Chapter 11
Climate Predictions, Seasonal-to-Decadal

Lisa Goddard

Glossary

Climatology	Reference period used to describe the characteristics of the climate, such as the mean annual cycle, or the expected statistics of weather or of year-to-year climate variability. The World Meteorological Organization recommends the most recent three full decades; e.g., in 2009, the WMO climatology period would cover 1971– 2000.
External forcing	Factors that influence the climate system but are not explicitly driven by the climate system, such as human emissions of greenhouse gases, changes in the sun's radiation, and volcanic emissions.
Forecast	The guidance offered by a forecaster or forecast center on the future climate conditions. A forecast could be based on a single prediction, but typically is a distilled product that involves recalibrated model predictions and often multiple prediction inputs.
Internal variability	The chaotic evolution of a fluid, such as the ocean or atmosphere, due to nonlinear dynamics that are sensitive to small uncertainties or variations in initial conditions. Depending on timescale, internal variability may refer to that generated internally to the atmosphere, to the ocean, or due to

This chapter was originally published as part of the Encyclopedia of Sustainability Science and Technology edited by Robert A. Meyers. DOI:10.1007/978-1-4419-0851-3

L. Goddard (✉)
Forecasting and Prediction Group, International Research Institute for Climate Society (IRI), The Earth Institute of Columbia University, Lamont Campus, 228 Monell Bldg. 61 Route 9W, 10964-8000 Palisades, NY, USA
e-mail: goddard@iri.columbia.edu

P.J. Rasch (ed.), *Climate Change Modeling Methodology: Selected Entries from the Encyclopedia of Sustainability Science and Technology*,
DOI 10.1007/978-1-4614-5767-1_11,

	ocean–atmosphere interaction. It is the part of the seasonal-to-decadal climate that is not deterministically predictable.
Prediction	The future climate conditions indicated by a single prediction model, which could be statistical or dynamical. These differ from climate change projections in that information of the climate state at or near the initial time of the forecast is highly relevant to its future evolution.
Teleconnections	Climate variability in one region that is driven remotely by climate variability in another region. This typically refers to regional patterns of climate anomalies over land and/or oceans that result from specific ocean phenomena, such as during El Niño events.

Definition of the Subject and Its Importance

Seasonal-to-decadal climate prediction seeks to quantify the likely evolution or change of the climate system over a specific time horizon of months to years. Climate predictions based on dynamical models incorporate all relevant processes to the extent possible, including anthropogenic climate change, but most importantly those processes that govern the likely evolution of natural climate variability. The predictions, if well calibrated, describe the probability of a given magnitude of change in the mean climate or changes in the characteristics of the weather over the forecast period. For example, a seasonal forecast for next winter might indicate a greater likelihood for the seasonal mean temperatures to be colder than usual, or might indicate the likelihood for more frequent storms over the 3-month period.

Seasonal prediction is a fairly well-established enterprise with a number of forecast centers around the world issuing real-time seasonal predictions–based dynamical models [1]. Increasingly, national meteorological and hydrological services create seasonal forecast products based on their own statistical or dynamical prediction tools and/or incorporate predictions from the international centers. Decadal prediction is a much newer endeavor and is still considered experimental [2]. Only a few groups have attempted decadal-scale climate predictions intended to capture the evolution of natural decadal variability for the coming decade from a global circulation model [3–5], and although the results indicate there may be added information from these predictions relative to the more familiar climate change projections of the Intergovernmental Panel on Climate Change (IPCC), it is not clear that the added information results from better prediction of the decadal-scale climate variability that would exist even in the absence of increasing greenhouse gases.

Climate forecasts are potentially valuable to society on seasonal-to-interannual timescales to inform resource management, planning decisions, and on decadal timescales to inform longer-term plans and infrastructure investment. Even in the climate change context, decadal prediction could prove important, as the climate experienced regionally for the coming decade(s) will likely be some combination of anthropogenic climate change and natural decadal variability. Decisions and investments related to climate change adaptation typically apply to the next 10–20 years into the future, rather than 80 years into the future. Thus better information on evolution of the climate and changes in risks of climate extremes can lead to more appropriate planning. However, climate predictions are necessarily probabilistic, and in the case of decadal predictions are yet to be established as skillful. Thus it is important that decision systems be designed and optimized to account for the inherent uncertainty in future climate, that can still allow benefits to be realized in times of favorable climate and losses to be mitigated in times of adverse climate.

Introduction

Climate varies on all timescales, from seasonal variations to millennial ice ages. Prediction of the climate at timescales that are relevant to societal decisions, but extending beyond weather forecasts, has been roughly broken into three classes: seasonal-to-interannual prediction that addresses the changes in seasonal climate and its weather characteristics a couple months to a year in the future, decadal prediction, sometimes referred to as near-term climate change prediction that addresses changes in the mean climate and its characteristics for a couple years to a couple decades into the future, and climate change projections that consider changes in the mean climate and its characteristics 50–100 years in the future.

The seasonal-to-interannual timescale dominates the climate that is experienced locally. On a local-to-regional scale, year-to-year variability almost always explains the majority of the variance in the observed climate (e.g., Fig. 11.1). Year-to-year variability is where most impacts are experienced. However, it is the superposition of the three climate timescales that can lead to changes or trends in the frequency of adverse years. Extreme examples are potentially the protracted drought conditions in the western United States from the mid-1990s to the early twenty-first century [6], the 2003 European heat wave [7], or the extremely active hurricane season 2005 [8], which was accompanied by many land-falling hurricanes in the United States such as Katrina.

The primary difference between prediction of climate variability on different timescales is the drivers, or phenomena, associated with those impacts. This leads to differences in the way prediction systems are designed to predict the climate fluctuations and associated impacts on different timescales. Seasonal-to-interannual prediction is an initial value problem; by initializing the climate system close to the observed state at the beginning of the prediction, a dynamical model will aim to capture the likely evolution of the climate system. At the other end of the time spectrum, climate change projection is a boundary value problem, which means that

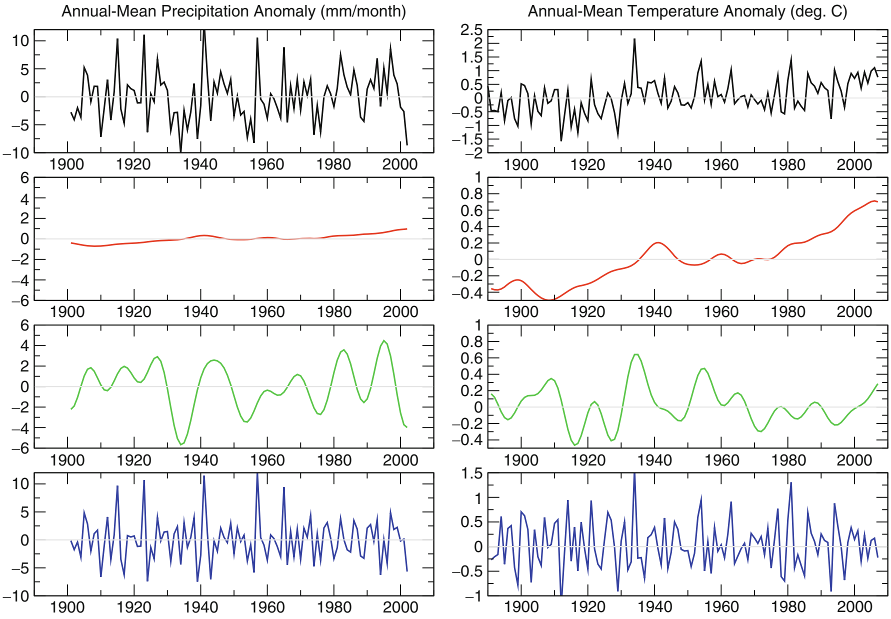

Fig. 11.1 Example of simple decomposition of (**a**) temperature and (**b**) precipitation averaged over the state of Colorado in the United States. The *top* panels (*black*) show the observed annual mean time series. The second panels (*red*) represent "climate change" time series, in which the climate changes are consistent with the globally averaged temperature, obtained by decadally filtering the time series and regressing it against a similar low-frequency filtered time series of globally averaged temperature. The *third* panels (*green*) represent the "natural decadal variability," which is low-frequency time series that is not coincident with globally averaged temperature changes, obtained as the difference between the low-frequency filtered time series and the "climate change" time series. The *bottom* panels (*blue*) represent the year-to-year variability on top of the low-frequency changes, which is the difference between the full time series and the low-frequency filtered time series. Note that there is no attribution to anthropogenic changes or physical phenomena in any of these time series. Details are likely to change with different filtering parameters and with different approaches to estimate global warming

the driver of the climate change is external to the climate system and imposed upon it. Anthropogenic increases in greenhouse gases are due to man's activities and are not part of the natural climate system. Climate change projections depend on correctly projecting the changes in the Earth's atmospheric composition and the subsequent changes in the Earth's energy balance. Decadal prediction lies at the intersection between seasonal-to-interannual prediction and climate change projection; it is an initial value as well as a boundary value problem. Decadal prediction depends both on initializing the climate system close to the observed state, especially the slowly evolving components, and on correctly representing the changes in Earth's energy budget.

