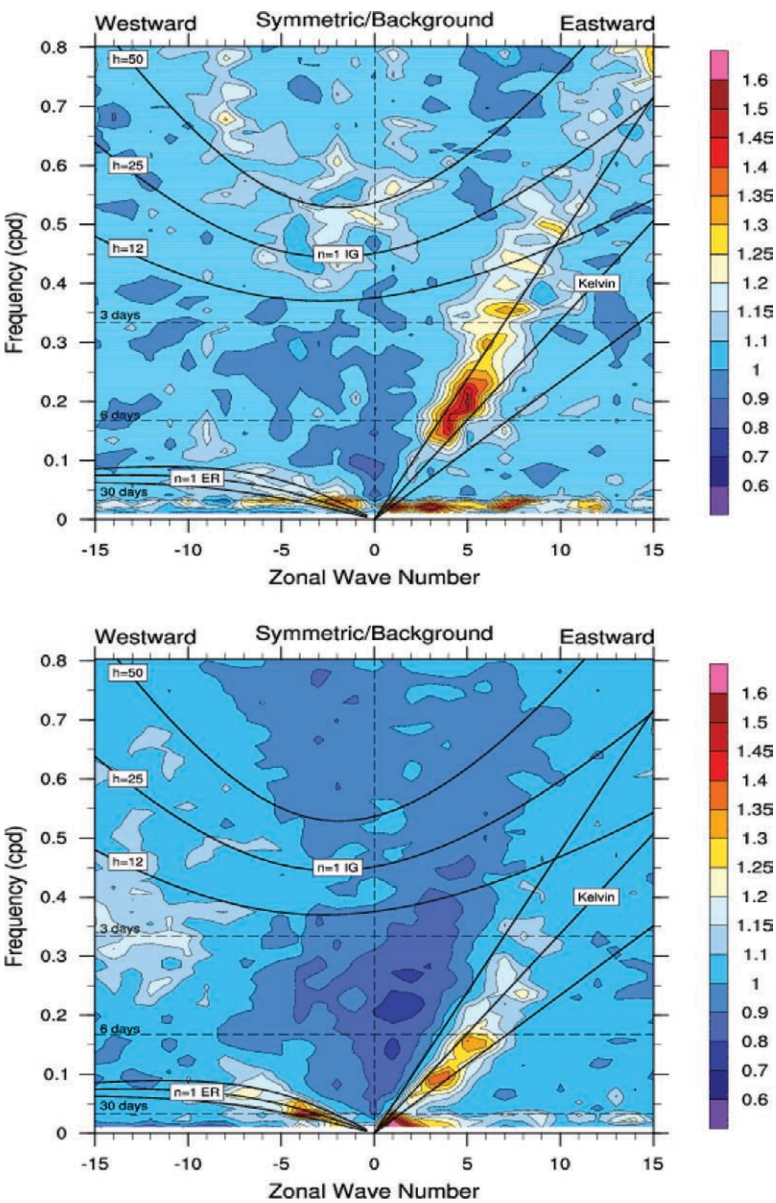

Fig. 3. Space–time spectrum of the 15°S–15°N symmetric component of precipitation, divided by the background spectrum. (top) Observational estimates from an atmospheric reanalysis product and (bottom) results from a coupled climate model simulation.

Value of testing models on all time scales. A paradigm has long been that it is not essential to get all of the details of weather correct as long as their statistically averaged effects on the climate system are adequately captured. A key question is whether the rectification effects of small-scale and high-frequency weather events can be adequately captured if the details are not explicitly represented. Water resources are a case in point because they rely on good predictions of precipitation. This means not only precipitation amount but also precipitation intensity, frequency, duration, and type (snow versus rain). The character of precipitation affects runoff and flooding, and thus soil moisture and streamflow.