This is not to say that predictions on longer timescales do not contain the higher frequency phenomenon. However, there is a predictability limit for natural climate variability, which refers to how far into the future some aspect of climate variability can be predicted before the uncertainty, or range of possibilities, approaches the climatological uncertainty. At that point little to no predictive information remains. The limit of predictability is not necessarily a fixed quantity. It changes with the phenomenon, but also changes with time, meaning that at some times a phenomenon will be more predictable than others and thus the evolution can be predicted farther into the future. It is not possible to determine what the true limit of predictability is or should be [9]. The model(s) that can predict the phenomenon with the greatest fidelity when compared to observations over some long history containing many realizations of the phenomenon determine the *current* limit of predictability.

In order to make a prediction one must first determine what is to be predicted. If the aim is to predict local-to-regional scale climate over land, one must know the driver of that climate variability. Numerous research and prediction studies have demonstrated that it is the large-scale variability in the pattern of surface temperature, and in particular the sea surface temperatures that drive the predictable aspect of changes in the atmospheric circulation and thus regional temperature and precipitation. But what drives that sea surface temperature variability? The sea surface temperatures must be predicted if it is hoped to predict the associated terrestrial climate impacts. Once the ocean phenomena or processes relevant to sea surface temperature variations are identified, the climate models must be capable of simulating those. Furthermore, if the prediction of some phenomenon from a particular model is to provide actionable information, then the phenomenon must be predictable above the other ongoing processes in the climate system; in other words, the signal of the phenomenon must be predictable above the background noise of the climate system. In the next section, an example of this process of identification, model validation, and prediction based on the El Niño-Southern Oscillation (ENSO) phenomenon and seasonal climate prediction is presented.

Brief History of ENSO Prediction: Impacts of the ENSO phenomenon have been experienced for centuries, long before the phenomenon itself was identified. The peoples of Peru used the term El Niño to refer to the expected changes in the local climate and fish stocks associated with a seasonal reversal of the current system off the coast of western South America, because these changes occur near the end of the year at a time near Christmas (El Niño is Spanish for the Christ child). However, they also noted that warm seasonal waters associated with the change of currents, would occasionally be very warm and would also bring abundant rainfall. It is these extreme years, which recur about every 3–7 years that are now called El Niño events. Farmers in drought-prone regions of the Andes even developed a method to predict the coming of the increased rainfall during these events by monitoring the visibility of a star in the Pleiades constellation [10]. What they were observing was the shift of convection from the western tropical Pacific into the central Pacific in concert with the development of an El Niño event (Fig. 11.2).

Sir Gilbert Walker could be said to be the pioneer of seasonal forecasting as he sought to quantify the atmospheric component of ENSO, the Southern Oscillation,

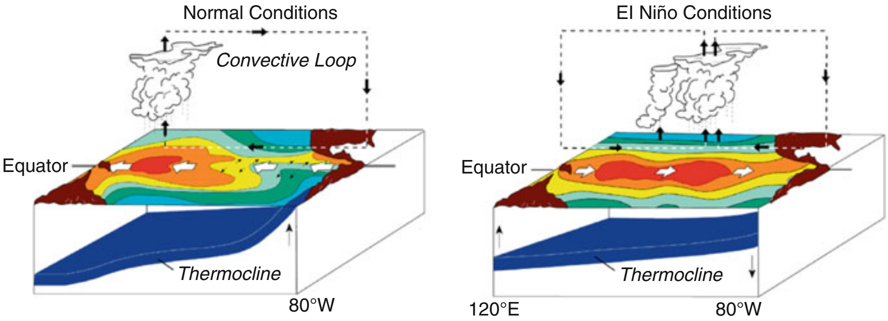

Fig. 11.2 Schematic drawing of the tropical Pacific ocean–atmosphere state during (**a**) average or neutral conditions in which trade winds blow east to west, pushing warm surface waters to the western Pacific, which pushes down the thermocline (separation between warm upper ocean and cold deep ocean) and concentrates the deep convection in the western Pacific; (**b**) El Niño conditions in which the thermocline becomes deeper in the eastern Pacific and warm water moves westward, which weakens the east–west Trade Winds and allows the convection to move into the central Pacific (Source: http://www.tao.noaa.gov/proj_overview/tao_tour_ndbc.shtml)

and its relationship to regional climate variability, such as the devastating droughts in India [11]. To accomplish this he examined correlations between 32 stations across the world for fields of sea level pressure, temperature, rainfall, and riverflow. He discovered that negative excursion of the Southern Oscillation Index was associated with increased likelihood for drought over India; his empirical model has not been much improved upon over the last century for that region. Researchers have continued to improve upon the foundation that Walker laid for ENSO teleconnections (Fig. 11.3). Maps that show significant correlation between regional temperature and precipitation changes to ENSO events for specific 3-month average seasons are widely used to illustrate ENSO's global reach [12, 13]. However, these teleconnection patterns represent expectations based on statistics and are not guaranteed to occur in any specific event; the probabilistic likelihood of a regional impact [14] is a further refinement of the climate anomalies due to ENSO, and something that climate prediction models should be expected to replicate in their ensemble distributions over time.

It was not until the second half of the twentieth century that researchers discovered that the Southern Oscillation was associated with changes in the large-scale sea surface temperature pattern over the tropical Pacific; it was the coupled interaction between the east–west sea surface temperature gradient and the low-level winds between the high and low pressure centers of the Southern Oscillation that led to the growth of Niño events [15]. It was soon after recognized that the change in the winds due to the changes in sea surface temperatures, associated with the Southern Oscillation, modified the distribution of the upper-ocean mass field below the surface [16], and that the adjustment of these perturbations to the mass field could lead to the eventual decay of the El Niño event and possible initiation of the opposite phase, La Niña.

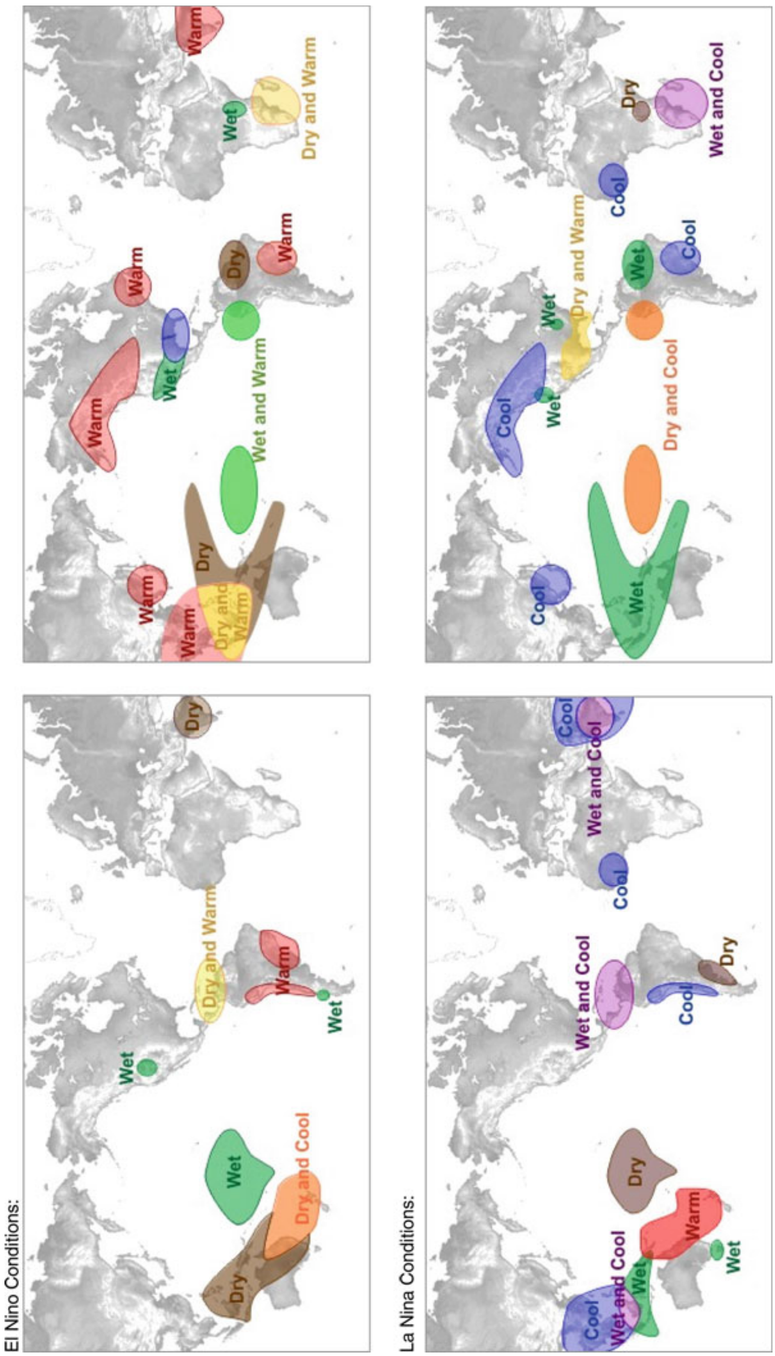

Fig. 11.3 Expected climate anomalies for (**a**) El Niño events during northern hemisphere summer when events are developing, and (**b**) El Niño events during northern hemisphere winter when events are mature; and for (**c**) La Niña events during northern hemisphere summer, and (**d**) La Niña events during northern hemisphere winter (Source: http://www.srh.noaa.gov/jetstream//tropics/enso_impacts.htm)

In the 1980s simple dynamical models [17–19] were developed that simulated the coupled air-sea processes central to ENSO and reinforced the theory that had been informed primarily by observations. The first experimental El Niño forecast was published in 1986 [20], using one of these simplified dynamical models. Since then more complex models have been built that capture not only the dominant processes behind ENSO but also provide a more complete representation of the climate system to better capture uncertainties in ENSO. These models also simulate the atmospheric teleconnections that lead to changes in sea surface temperatures of other ocean basins and to changes in the terrestrial climate. These are the impacts that served as the initial motivation for the study of ENSO. Finally, through the process of identification of a primary driver of seasonal climate variability and the dominant physical processes behind it, and the development of models that could simulate and predict this driver and its teleconnections, seasonal prediction was born.

The prediction of decadal-scale climate variability is a much more recent endeavor. Although research on decadal climate variability through the use of observations and models is not new [21–26], a community-wide effort in this area is new. The motivation to predict decadal climate variability has arisen in part from a desire to use the climate change projections that appear in the Working Group 1 report of the Intergovernmental Panel on Climate Change [27] to inform sectoral decision making, [28] as well as plans and investments toward climate change adaptation. For these societal needs, climate information for the next 5–20 years becomes more relevant than that for the next 100 years. The other side to the motivation behind experimental decadal predictions is the realization that there are processes inherent in the natural climate system evolving at decadal-to-multidecadal timescales, and the mounting evidence that dynamical models have some ability to simulate some aspects of the observed variability [29, 30].

As the successes and failures in climate prediction are considered, it must be borne in mind that climate predictions are necessarily probabilistic. They indicate the likelihood of a range of possible outcomes. The magnitude of this range of outcomes, often referred to as the uncertainty or probability distribution, is sensitive to uncertainties in the initial conditions from which the predictions evolve, to uncertainties in external forcings, and to errors in prediction models. The value about which the uncertainty is centered is sensitive to the external forcings and to information in the initial conditions that may lead to specific, robust evolution of the climate system. Particularly in the case of decadal prediction, which is still in the experimental phase, success refers to relative performance, or agreement between prediction and observations, compared to the state of predictions beyond the seasonal timescale, namely, climate change projections. In other words, much of the judgment of decadal prediction in these early experiments focuses on the added forecast quality from the initial conditions relative to that from the boundary conditions, or external forcing. Therefore, success in the eyes of the climate community may not constitute information that is accurate enough or specific enough to be actionable.

Although both seasonal prediction and decadal prediction experiments, and climate change projections for that matter, use the same type of dynamical models, substantial differences exist between their application for these different timescales of prediction. The following sections contain discussions of Drivers of Variability, Model Fidelity, Prediction Systems, and Internationally Coordinated Efforts, first for the seasonal-to-interannual timescale, followed by a similar analysis for the decadal prediction problem. The only difference in the structures is that the section on seasonal-to-interannual prediction also contains a discussion of Forecast Skill. The echoed structure is intentional in that many of the issues and approaches will be similar for both timescales. However, there are important differences in what is known about the drivers of climate variability at these different timescales as well as differences in the maturity of the prediction systems.

Seasonal-to-Interannual Prediction

Seasonal-to-Interannual Prediction: Drivers of Interannual Variability

Seasonal-to-interannual prediction derives from initial conditions of the climate system. Unlike weather forecasts, where the relevant initial condition is the atmospheric state and the sea surface temperatures are approximately constant, seasonal forecasts depend more on the initial condition of the ocean. The evolution of the ocean state, particularly the density structure and the currents, leads to changes in the pattern of sea surface temperatures that can then influence the atmospheric circulation.

The dominant pattern of surface temperature variability, after accounting for global warming, is that of the El Niño-Southern Oscillation (ENSO) (e.g., [31]). For this reason ENSO has received a great deal of attention in studies of climate prediction on seasonal-to-interannual timescales. Changes in winds and precipitation are associated with these global temperature pattern changes.

El Niño events recur about every 3–7 years on average, and are somewhat locked to the annual cycle in that they tend to develop and grow through the middle of the year and tend to peak near the end of the year. During an El Niño event when much of the warm water in the western equatorial Pacific moves eastward, the region of deep convection also moves eastward into the central Pacific (Fig. 11.2), and in some cases reaches as far as the coast of South America. Since the equatorial Pacific spans nearly half the circumference of the Earth, a shift of the largest region of deep convection from the far western Pacific to the central equatorial Pacific represents a huge spatial shift in where the tropical atmosphere is heated.

In the tropics, where the effect of Earth's rotation is weaker, the atmospheric response to the pattern of sea surface temperatures is thermally direct. The low-level winds converge toward the warmest water, or equivalently, to the region of lower pressure. This is true of the mean conditions as well as the anomalous conditions. Since the lower atmosphere is very humid in the tropics, the regions of converging low-level winds produce an upward flow of very moist air and heavy precipitation with a very large latent heat release to the atmosphere associated with water vapor condensation. Near the top of the troposphere, relatively dry air is expelled from these regions of strong deep convection, and that air then sinks. The sinking dry air suppresses convection. The regions of warmest sea surface temperatures and associated strong deep convection are located typically over the western Pacific warm pool and the western hemisphere warm pool, which encompasses the northeastern tropical Pacific extending to the northwestern tropical Atlantic. Variations in these warm pool regions have direct impacts on the climate in the neighboring regions, but changes in the strength and location of those convective centers can also impact regional climate remotely though changes in atmospheric circulation.

The resulting changes in the atmospheric circulation can lead to warmer conditions in the other tropical oceans [32, 33], which carry additional regional climate impacts. For prediction of the regional climate due to tropical sea surface temperature changes outside the Pacific, it is important to be able to predict those sea surface temperatures. For example, the tendency for northeastern Brazil to be drier than normal during an El Niño event (Fig. 11.3) is due in part to the anomalous subsidence from the shift in deep convection over the central Pacific, but it is also due to associated warming of the sea surface temperatures over the north tropical Atlantic [34]. Similarly, wetter conditions in eastern Africa associated statistically with El Niño events are now known to result from the warming of SSTs in the western Indian Ocean that are also associated with El Niño events [35]; an El Niño event that is not accompanied by warm SST anomalies in the western Indian Ocean leads to drier conditions over East Africa due to anomalous subsidence resulting from El Niño's enhanced convection in the central Pacific.

El Niño can affect weather and seasonal climate outside the tropics through changes in the position and strength of the storm tracks. When the warm water that normally resides in the western Pacific extends across the Pacific, it changes the large-scale temperature differences between the tropical and the midlatitudes. This allows the storm track associated with the subtropical jet stream to strengthen over the central and eastern subtropical Pacific where it is usually weaker and more variable. Additionally, the warming of the equatorial Pacific region as a whole allows the amount water vapor in the lower atmosphere to increase. The combination brings more frequent and stronger storms into the southern tier of the United States during El Niño events. This impact on extratropical climate is seen in the winter hemisphere because this is when the jet stream is strongest. So although a similar influence can be discerned for storm track headed toward South America, the impact is less robust, since El Niño events are typically growing during southern hemisphere winter in the middle of the year. During the northern hemisphere winter is closer to the time when El Niño events are mature.

It is the large-scale changes in the patterns of low-level heat and moisture that drive changes in the atmospheric circulation. El Niño happens to be the dominant phenomenon influencing that and the focus of those changes is primarily over the tropical oceans. However, changes in land-surface conditions, such as soil moisture or ice, can also influence regional climate. Soil moisture influences the overlying atmosphere primarily through evaporation, which can then influence precipitation as well as near-surface air temperature during certain times of the year [36]. Dry soil conditions, and thus a reduced ability of the surface to cool itself through evaporation, are likely to have contributed to the 2003 European heat wave [37]. Changes in patterns, extent, and timing of snow cover can also impact the atmospheric circulation through changes in land atmosphere energy exchange and may impart predictability to northern hemisphere wintertime temperatures [38] and also the strength of the East Asian monsoon [39].

Seasonal-to-Interannual Prediction: Model Fidelity

Once the main drivers of seasonal-to-interannual climate variability are identified, it is then necessary to ascertain whether the model to be used for seasonal-to-interannual prediction can replicate the drivers with sufficient realism. Change in patterns of SSTs is the dominant driver of seasonal-to-interannual climate variability worldwide. However, the regional terrestrial climate will only be predictable if the relevant SSTs are predictable [40]. Given that the El Niño phenomenon represents the majority of year-to-year variance in SSTs, including influencing the global ocean outside the tropical Pacific [41], most studies of the suitability of a model to predict seasonal-to-interannual climate will focus on the model's ability to predict El Niño. Of course, such studies of model fidelity help further elucidate the processes behind such phenomena.