The diurnal and annual cycles provide excellent tests for model evaluation. The model response to these well-known climate forcings can provide crucial insights on a host of important physical processes. For

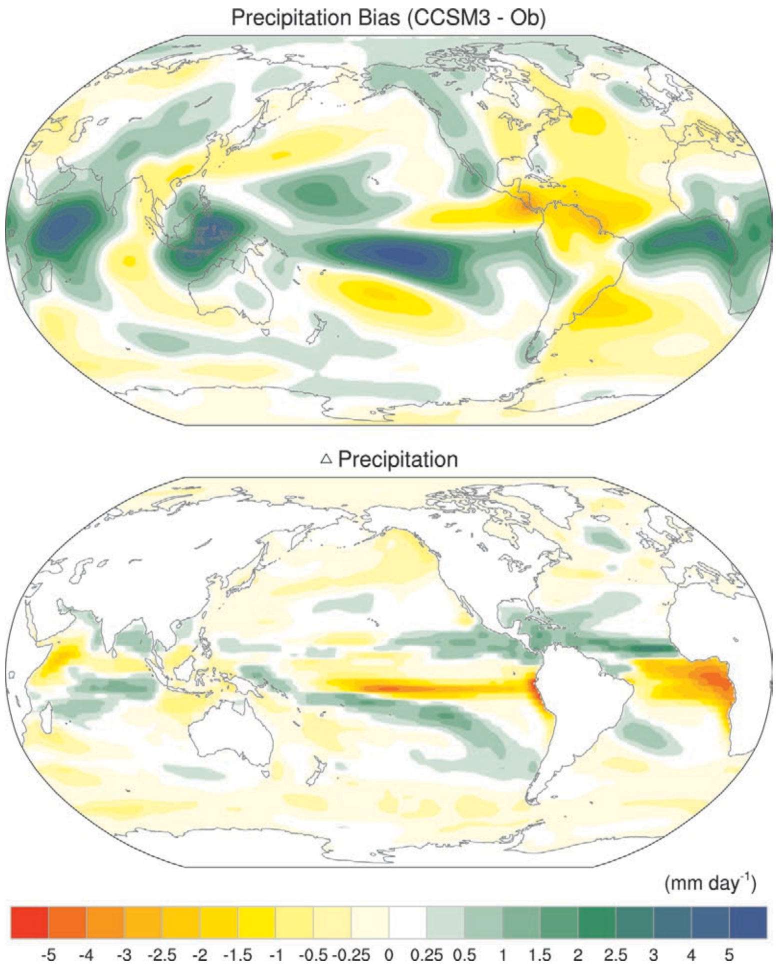

Fig. 4. (top) Difference between annual mean precipitation from a multicentury control simulation with CCSM3 and observational estimates (1979–2007) from the Global Precipitation Climatology Project (Adler et al. 2003). (bottom) Changes in simulated CCSM3 oceanic precipitation in a fully coupled simulation, but with ocean temperature and salinity restored to observed values in the STEB regimes off the coasts of southwest Africa, Peru–Ecuador–Chile, and Baja–southern California. Note the reduction in rainfall biases not only locally but across the tropical oceans. Adapted from Large and Danabasoglu (2006).

example, the diurnal cycle is strongest in summer over land and affects the timing, location, and intensity of precipitation events. Models typically have an onset of precipitation that is too early in the day and with insufficient intensity compared with observations, demonstrating the need to improve boundary layer and convective processes in models (e.g., Trenberth et al. 2003; Trenberth 2008a). The annual cycle is an obvious strong test for measuring the response of a model to a major climate forcing, albeit one that affects only those parts of the climate system capable of responding on such a short time scale. Interannual variability, such as how well models simulate ENSO, provides another necessary but insufficient test of models. These tests highlight the shortcomings and help identify steps to be taken to build confidence in models (WCRP 2008).

PREDICTION ACROSS SCALES. *Effect of initial conditions.* For weather prediction, detailed analyses of the observed state of the atmosphere are required, but uncertainties in the initial state grow rapidly over several days. Other components of the climate system are typically fixed as observed. For climate predictions, the initial state of the atmosphere is less critical, and states separated by a day or so can be substituted. However, the initial states of other climate system components become vital. For predictions from a season to a year or so, the SSTs, sea ice extent and upper-ocean heat content, soil moisture, snow cover, and state of surface vegetation over land are all important. Such initial value predictions are already operational for forecasting El Niño, and extensions to the global oceans are under way. For the decadal prediction problem, increased information throughout the ocean could be essential (Smith et al. 2007; Trenberth 2008b; Meehl et al. 2009; Shukla et al. 2009). Initial conditions for the global ocean could conceivably be provided by existing ocean data assimilation exercises. However, hindcast predictions for the twentieth century, which are desirable to test models, are severely hampered by poor salinity reconstructions prior to the early 2000s when Argo floats began to provide much better depictions of temperature and salinity in the upper 2000 m of the near-global ocean. Some challenging research tasks are developing optimal methods for initializing climate model predictions with the current observational network and identifying an optimal set of ocean observations to use for initializing climate predictions (Meehl et al. 2009).