The first attempt to predict El Niño employed a very simple model of the tropical Pacific Ocean that consisted of a warm, lighter, upper ocean overlying a cold, heavier deep ocean [17]. The depth of the upper layer determined the temperature at the surface in the eastern and central equatorial Pacific where upward currents are known to bring cold water from the deeper ocean into the upper layer and cool the surface; the more shallow the upper layer, the easier for the upwelling currents to bring cold water to the surface. The surface temperature anomalies in the east influence the east–west temperature gradient, which affects the strength of the trade winds, which affect the slope of the interface between the upper and lower ocean layers, and thus affects the eastern equatorial surface temperature. This describes the classic Bjerknes feedback mechanism [15] that maintains the mean state as well as the coupled air-sea feedbacks that can evolve an El Niño or La Niña event. Off the equator in the western Pacific the anomalous winds create depth anomalies of the opposite sign to those in the eastern equatorial Pacific, which can then adjust via equatorial wave dynamics, eventually causing the decline of the current event (e.g., El Niño) and potentially initiating an event of the opposite sign (e.g., La Niña). The positive feedback growth together with the delayed negative feedback that can cause

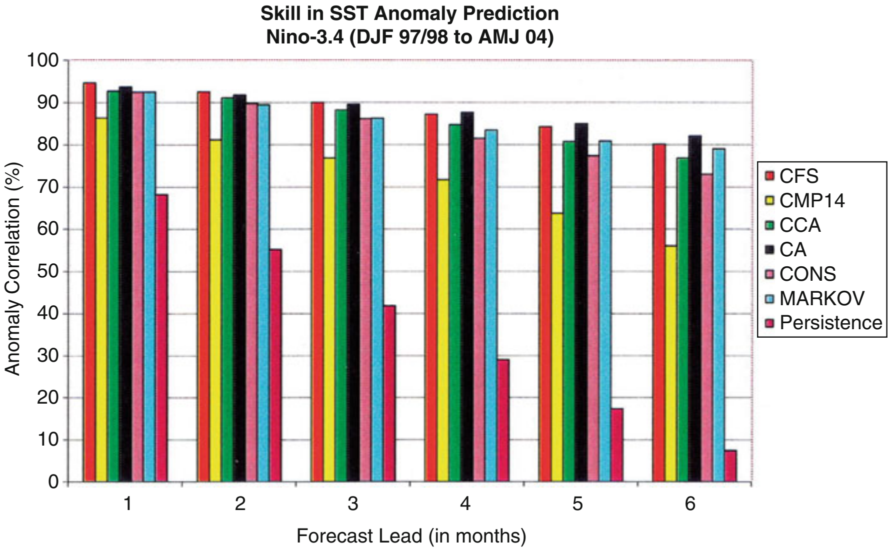

Fig. 11.4 Anomaly correlation (%) by various methods of the seasonal mean Niño-3.4 SST as a function of lead (horizontal; in months). The results are accumulated for all seasons in the (target) period DJF 1997/1998 to DJF 2003/2004. Except for CFS (the Climate Forecast System) coupled ocean–atmosphere model of the National Weather Service's Climate Prediction Center (CPC), all forecasts were archived in real time at CPC from 1996 onward. CMP14 is the previous coupled model, *CCA* is canonical correlation analysis, *CA* is constructed analog, *CONS* is a consolidation (a weighted mean), and MARKOV is an autoregressive method (From [44])

the turnabout from one phase to the next was named the Delayed Oscillator mechanism [19]. Variants on this central idea, such as the Recharge Oscillator [42] have since been formulated as observations of the tropical Pacific became available [43] and as the tropical Pacific air-sea variability was studied in more models.

Although the first models to successfully predict El Niño in the late 1980s were very simplified compared to the complexity of the real ocean–atmosphere system, they still remain viable prediction tools. It is very difficult to represent all the physical processes in the tropical ocean–atmosphere system precisely, and because of the strong interconnectedness of these processes, small errors in the representation of one process leads to associate errors in others. Thus it was not until the early twenty-first century that coupled ocean–atmosphere models of full complexity clearly demonstrated parity with simpler prediction models (Fig. 11.4) [44]. The metric most commonly presented to represent a model's ability to predict El Niño is the NINO3.4 index of sea surface temperature, which is the average of the temperature anomaly over the central equatorial Pacific from 5S–5N and 170W to 120W, as this is the region that exhibits the highest correlation with terrestrial climate anomalies worldwide [45].

However, this simple index does not capture all of the characteristics of El Niño. The timing and spatial structure of El Niño-related sea surface temperature anomalies can also influence the resulting teleconnections [46]. Additionally, single metrics such as correlation or mean error can mask the conditions under which El Niño is predictable. Most dynamical systems, particularly those with a chaotic component, exhibit conditional predictability meaning that there are times when the system is more predictable than others [47]. Thus it is also common to present the prediction history of models, to show how observed sea surface temperatures along the equator vary compared to the predictions as a function of lead time [48]. A common finding from such qualitative examination is that although models may do well in predicting the occurrence of an El Niño event, they have difficulty predicting the magnitude of large events or locating the variability far enough east during strong events [49, 50]. Such biases have repercussions for predicting the associated climate anomalies.

Predicting the driver of the climate anomalies is the first step. Next is to predict the associated climate anomalies. Biases in prediction of the drivers, such as El Niño events that do not exhibit the strength or structure of observed events, lead to biases in regional climate prediction. One way to circumvent some of the error in predicted SSTs is to statistically correct them before providing this information as boundary conditions to the atmospheric model. This approach is known as two-tier forecasting because the SSTs are predicted first and the climate is predicted second using an atmospheric GCM. Changes in the atmospheric circulation do not feed back onto the SST anomalies. Because El Niño is the largest driver of climate anomalies, and El Niño teleconnections are driven by the ocean variability, this is a viable approach. However, outside the tropical Pacific a notable fraction of the ocean variability is driven by the atmosphere, and thus in those regions heat and momentum fluxes will not be properly represented by two-tier forecasts.

One-tier forecasts, where the ocean and atmosphere evolve together, allow for a more physically consistent evolution of the ocean–atmosphere system. Coupled ocean–atmosphere models are increasingly the prediction tools of choice at operational forecast centers around the world [1]. However, due to model biases over some parts of the tropical ocean, regional climate prediction remains problematic with coupled models. In particular coupled models have great difficulty in representing the mean state of the tropical Atlantic, with the warmer water occurring in the western instead of the eastern equatorial Atlantic [51]. As a result, the tropical Atlantic SST variability is not predicted with any skill for most seasons by the current generation of coupled models, and the potential predictability of climate variability over western Africa and northeastern Brazil is substantially degraded compared to what it would be with skillful SST predictions [40].

Other biases that have been known for decades still persist in coupled ocean–atmosphere models and limit the quality of climate predictions. Such systematic biases include a double intertropical convergence zone over the Pacific, poor representation of regions of stratus clouds over the eastern subtropical and extratropical oceans, and vertical temperature gradients that are too diffuse in the equatorial Pacific where the warm upper ocean transitions to the cold deep ocean. The processes responsible for these features in Nature and how they are represented in models are active areas of research. Recent modeling experiments using models with a spatial resolution of tens of kilometers rather than hundreds of kilometers does reduce some of these biases by better resolving certain climate processes.

Seasonal-to-Interannual Prediction: Prediction Systems

Prediction systems are based on observations, models, and their connection through data assimilation systems. The three together form the three-legged chair of prediction systems [9]. Any weak leg compromises the system, and improvements in one leg often lead to improvements in the other legs.

Predictability of seasonal-to-interannual climate variability arises from the initial conditions of the ocean, particularly those conditions in the tropical Pacific Ocean that carry some signal of future El Niño conditions. Observations of upper ocean heat content anomalies in the other tropical oceans are also important for prediction as they can influence the persistence of local sea surface temperature anomalies as well as moderate the impacts of El Niño-related teleconnections in the region. Therefore, it is important to adequately observe the tropical ocean state. However, since models have errors in their representation of the real world, using the observations too faithfully to describe the initial conditions for model forecasts can cause problems. This is where data assimilation is essential to prediction systems.

Data assimilation is the process used to produce initial conditions for a dynamical model by combining observations with other information from a previous simulation of the model. If this is not done carefully, the introduction of the observations into the models can lead to initialization shock when the prediction is started. Initialization shock is a term used to identify the rapid development of model errors when a simulation is started. One approach to minimizing this problem is called anomaly initialization in which observed anomalies of the ocean state rather than the full state are added to the model's mean state to arrive at initial conditions. Other data assimilation methods address the mismatch between the spatial and temporal characteristics of the variability between Nature and the model. Currently, the atmosphere, ocean, and land components of prediction models are initialized separately. The data assimilation efforts are separate, and thus consistency in the initial states and tendencies of these components is not ensured. Methods to assimilate observational data into the coupled model as a whole are being investigated starting with the coupled ocean–atmosphere system [52].

Recent advances in El Niño prediction skill at the European Centre for Medium-Range Weather Forecasts in the United Kingdom were accomplished by both improvements to their model and improvements to the ocean data assimilation system [53]. Additionally, retrospective forecasts, also called "hindcasts," of the NINO3.4 El Niño index from 1960 to present from that forecast system have demonstrated the value of the observations provided by the Tropical Atmosphere–Ocean array of data buoys that measure temperatures of the upper 500 m of the tropical Pacific Ocean, some at the equator also measuring ocean currents, as well as temperature, winds, and humidity at the surface. At the time when the array of buoys was completed in the early 1990s, the forecast error of the NINO3.4 index dropped dramatically [54]. This result is most clearly demonstrated in forecasts that are initiated in February, when the biases in the model are at a minimum. This echoes the connected nature of these three elements of forecast systems; observations and their assimilation into models are crucial for prediction, but better models better elucidate the value of the observing network.

Even at that point when models, the observing network, and the use of those observations for forecast initial conditions becomes essentially perfect, climate forecasts will still contain uncertainties. Small, almost imperceptible, uncertainties in the initial state or the detailed evolution of some small-scale processes will lead to some divergence in the future state. This is the chaotic element of the climate system, sometimes referred to as the "butterfly effect." Where uncertainty is due to errors, there is the potential to reduce it. However, it is not necessarily the goal of forecasters to eliminate uncertainty, as this would be unrealistic, but to quantify it to the extent possible. Better models that can capture the random nature of processes, such as turbulence or convection, would improve process-related contributions to uncertainty. Better representation of such processes may actually increase the uncertainty in forecasts, relative to what models now indicate. Better observations, more complete observational networks, and improved data assimilation techniques can better indicate the uncertainties that arise from initial conditions [55, 56].