The mass, extent, thickness, and state of sea ice and snow cover are vital at high latitudes. The states of soil moisture and surface vegetation are especially important in understanding and predicting warm-season precipitation and temperature anomalies along with other aspects of the land surface, but they are difficult to quantify. Any information on systematic changes to the atmosphere (especially its composition and influences from volcanic eruptions) as well as external forcings, such as from changes in the sun, are also needed; otherwise, these are specified as being fixed at climatological average values. The errors induced by incorrect initial conditions should become less apparent as the simulations evolve as systematic "boundary" and external influences become more important, but they could still be evident through the course of the simulations.

A good rule of thumb for prediction is that an upper bound on predictability corresponds approximately to one life cycle of the phenomenon being considered. Hence, one could hope to predict a single convective element, cyclone wave, MJO cycle, ENSO warm event, or fluctuation of the Atlantic MOC over its life cycle, *but not* the second-generation event. This rule of thumb is consistent with the climate system being a chaotic dynamical system with limited predictability. Additional predictability, however, could arise from the slowly evolving components of the climate system.

The pathways leading from high-frequency processes to low-frequency phenomena, however, may progressively involve more aspects of the climate system. For example, convection associated with the MJO needs the ocean mixed layer to be accurately specified in the initial state. Thus, it follows that the MJO influence on ENSO needs an accurate depiction of the initial state of the Southern Oscillation and the thermocline slope across the equatorial Pacific. A unified modeling approach to climate system prediction, in principle, lets all of these interactions occur as they do in nature. If the models fall short, one can track how and learn why.

Effect of systematic errors. Another significant obstacle is the systematic errors present in current AOGCMs. Some of these errors, such as the double ITCZ (Fig. 4, top), are very persistent and have been present in multiple generations of coupled models. One approach to addressing such errors is to vary the parameters in various physical parameterizations within the range of uncertainty based on observations in an effort to reduce the known biases and to form an ensemble of the uncertainty. A second approach is to improve the models so that they more accurately simulate the phenomena in question. This can occur through enhanced resolution, improved knowledge of the relevant physics from observations, improvements in the parameterizations of unresolved physics, and numerical experimentation to better understand existing parameterizations.

Efforts to reduce the systematic errors are crucial, because biases in the mean state could affect a climate model's climate sensitivity (the response to altered radiative forcing) and, thus, its utility as a predictive tool. Quantifying the effects of systematic errors is difficult because of the highly nonlinear nature of the climate system. One promising approach, at least for the atmospheric component, is to run it in NWP hindcast mode and observe the biases as they develop (Phillips et al. 2004).

To understand the implication of systematic errors on forecast skill, it is important to note how coupled forecasts are initialized. Because of the limitations of both observational ocean data and computer resources, one way to initialize a coupled model is to start with initial states determined separately for the atmosphere and ocean (e.g., coupling an atmospheric initial state to an ocean reanalysis product). However, the subsurface ocean thermal state associated with the ocean initial condition is likely significantly different than the climate of the free-running coupled model. As a consequence, at forecast initialization, the coupled model rapidly adjusts away from the observed climate estimate toward the coupled model climate that is itself a product of its own systematic errors. This adjustment in the tropics is primarily accomplished via Kelvin waves, which ultimately lead to an erroneous SST response 2–4 months into the forecast evolution. This is often referred to as an "initialization shock" or "coupling shock." One approach to address coupling shock is through "anomaly initialization" (Schneider et al. 1999; see also Smith et al. 2007; Keenlyside et al. 2008; Pohlmann et al. 2009). In this approach, models are initialized with observed anomalies added to the model climate, rather than initialized with observed values, and the model climate is removed to obtain forecast anomalies.

Ultimately, the solution to this problem is to improve the simulation of the coupled modes of the climate system. For example, preliminary results with the National Oceanic and Atmospheric Administration (NOAA) climate forecast system (CFS) indicate that a higher horizontal resolution model has more irregularity of tropical eastern Pacific SST associated with ENSO, and the amplitude of the SST variability is in better agreement with observed estimates. Atmospheric model resolution experiments conducted with the Italian Decadal and Interdecadal Climate Variability: Scale Interaction Experiment (SINTEX) coupled model also indicate significant improvements in simulated ENSO periodicity with increasing atmospheric model resolution (Navarra et al. 2008). However, as shown in Fig. 2, improvements to the parameterization of deep atmospheric convection have also led to a better simulation of ENSO frequency in the CCSM (Neale et al. 2008), and Toniazzo et al. (2008) demonstrate the sensitivity of the simulation of ENSO in a version of the Hadley Centre coupled model to perturbed atmospheric parameters. Therefore, improvements in model fidelity with increasing resolution are likely part of the solution, but not the entire answer. Active research efforts on how to initialize the coupled modes of the coupled models, given that they do not agree with those of nature (Zhang et al. 2007), recognize that the best state estimate for the individual component models may not be best for coupled forecasts. Much of the research focuses on how to identify the slow manifold described by the observed estimates and the coupled model, and how a mapping between them can be derived. A promising avenue is the use of fully coupled assimilation systems (S. Zhang et al. 2007).

Predictability. Although deterministic atmospheric predictability is limited to approximately two weeks (e.g., Kleeman 2007), on longer time scales at least two types of predictions may be possible. The first is a prediction of the internal variability of the climate system based on an initialized state of the ocean, atmosphere, land, and cryosphere system. Coupled ocean–atmosphere interactions, for instance, are likely important for understanding the temporal evolution of some extratropical, regional modes of climate variability, such as the North Atlantic Oscillation (Hurrell et al. 2006) and local modes of coupled variability in the Atlantic and Indian Ocean basins (e.g., Xie and Carton 2004; Webster 2006). Moreover, land surface processes, and the influence of the stratosphere on the state of the troposphere, might also be a significant source of predictability, at least on seasonal time scales (e.g., Baldwin et al. 2003).

First attempts at "decadal prediction" with an AOGCM showed reduced error growth in large-scale averaged surface temperature over 10-yr periods as a result of the initialized climate state (Smith et al. 2007; Keenlyside et al. 2008; Pohlmann et al. 2009). Decadal-scale predictability in the ocean may occur from the thermal inertia of the initialized anomalies in ocean heat content, but additional predictability may also arise from fluctuations in gyre and overturning circulations (e.g., Delworth and Mann 2000; Dong and Sutton 2005), particularly in the Atlantic (Fig. 5). Multidecadal variations in Atlantic SSTs have been linked to low-frequency boreal summer changes in rainfall and drought in the continental United States (e.g., Schubert et al. 2004; Sutton and Hodson 2005) as well as hemispheric-scale temperature anomalies (R. Zhang et al. 2007). They may also have implications for North Atlantic hurricane forecasts (e.g., Zhang and Delworth 2006). It is possible that decadal-scale predictability exists in the Pacific Ocean as well (e.g., Meehl and Hu 2006).

In addition to the potential sources of predictability from the initial values of the system, predictability may also be derived from past and future changes in radiative forcing (Hansen et al. 2005; Solomon et al. 2007; Smith et al. 2007). Past emissions of greenhouse gases have committed the climate system to future