The uncertainty in climate forecasts should thus be considered as a range of possible outcomes. Typically the range of possible outcomes, or probabilities, are presented relative to the past climate history of the last several decades. A common format used by many operational forecast centers is tercile classes. For example, the precipitation for a given location over the last 30 years is used to quantify the above-normal category as the wettest 10 years, the below-normal category as the driest 10 years, and the near-normal category as those in between. In this case, the climatological probabilities are 33.3% for any category without any further knowledge. This should be the forecast probability for each category if there is no signal in the current prediction or if the prediction tools have no skill in that region and/or season. If skill and signal exists, then the forecast probabilities will differ from the climatological probabilities (Fig. 11.5). If the signal in the forecast indicates likelihood for wetter conditions, then the probability for above-normal precipitation will be higher than 33.3% and the probability for below-normal precipitation will be less. Alternatively, the forecast can be represented as the probability for exceeding or not exceeding some quantitative value.

One of the most important qualities of probabilistic forecasts is that the probabilities are reliable, or representative of the frequency of occurrence. The other important quality is that they are sharp, or differ substantially from the climatological probabilities. Diagnostics of these forecast characteristics can be visualized through reliability and attributes diagrams (Fig. 11.6) and quantified

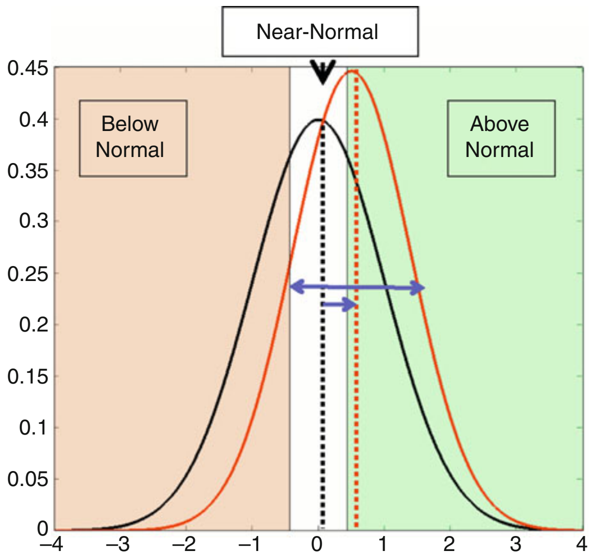

Fig. 11.5 Schematic of a probabilistic forecast distribution relative to a distribution of the historical climate observations. The values (*horizontal axis*) have been normalized with a mean of 0. The *shaded* regions represent the above-normal tercile (*green*) and the below-normal tercile (*brown*) of the historical distribution

through reliability and resolution skill scores, respectively [57]. A reliability diagram shows the complete joint distribution of forecasts and observations for a probabilistic forecast of an event or forecast category (such as the above-normal tercile). In a reliable forecast system, the probability assigned to a particular outcome should be the frequency with which – given the same forecast – that outcome should be observed. The information supplied by reliability diagrams includes calibration, or what is observed given a specific forecast (e.g., under and overforecasting), as well as resolution and refinement which is the frequency distribution of each of the possible forecasts giving information on the degree of aggregate forecaster confidence (small inset graph in Fig. 11.6). Reliability diagrams can further indicate whether there are systematic biases in the forecasts, such as not predicting enough occurrences of above-normal temperatures. Such probabilistic verification, such as reliability diagrams also can be useful for estimating event-specific prediction skill, for example if El Niño events were better predicted than La Niña events or drought conditions were better predicted than very wet seasons. A distinction in prediction skill between the cases of high and low variability calls for further examination of the physical causes of the discrepancy and whether it is inherent to the climate system dynamics or a shortcoming of the model(s).

It is a common feature of dynamical model predictions to be overconfident, indicated by a reliability curve that is more horizontal than the 45° angle that would indicate a reliable prediction system. For example, an overconfident forecast would be one in which a forecast that indicates above-normal rainfall is 80% likely in a given season, but overtime that forecast is followed by observations of above-normal rainfall 40% of the time. Such overconfidence can arise from errors in both the forecast signal and the forecast uncertainty.

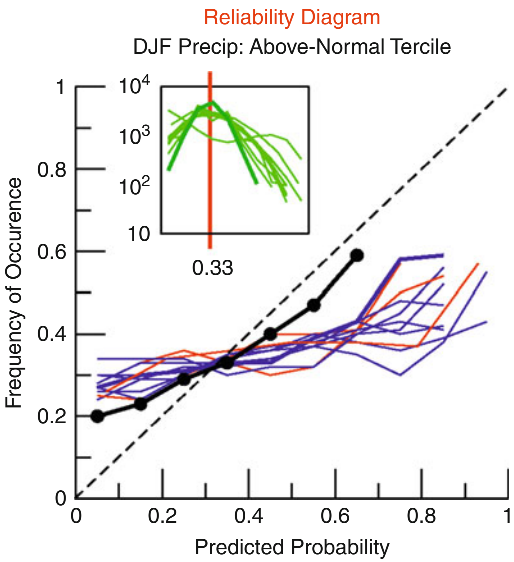

Fig. 11.6 An example of a reliability diagram, which indicates the skill of probabilistic forecasts. The diagram compares the forecasted probability of an event (in this case, above-normal winter rainfall in North America) to its observed frequency. A perfect forecast is represented by the *dashed line*, a *horizontal line* represents a forecast identical to climatology, and *sloped lines* are potentially skillful. The *blue* and *red lines* correspond to individual CGCMs and AGCMs, respectively, and are more horizontal than the *black line*, which represents the mean of these models. While the mean of the models is more reliable than any of the individual models, it tends to be underconfident for rare events (the *black line* lies above the perfect forecast line for low-probability events). Typically, a histogram accompanies a reliability diagram (*inset*), indicating the number of times that forecasts of various confidence levels were issued (Source: Adapted from [58])

Recalibration of predictions and multi-model ensembling are two approaches used to improve forecast reliability. Multi-model ensembling, which combines the prediction of several dynamical models, can improve the reliability and overall skill of predictions in two ways. First, although all models have errors, they do not necessarily have the same errors, thus combining the models reduces the systematic errors that would exist in the prediction from a single model. This can lead to reduced error and thus increased correlation skill in El Niño predictions, for example (Fig. 11.7) [59]. Similarly, it can increase the spatial coverage for where there is skill in capturing the predictable signals in the climate. The second advantage is the improvement in uncertainty estimation by considering the random errors and different parameterizations of random processes that give rise to the range of possible outcomes.

Multi-model ensembling can lead to overall better information on the climate signal and its uncertainty [60], and thus on forecast reliability (Fig. 11.8). Different approaches exist to combine models. The most straightforward is to treat all models equally. Particularly for prediction systems with short retrospective forecast

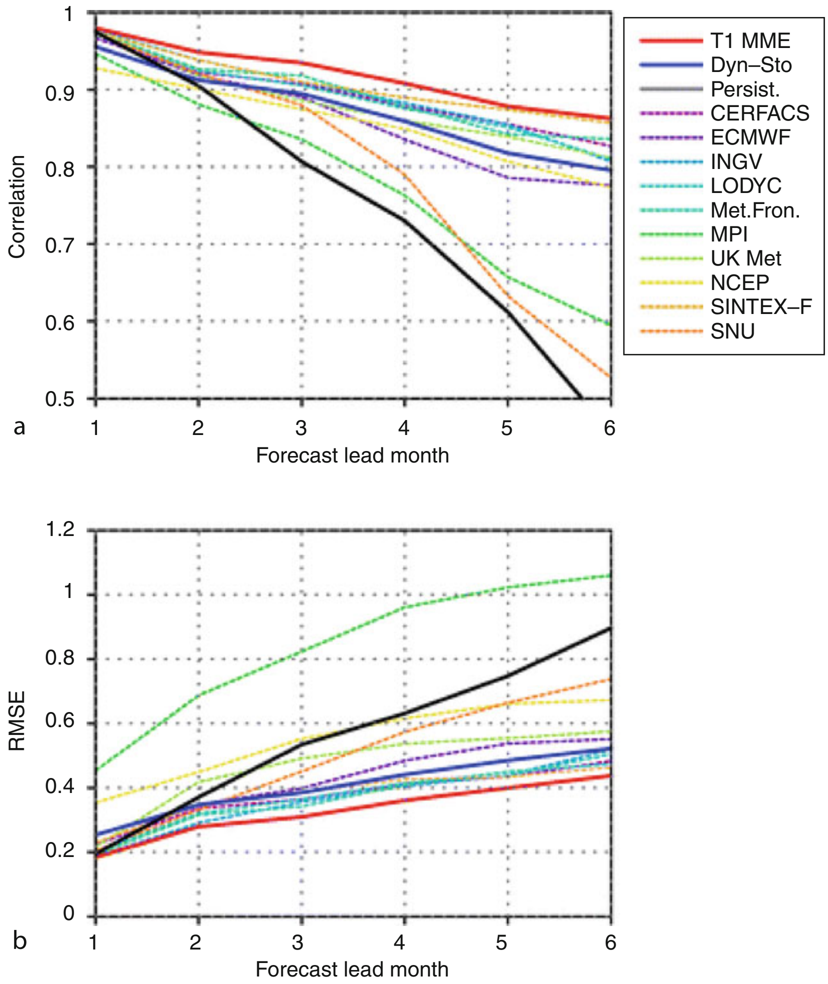

Fig. 11.7 (**a**) Anomaly correlation coefficients and (**b**) RMSE of NINO3.4 index during 1980–2001 with respect to lead time after removing the mean bias. The mean skill for all four cases including February, May, August, and November initial conditions is shown. *Black* for observation, *red* for 10 CGCM multi-model ensemble, *blue* for the Stat-Dyn forecast, and *colored dots* for individual coupled models as shown in the legend, respectively (From [59])

histories of about 25 years or less, it will be difficult to discern differences in forecast quality between comparable models. This is the typically situation with one-tier prediction systems that use coupled ocean–atmosphere models, because the ocean observations used in the forecast initialization is only available since the late 1980s. For two-tiered forecast systems that use atmosphere-only models the ocean temperatures can be predicted statistically, which allows for longer histories of retrospective forecasts. In these systems, it becomes possible to discern differences