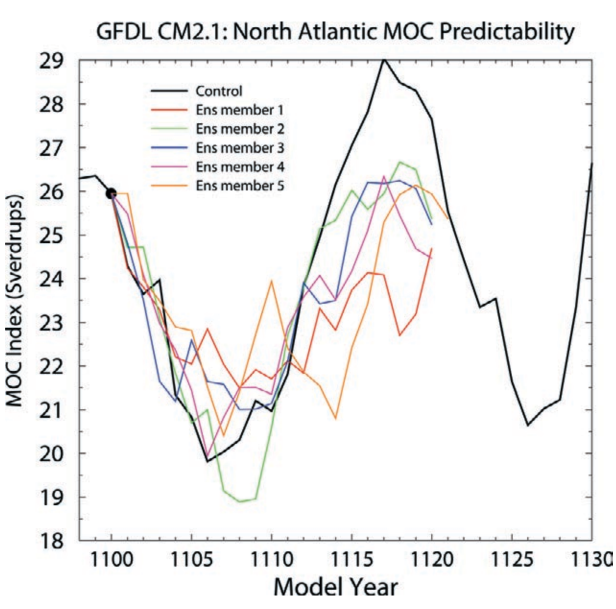

Fig. 5. One example of decadal-scale predictability of the Atlantic MOC as computed in the Geophysical Fluid Dynamics Laboratory Climate Model version 2.1 (GFDL CM2.1) global coupled climate model. A five-member ensemble of predictability experiments is shown, in which each ensemble member used identical initial conditions for the ocean, land, and sea ice. These are taken from 1 Jan 1101 in a long control integration. The ensemble members differed in their atmospheric initial conditions, which come from 6, 11, 16, 21, and 26 Jan from the same year in the control integration. The quantity plotted is an index of the MOC, defined as the maximum streamfunction value in the North Atlantic each year, indicating the northward mass flow in the upper layers of the North Atlantic (1 Sv = 10^6 m^3 s^{-1}). The relatively low spread among ensemble members in the first 10 yr suggests substantial decadal predictability. Additional ensembles were calculated, some of which had similar predictability, and others of which had very little predictability.

warming as the ocean comes into equilibrium with the altered radiative forcing. In addition, the best-possible estimates of future emissions of radiatively important pollutants are needed for making predictions, as well as modeling capabilities, to accurately simulate both how these pollutants affect the global energy, carbon, and sulfur cycles, and how the climate system subsequently responds to that altered forcing. In this regard, the phase and amplitude of the solar cycle and unpredictable volcanic eruptions can be significant "wild cards" to such predictions (Ammann and Naveau 2010).

Single versus multiple model predictions. The purpose of ensemble prediction is to quantify the uncertainty in the forecast from errors in the initial conditions, errors in the model (or multiple models), or a fundamental lack of predictability in the phenomenon itself (e.g., Hawkins and Sutton 2009). This technique is commonly used for NWP where many ensemble members are generated from the same model. It is also relevant for seasonal forecasting where more than one model can be used, because a simulation average across different models is presently more skillful than a simulation from a single model (e.g., Glecker et al. 2008; Kirtman and Min 2009).

The rainfall variability simulated by nine-member ensembles of several state-of-the-art AGCMs forced by observed SSTs (Fig. 6) is very different in the rainfall (signal) variance (first column) despite the

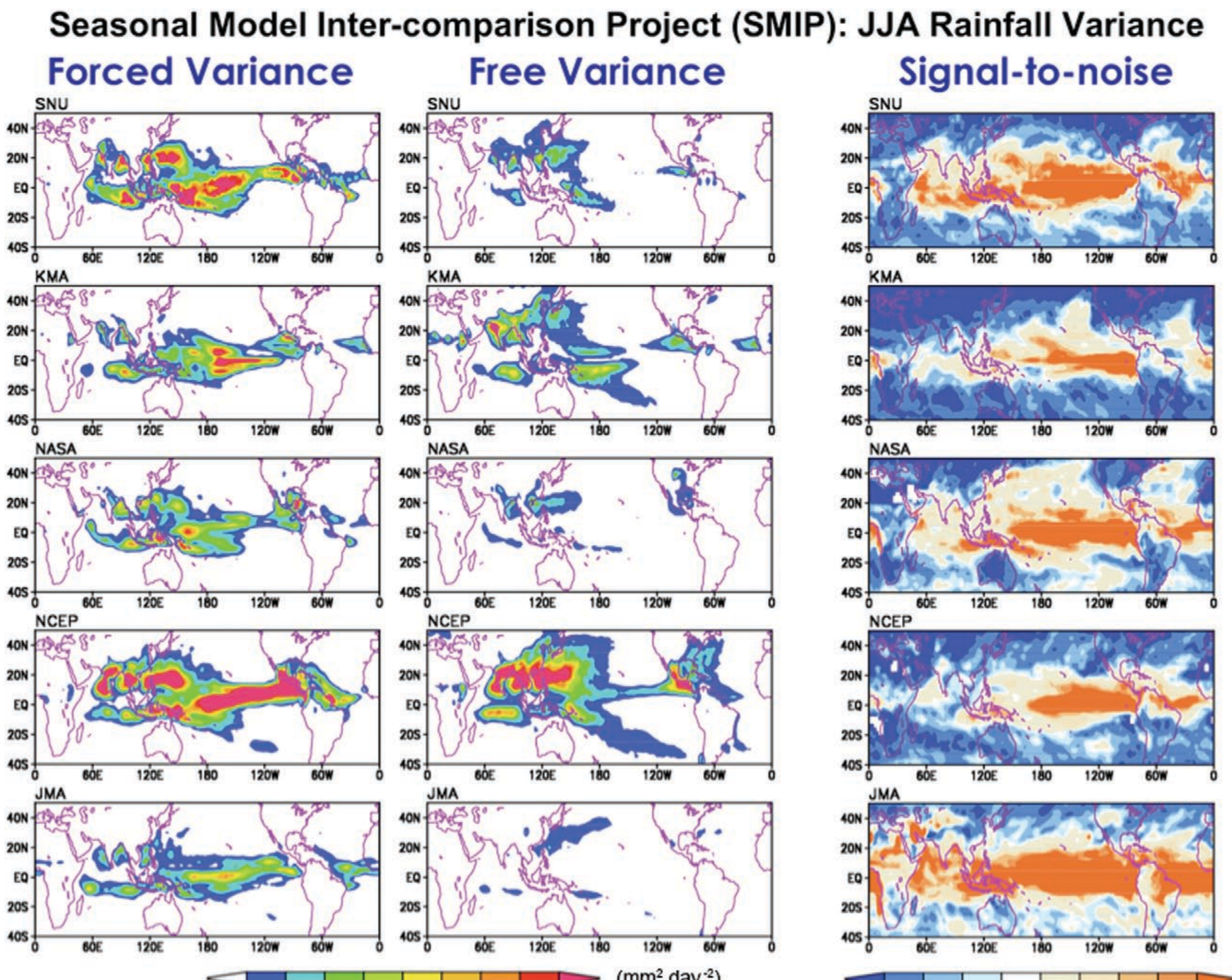

Fig. 6. Rainfall variability simulated by several AGCMs forced with observed sea surface temperatures. Each model simulation includes an ensemble of nine initial conditions, the differences in which are designed to mimic potential observational errors. The first column shows the rainfall variance of the ensemble mean of each model. This is the signal variance. The second column shows the variance about the ensemble mean or the variance resulting from atmospheric internal dynamics. The last column is the ratio of the ensemble mean variance divided by the internal dynamics variance, i.e., a signal-to-noise ratio. [Results are from WCRP/CLIVAR/WGSIP SMIP project and the figure is courtesy of In Sik Kang Seoul National University.]

common SST forcing. This uncertainty reflects differences in model formulation, and it is larger than the uncertainty resulting from the initial conditions (middle column), highlighting the utility of the multimodel approach.

There are a number of different strategies currently employed to combine models for the purpose of prediction. The simplest and most common approach is to have the various modeling centers make ensemble predictions and then devise statistical strategies (i.e., Bayesian, linear regression) for combining the models (e.g., Palmer et al. 2004). It is also possible to take a specific model and systematically probe the uncertainty in the model formulation by varying the parameters in the model (Stainforth et al. 2005). Both approaches have strengths and weaknesses, but neither strategy is completely satisfactory in terms of adequately resolving the uncertainty. Another recently proposed methodology is to use stochastic–dynamic parameterization techniques, which perturb parameterizations in such a way as to improve on the benefits of a multimodel ensemble by using a single model (Palmer et al. 2009, manuscript submitted to *J. Climate*).

Verification. A quick scan through the *Journal of Climate* reveals a dizzying array of different climate metrics that are both interesting and important. Furthermore, the attraction to use metrics to select the "best" model for an application is problematic (Gleckler et al. 2008). Metrics differ in variable, time scale, space scale, or functional representation. The same is not true in weather prediction, where some estimates of both prediction limits and the impact of different weather prediction metrics can be determined. The skill of daily weather forecasts can be verified many times, and a quantification of model skill is relatively straightforward. The problem is more difficult for seasonal prediction because a large number of seasons and those forecast states must pass in order to build up forecast verification statistics.

For decadal and longer time scales, the problem of quantifying prediction skill becomes even more difficult, and the metrics will likely involve how the forecasts are used in applications. Even if we could test long-term climate models with all possible climate metrics proposed in the last decade of journal papers, we have no current method to prioritize or weight their impact in measuring uncertainty in predicting future climate change for temperature, precipitation, soil moisture, and other variables that are of critical interest to society.