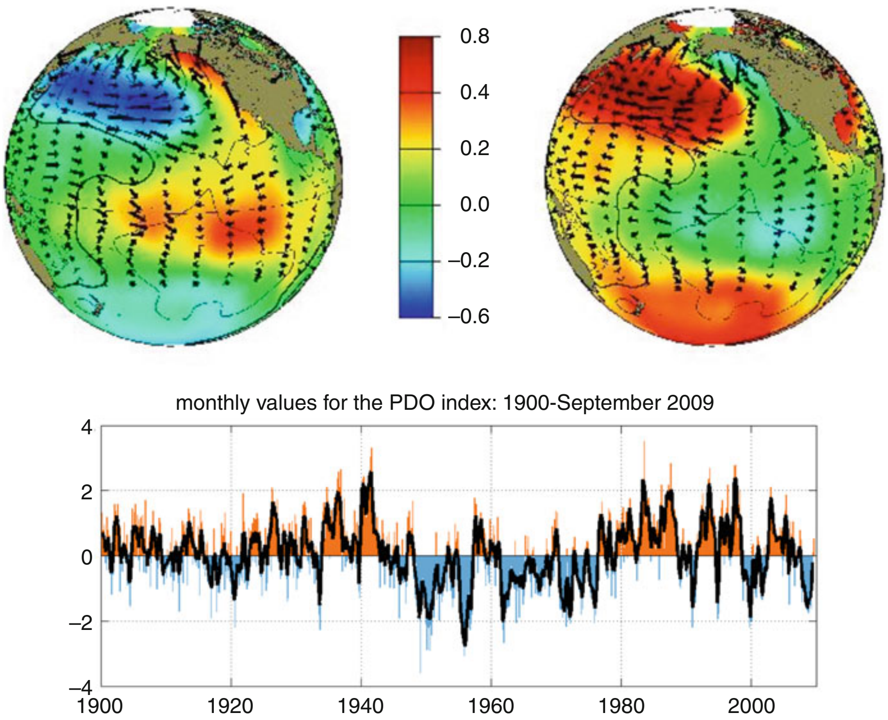

Fig. 11.8 (**a**) The positive (*left*) and negative (*right*) phases of the "Pacific Decadal Oscillation" (PDO), a long-lived El Niño-like pattern of Pacific climate variability, shown in terms of (**a**, *left*) the positive phase in sea surface temperatures (*colors*), sea level pressure anomalies (*contours*), and anomalous low-level winds (*arrows*), and (**b**) the time series of the PDO (Taken from http://jisao.washington.edu/pdo/)

in regional forecast performance and to use that information to give more weight to better performing models, which can lead to further improvements in forecast reliability [61, 62].

An alternative approach to performance-weighting models is to recalibrate the models prior to combination [63]. Recalibration has the advantage of improving forecast quality of individual models. It is also more viable for prediction systems with limited retrospective forecast histories, although a minimum of about 25 years is still required to identify systematic biases in seasonal-to-interannual variability. The recalibration of predictions is an attempt to account for systematic biases in both the signal and uncertainty in the predictions at a given location. Recalibration can also be used to account for spatial biases in the forecasts by comparing observed and predicted seasonal climate over several decades [9].

Reliable forecast information may still not provide enough specificity for those who wish to include seasonal-to-interannual climate forecasts in their decision models, such as those in the agricultural or water sectors. The spatial mismatch of the information, the fact that decision makers in sectors such as agriculture and water require information at much higher resolution, even if it means greater uncertainty, is a commonly cited reason for not using the operational forecasts [64]. There may also exist the desire for greater temporal resolution, such as the characterization of the weather within the climate that might predict the likely number of dry spells of a given duration. In some cases, certain weather characteristics of the seasonal climate may be more predictable than the seasonal totals (e.g., [65]). One way to address the information mismatch between the coarse spatial resolution, or the quality of the higher temporal variability, from global seasonal climate forecasts and the more detailed needs of the end user is through downscaling techniques. In statistical downscaling, the global climate forecast provides the input parameters for an empirical model with high spatial resolution. Statistical techniques can also be used to infer the signal in the weather characteristics relative to the seasonal mean, based on changes in the large-scale background climate, such as those empirically related to ENSO [66, 67], or to changes in atmospheric circulation [65]. In the dynamical downscaling, the global forecast is used to provide lateral boundary conditions to a high-resolution nested regional atmospheric model. While it may provide greater detail of the mean climate by better resolving terrain and coastlines, it has not been robustly demonstrated that dynamical downscaling improves prediction of the climate variability relative to the global model. Dynamical downscaling cannot overcome large-scale errors in the global model driving the nested model, and in many cases will exacerbate those errors. With increases in computing power, global climate models are starting to close the gap by providing fine spatial resolution, and attempting to provide better representation of weather transients that may be of interest to the end user. However, for the next decade or so downscaling techniques, particularly statistical downscaling will continue to add value to seasonal-to-interannual forecasts.

Seasonal-to-Interannual Prediction: Forecast Skill

Forecast skill is a measure of how accurately the prediction system can predict the observed climate variability or how well the probabilities describe the frequency of occurrence of particular outcomes. Measures of accuracy between the best guess, or most likely outcome, of the forecasts and what was observed are often referred to as deterministic measures, meaning they are concerned with verifying the prediction for a single specific outcome, such as a prediction for an above-normal temperature or 2°C warmer than average in the coming season. The metrics for deterministic quantitative forecasts include the Brier skill score and its decomposition, which includes anomaly correlations or root-mean squared errors. The quality, or skill, of deterministic categorical forecasts can be assessed using a variety of measures. There is no single measure of forecast performance that can indicate all aspects of forecast quality [68]. Additionally, forecast producers may be interested in different aspects of forecast performance than users of the forecast information. The World Meteorological Organization has compiled a list of recommended deterministic and probabilistic verification measures for seasonal predictions entitled, The Standard Verification System for Long-Range Forecasts [69].

Keeping in mind that there are different, complementary measures of forecast skill, the accuracy of predictions is typically used to estimate the limit of predictability. The limit of predictability is a function of the predictable signal and the unpredictable chaotic, or noise, component in the climate system. With an ensemble of predictions from a single model or a set of models, the signal and noise can be estimated from that set of information. The signal would be the predicted information that the ensemble has in common and the noise is the range of discrepancy about the signal (Fig. 11.5). When the forecast is initialized, the ensemble contains very little noise, but as the prediction proceeds, the chaotic processes in the climate system lead to divergence of the ensemble members. The limit of temporal predictability is reached once the magnitude of the noise becomes comparable to the signal. This in part, determines how far into the future the certain aspects of the climate can be predicted. Similarly, the average signal-to-noise ratio for a given region, season, variable, etc. describes the expected climate predictability in that case. Since Nature has only one realization, it is not possible to estimate the inherent limit of predictability of the climate system [9]. Estimates of the limit of predictability can be determined in a given prediction system as described above, but that will be only an estimate, and will be different for different forecast systems. At best, the most accurate prediction system for a given region, season, variable, etc. represents the limit of predictability for that case, and should be considered the lower limit of predictability, as the prediction accuracy is found to be at least that good and may improve further with improved models and data assimilation systems.

Given that real-time predictions have been in production for more than a decade now [1], several properties of forecast skill have emerged for seasonal-to-interannual predictions. First, predictions of seasonal mean temperature are more predictable than those for seasonal precipitation totals. This is related in part to the larger-scale nature of temperature anomalies and the processes behind them. Even the coarse resolution global climate models can represent fairly accurately the changes in seasonal temperatures. Precipitation processes and patterns have much smaller spatial scales and are more affected by local scale features. While the global models may be able to capture large-scale shifts in regions of convection and storm tracks, they may have difficulty with the characteristics of storms or local convective activity. The potential importance of local scale processes on precipitation variability also means that the noise component of seasonal precipitation variability is larger than that for temperature. As a result, more ensemble members are required to estimate the seasonal signal for precipitation than for temperature. The second robust property of seasonal predictions is that the tropics are much more predictable than are the extratropics. In the tropics, the atmospheric circulation is more explicitly tied to the changes in patterns of surface temperatures, and the noise in the resulting atmospheric circulation is relatively small. A third and notable property of the predictions, which actually applies to predictions at all timescales, is that there is conditional skill in the expected accuracy. There are times when the initial and evolving state of the climate system carries a much larger predictable signal than other times. For seasonal-to-interannual forecasts this coincides with El Niño events. For seasonal predictions over the United States most predictability derives from El Niño or La Niña conditions [70]. Similar results hold on a global scale too; the fraction of land area over which skillful forecasts can be made is up to twice as large during El Niño or La Niña conditions than in their absence [71]. Moreover, since these events have an inherent timescale of 6–12 months, or longer, the time horizon into the future that skillful forecasts can be issued is also expanded.