There has been some recent progress in this direction using perturbed physics ensembles (PPEs; Stainforth et al. 2005). PPEs are climate models that perturb uncertain physical parameterizations instead of initial conditions. The nondimensional error in Fig. 7 (from Murphy et al. 2004) is defined as the ratio of the climate model rms error versus observations to the interannual natural variability of the same climate variable metric; in essence, it is a signal-to-noise measure. A large range of a given nondimensional climate metric indicates sensitivity. The whisker plots in Fig. 7 confirm the intuition that climate variables associated with energetics (cloud, radiation, and sea ice) appear more sensitive than classical weather dynamical variables (e.g., 500-hPa streamfunction). Further work along these lines is critically needed to discover methodologies to define rigorous climate metrics that are capable of determining climate prediction uncertainty. The essential question is this: what climate metrics for hindcast climate prediction accuracy can be used to determine the uncertainty bounds on future climate prediction accuracy? If this question can be answered, a second benefit will be the ability to more rigorously define climate observation requirements.

CONCLUDING REMARKS. Strategies for a more unified approach to climate system prediction currently include the following: i) using Intergovernment Panel on Climate Change (IPCC) class coupled climate models for predictions on time scales from days to decades; ii) using NWP class models for seasonal-to-decadal prediction, after modification to properly account for changing radiative forcing; and iii) developing very high-resolution models with mesoscale processes explicitly resolved, either globally or by nesting high-resolution regional models within global climate models. There are other emerging approaches as well, such as the concept of beginning integrations with higher resolutions to satisfy weather forecast requirements, and then cascading down to lower-resolution versions of the model with consistent physical parameterization schemes for longer time-scale predictions. All of these approaches attempt to remove the distinction between weather and climate by taking advantage of the processes and mechanisms that characterize the climate system at all time and space scales. Quesitons are being raised as to whether model development efforts should be focused on improving AOGCMs before attempting ESMs, with their added complexities of coupled carbon and nitrogen cycles, chemistry, aerosols, dynamic vegetation, and other components. With a unified modeling approach, the common processes can be addressed in both classes of models and progress can be made on both fronts.

There are other potential benefits of using similar models for predictions on different time scales; among them are skill improvement in both weather and climate forecasts, stronger collaboration and shared knowledge among those in the weather and climate "communities" working on physical parameterization schemes, data assimilation schemes and initialization methods, and shared infrastructure and technical capabilities.

A significant step forward is a planned set of coordinated climate change experiments called the Coupled Model Intercomparison Project phase 5 (CMIP5; K. Taylor et al. 2009, personal communication; online at http://cmip.llnl.gov/cmip5/docs/Taylor_CMIP5_design.pdf). The strategy is to approach the climate change prediction problem in a unified way with two classes of related climate models to address two time scales: higher-resolution (~50 km) AOGCMs for decadal predications out to about the year 2035 (Meehl et al. 2009), and lower-resolution (~200 km) versions of the same models, but with a coupled carbon cycle and perhaps simple chemistry, dynamic vegetation, and prognostic aerosols for century and longer climate change integrations. The latter experiments would quantify the magnitude of important feedbacks that will determine the ultimate degree of climate change in the second half of the twenty-first century (Meehl and Hibbard 2007; Hibbard et al. 2007).

Computer resource and other limitations will likely dictate that resolving certain processes and phenomena could still require alternative strategies for many years into the future. A case in point is the need to represent hurricanes in a special class of climate models that could include embedded regional models with resolutions of about 5 km in order to adequately depict their extreme intensity and their effects on the ocean and the energy and water cycles.

Additionally, current and future efforts with ESMs will allow for more complete assessments of the physics of climate change by including additional components

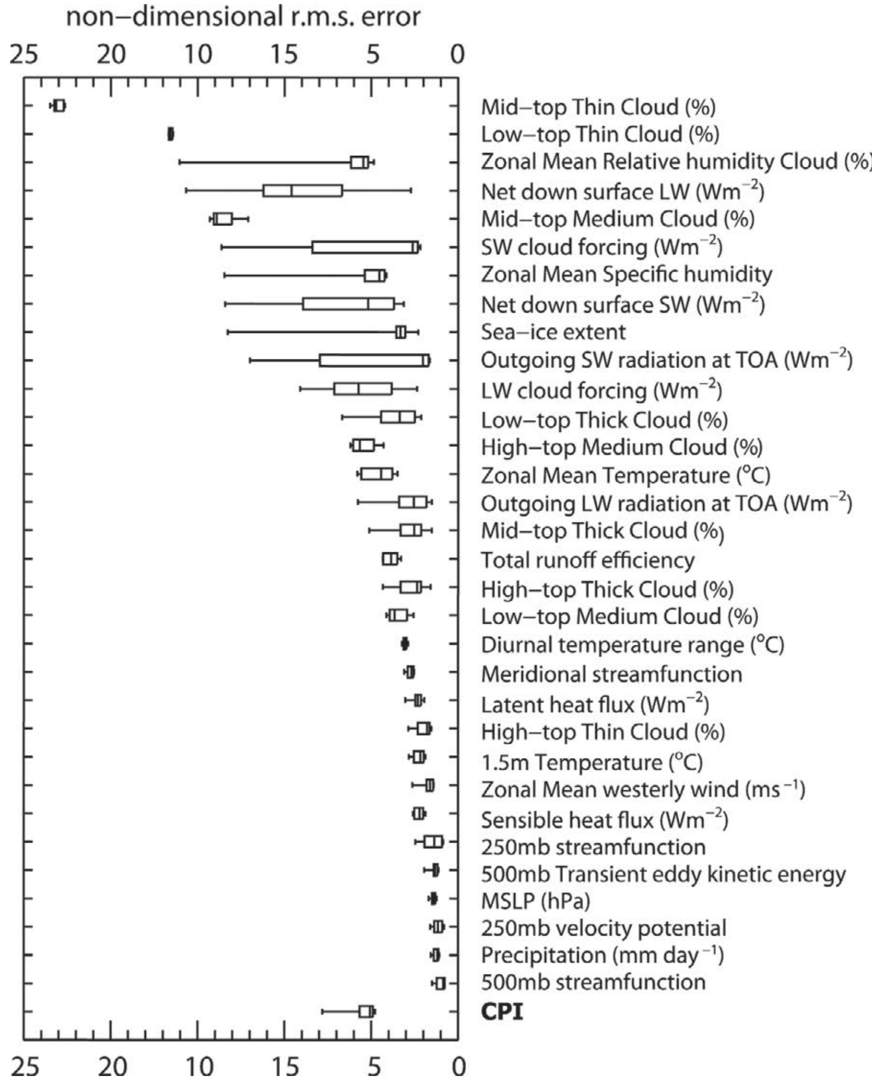

Fig. 7. Values of the climate prediction index (CPI) of Murphy et al. (2004), and its 32 components (black boxes and bars, representing surface and atmospheric variables) from the PPE. The components are calculated as the rms difference between simulated and observed present-day climatological mean patterns divided by the rms value of the standard deviation of simulated interannual variations. The plot shows averages of values calculated separately for each season of the year. Bars show the full range of the ensemble distribution of values, boxes show the range encompassed by the 5th and 95th percentiles, and the horizontal line within each box shows the median. The CPI is calculated as the rms value of the 32 components for a given ensemble member. Adapted from Murphy et al. (2004, see their article for more detail).

and processes that are not essential to the shorter time scales. The computational burden of the ESMs will test the feasible limits of the explicit resolution of multiscale interactions and more regional discrimination of climate change impacts. Moreover, given relatively large systematic errors, the additional feedbacks from more interactive components of ESMs clearly increase the uncertainty in the magnitude and nature of the climate changes projected in future scenario simulations. The time-evolving ingredients required for future scenario integrations with ESMs also still must be estimated as a range of possible outcomes based, to a large extent, on the unpredictable nature of human actions. These, along with observational data needs, logistical issues related to coupling strategies and coupled initialization, and the scientific questions related to the myriad of unconstrained and poorly understood feedbacks, are significant aspects of these emerging ESMs that will continue to stretch both computational and human resources for the foreseeable future. However, activities that have already begun indicate that we are moving into a new and exciting era of climate system prediction that will, by nature of the converging interests, modeling tools, and methodologies, produce greater interactions among previously separate communities, and thereby provide better predictions of the climate system at all time and space scales.

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