Seasonal-to-Interannual Prediction: Internationally Coordinated Efforts

Several internationally coordinated efforts have led to the understanding of seasonal-to-interannual climate variability and its prediction using dynamical models. One of the earliest was the Atmospheric Model Intercomparison Project (AMIP) [72]. This project was organized by the Working Group on Numerical Experimentation as a contribution to the World Climate Research Programme. Different atmospheric models were run with the same observed sea surface temperatures as boundary conditions for the period 1979–1988. The goal was to identify systematic errors as well as systematic responses to the boundary conditions across models. Without such a coordinated effort there had been questions whether the results from a single model were particular to that model or a more robust response expected of the climate system. Other coordinated activities followed.

In the late 1990s, experiments were carried out using different atmospheric models to test the predictability of seasonal climate relative to the variability of sea surface temperatures. Two important issues addressed in that collection of research were the relative impact of initial atmospheric conditions predictability of the seasonal climate and a suggestion that prediction skill could be improved through a multi-model approach. In the United States five modeling centers participated in this research under the Dynamical Seasonal Prediction (DSP) project. On the other side of the Atlantic, 11 different partners throughout Europe contributed to the Prediction of Climate Variations on Seasonal to Interannual Timescales (PROVOST) project [73].

Further research on seasonal predictability and the value of multi-model ensembles was conducted with coupled models from seven European modeling centers under the Development of a European Multimodel Ensemble system for seasonal to inTERannual prediction (DEMETER) project [74]. This project also encouraged research to determine the value of seasonal predictions through their use in models that use the climate data to make prediction over a wide range of interests, from agriculture to health. The next generation of DEMETER was ENSEMBLES, which continued to advance methods and application of seasonal predictions from European Earth system models, thus adding complexity to the dynamical prediction models [75]. The ENSEMBLES project also began to extend those predictions to decadal timescales. The Working Group on Seasonal to Interannual Prediction under the World Climate Research Programme is currently coordinating the Climate-system Historical Forecast Project (CHFP), which will provide access to a wide range of hindcasts to evaluate subseasonal-to-decadal predictions of the climate system, which also aims to quantify the predictability added by elements other than sea surface temperatures, for example through initialization and prediction of the land surface, the cryosphere, and the stratosphere [76].

Decadal Prediction (Experiments)

Decadal Prediction: Drivers of Decadal-Scale Climate

Decadal climate predictions sit between the seasonal-to-interannual forecasts of the next months to a year in the future and the climate change projections of 50–100 years in the future. There are many features of the climate system with timescales that vary over decades (decadal variability). The dominant drivers of climate features over decadal timescales are believed to be changing atmospheric composition, mainly increasing greenhouse gases, and slow changes in ocean circulation that lead to slow changes in the pattern of sea surface temperatures. The changing atmospheric composition changes the energy balance of Earth, which leads to warmer temperatures and other associated climate changes that manifest primarily as trends. The temperature trends are not spatially uniform. Ice-albedo feedback in higher latitudes leads to greater rates of warming there than at low latitudes. Land has a lower heat capacity than water, so the continents warm faster than the oceans. Ocean dynamics also play a role in the patterns of climate change warming, particularly in upwelling regions, where the radiative warming is offset by the upward advection of colder ocean water from depth.

What decadal predictions aim to capture that climate change projections do not is the predicted evolution of naturally occurring decadal-scale features. Climate change projections contain these processes and the associated variability, but since the climate system is not initialized with observations, the decadal evolution will not be temporally consistent with the observations. So one first test of a model is to see whether it is capable of simulating the dominant decadal-scale features observed in Nature.

Decadal-scale variability has been identified in Nature in both the Pacific and Atlantic Oceans. In the Pacific Ocean the variability is referred to as the Pacific Decadal Oscillation (PDO), or more correctly Pacific Decadal Variability (PDV). The pattern of PDV (Fig. 11.8a) has its signature in sea surface temperatures with cooler than normal temperatures in the midlatitudes of the North Pacific Ocean and warmer than normal temperatures in the eastern and central equatorial Pacific Ocean during the positive PDV conditions [22]. The time series associated with the projection of sea surface temperature anomalies on this pattern represents the PDO index (Fig. 11.8b). This sea surface temperature pattern is reminiscent of El Niño conditions, except that the magnitude of sea surface temperature anomalies is larger in the midlatitudes than in the tropics, and the tropical sea surface temperatures have a broader meridional extent. This pattern of sea surface temperatures is accompanied by sea level pressure anomalies in the North Pacific. A measure of the time series of changes in North Pacific sea level pressures is known as the North Pacific Pressure Index (NPPI). It was later realized that there is symmetry in the Pacific decadal variability such that a similar pattern of cooler than normal sea surface temperatures and anomalous low sea level pressure is also found in the midlatitudes of the South Pacific Ocean. The full Pacific view of decadal variability has been named the Interdecadal Pacific Oscillation (IPO, [77]). However, the PDO is the more commonly used index outside Australia.

The symmetry of ocean–atmosphere anomalies outside the tropics, and the resemblance to El Niño, suggests a role for El Niño in driving PDV. It is also notable that there is considerable year-to-year fluctuation in the PDO index. It is very difficult to identify in any particular year what phase, positive or negative, the PDV is in because within the protracted periods in which the PDV is preferentially of one sign or the other, there exist excursions of the index of opposite sign that may only last a year or two.

Simple model experiments have shown that El Niño events can affect the positive phase of PDV [41]. Model analysis suggests an atmospheric Rossby wave train emanating from anomalous convective heating in the central Pacific leads to anomalous low sea level pressure in the region of the Aleutian low, thus strengthening the westerly trade winds. The strengthened winds lead to cooling through enhanced evaporation and also drive southward Ekman flow that brings colder water from the north southward. Those changes in the ocean mixed layer can be sequestered from the atmosphere from one winter to the next due to changes in the ocean mixed layer depth and its connection to the surface from winter, when El Niño peaks, the storm track is strongest and the atmosphere can directly affect the upper ocean, to summer when the previous El Niño would have decayed, the storm track is relatively weak, and increased solar radiation stabilizes the upper ocean. The following winter when the westerly winds of the storm track again increase, the sequestered mixed layer temperature anomalies reemerge [78]. This reemergence mechanism is hypothesized to the main way that the year-to-year variability associated with El Niño and La Niña can be rectified into longer timescale variability. However, other processes may also contribute to PDV. Some mechanisms that have been proposed included ocean–atmosphere coupling of a basin gyre mode [25], excitation of midlatitude oceanic Rossby waves [79], and a complementary, possibly independent oscillation driven by the tropics particularly when El Niño events are focused toward the central equatorial Pacific [80].

Associated with the decadal changes in Pacific Ocean conditions, decadal-scale terrestrial climate anomalies have also been identified over the United States [22] and throughout the Pacific sector [81]. Many of these climate anomalies are consistent with El Niño-related teleconnection patterns, such as wetter conditions in the southern tier of the United States and drier conditions over the Pacific Northwest [82]. Although only a few realizations of each phase of PDV exist in the instrumental records, the broad pattern seems to be consistent across these cases. However, because it is likely that El Niño is a dominant driver of PDV, and is associated with similar terrestrial teleconnections, it is difficult to say with confidence that the PDV is somehow independent of the mere existence of extended periods when El Niño events are stronger or more frequent versus when El Niño events are weaker or less frequent.

Decadal-scale variability in the Atlantic is referred to as the Atlantic Multi-decadal Oscillation (AMO), or more correctly Atlantic Multi-decadal Variability (AMV), because there does not seem to be a spectral peak signaling a true oscillation. Because positive AMV conditions are associated with warming throughout the North Atlantic (Fig. 11.9), the index of AMV is simply the sea surface temperature anomaly averaged over the North Atlantic, and it is often detrended [83]. Other more elaborate means of isolating decadal-scale variability over the Atlantic have been used (e.g., [24]), but result in very similar time series, so the simple index is now the one most widely used.

The hypothesized mechanism driving the AMV is associated with changes in the Atlantic Meridional Overturning Circulation (AMOC). The AMOC brings warm and salty water from the tropical Atlantic poleward. At high latitudes, cold salty water becomes denser than the water below it due to heat fluxes from the westerly storm tracks and brine injection from sea ice formation. The heavy surface water then sinks and flows back equatorward as North Atlantic Deep Water. The sinking water is replaced by the surface flow from tropics to high latitudes. If the rate of sinking increases, the poleward flow of surface water increases, bringing more warm tropical water into the midlatitudes. This represents an increase in the strength of the AMOC, and the AMV index becomes positive. If the North Atlantic water gets too warm or if it freshens the rate of sinking water slows down, and the rate of transport of warm tropical water poleward slows down. This represents a decrease in the strength of the AMOC, and the AMV will become negative.

The AMOC is forced on all timescales. Because the Gulf Stream is the western boundary current of the wind-driven ocean gyre as well as contributing to the AMOC, changes in the winds will affect the AMOC as well as ocean temperatures. However, the multi-decadal-scale variability described above is a much slower process related to the inertia of the overturning circulation and the associated impact on the density properties of the Atlantic Ocean. Since observations of the AMOC have become available only since the end of the twentieth century, there is not enough observational evidence to quantitatively link the sea surface temperatures of the AMV with multi-decadal variability of the AMOC. However, the low-frequency variability of AMOC in some models is associated with a pattern of sea surface temperature anomalies that closely resembles the observed AMV pattern [83]. What has not been resolved is what process or collection of processes can influence the AMOC on long timescales. Some studies point to modification of the strength and local of the intertropical convergence zone over the Atlantic as a way to modify the salinity of the water transported from the tropics [84]. Others suggest that the North Atlantic Oscillation (NAO – also called the Arctic Oscillation, AO) plays a dominant role by influencing the strength of the winds, which then influence the rate of convection, or sinking of heavy water, in the Labrador Sea region with an estimated 10-year lag time [85]. Although this would be a fairly white noise process, the suggestion is that the ocean integrates the noise into a longer timescale red noise process, but one that might still carry some predictability due to persistence.

The teleconnections associated with the positive phase of AMV include wetter conditions over the Sahel and India and drier conditions over northeast Brazil, due to the northward shift of the intertropical convergence zone toward the relatively warmer conditions north of the equator [29]. Also the warm tropical North Atlantic provides more fuel for the growth of tropical storms, and empirically it is seen that more tropical storms grow to hurricane intensity during the positive, warm phase of AMV than during the negative or cool phase.

Decadal Prediction: Model Fidelity

The task of judging whether a model captures decadal variability in the Pacific or Atlantic oceans for the right reason is greatly complicated by the limited history of observations compared to the timescale of the variability. Since the measurements of surface temperature and sea level pressure go back to the nineteenth century, most comparisons are made to these fields. In many cases, the question of model fidelity is closely tied to examination of the processes involved in producing the variability in a particular model and to what extent those are observed in Nature. The difficulty with that approach is as described in the previous section: different models may not agree on which process(es) dominates, or is even involved.

Different models also may yield somewhat different spatial patterns or spectra than suggested by the limited observations [86]. A similar situation exists relative to El Niño in coupled dynamical models [87], and this has not prevented the use of those models for El Niño prediction. Thus, the most important factor may be simply whether or not a model is capable of capturing a reasonable representation of decadal variability in sea surface temperatures, as this is how whatever changes are occurring in the ocean will be communicated to the atmosphere.

Exactly how best to validate decadal variability in the models is an area of active research. To date, more work has been focused around Atlantic variability perhaps because of the recognition of the role of the AMOC in the AMV. The idea is that if the AMOC is responsible for the AMV, then it is the AMOC that a model must be able to predict from a given set of initial conditions. The AMOC must then produce a surface temperature of reasonable resemblance to Nature, and the overlying

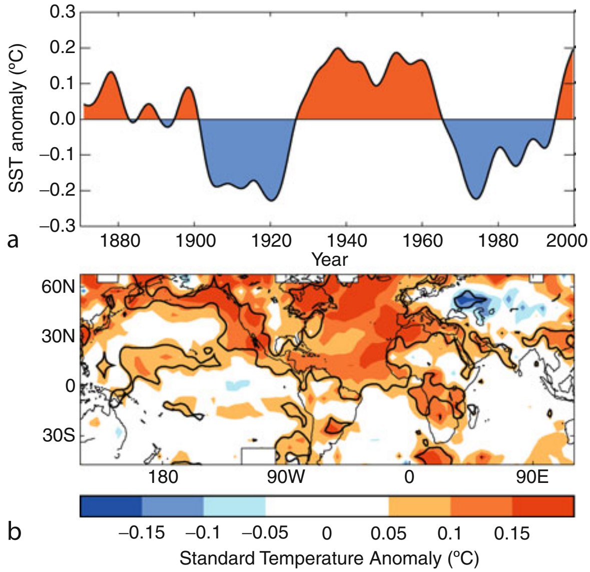

Fig. 11.9 (**a**) AMO index derived from detrended area-weighted mean North Atlantic SST anomalies by using a Chebyshev filter with a half-power period of 13.3 years. (**b**) Surface temperature anomaly associated with one positive standard deviation of the AMO index, calculated by regression of surface temperatures with the index and scaled by its standard deviation. The solid contour bounds regions significant at the 90% limit of a two-sided *t*-test accounting for autocorrelation (Source: From [83])

atmosphere must be able to respond to the changes in surface temperature in a way that captures the observed teleconnections. Again, the difficulty is that very few realizations of the variability exist in the observational record, although paleoclimate reconstructions of past temperature or precipitation suggest that, for example, multi-decadal variability consistent with observed AMV has impacted regional climate 400–500 years back [88]. But the few realizations of the spatial pattern of sea surface temperatures makes it difficult to know which parts of the pattern of anomalies are robust across events and which are variable from one positive phase to another.

For PDV, most models capture the response of the midlatitude Pacific Ocean to El Niño variability. However, they often do not demonstrate the same level of multi-year persistence through a reemergence mechanism. Different models are also influenced to differing degrees by other processes hypothesized to contribute to PDV, including the white noise imposed by variability in the storm track. As a result the patterns of PDV, such as where the sea surface temperature anomalies are focused and the magnitude of that temperature variance, also differ among models.

Some modeling studies have shown that at least the atmospheric models can translate the changes in patterns of sea surface temperature into realistic teleconnections. For example, using observed heat fluxes from the positive, warm phase of AMV in the Atlantic Ocean to drive an atmospheric model leads to decadal-scale changes consistent with observed changes in precipitation over the Sahel and India and also in the wind shear over the tropical North Atlantic relevant to hurricane formation (Fig. 11.10) [30]. Thus as with El Niño, if the sea surface temperatures can be predicted then there may be at least some predictability of the associated terrestrial climate impacts.

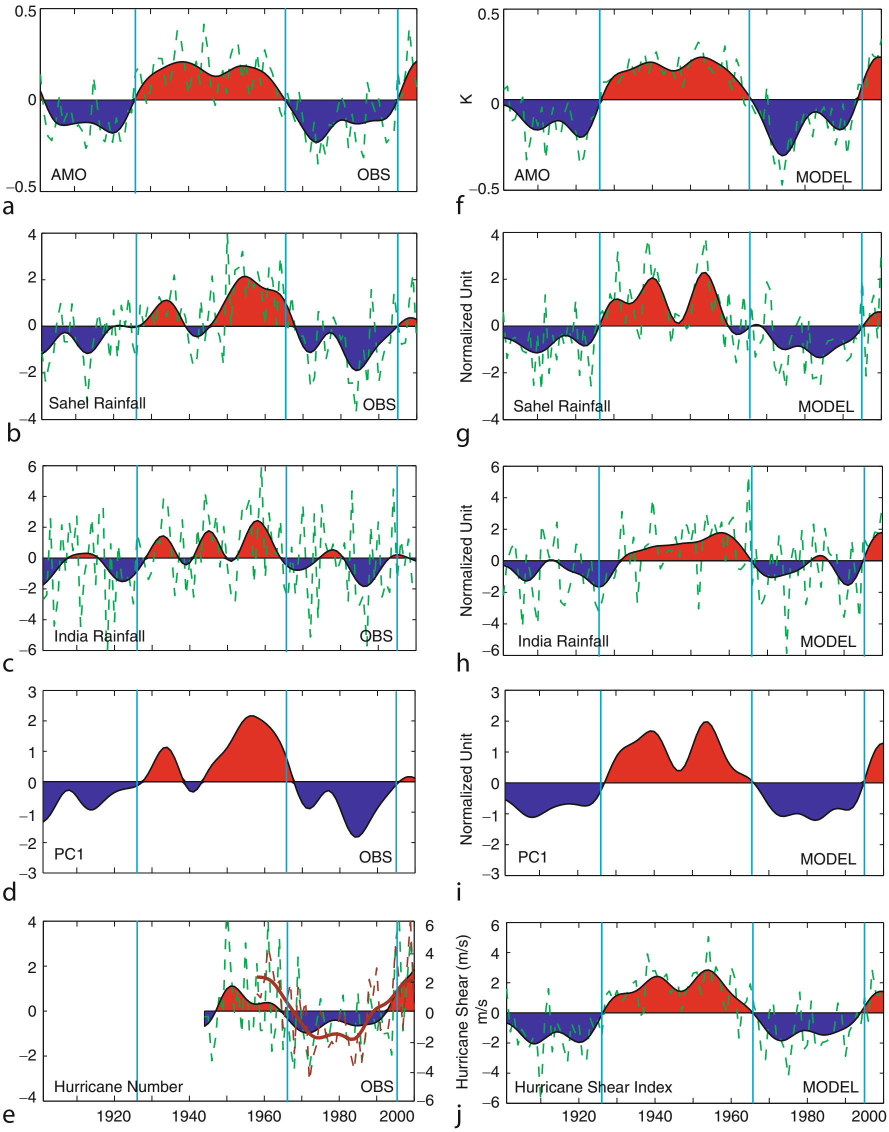

Fig. 11.10 Observed and modeled variability. The *color shading* is the low-pass filtered (*LF*) data and the *green dash line* is the unfiltered data. (**a**) Observed AMO Index (K). (**b**) Observed JJAS Sahel rainfall anomalies (averaged over 20°W–40°E, 10–20°N). (**c**) Observed JJAS west central India rainfall anomalies (averaged over 65–80°E, 15–25°N). (**d**) Observed time series of the dominant pattern (PC 1) of low-frequency JJAS rainfall anomalies. (**e**) Observed anomalous Atlantic major Hurricane number (axis on the *left*, original data from the Atlantic basin hurricane database-HURDAT, with no bias-type corrections from 1944 to 1969, there is no reliable data before 1944) and observed Hurricane Shear Index (1958–2000) (m/s, *brown solid line* for LF data, *brown dash line* for unfiltered data, axis on the *right*). (**f**) Modeled AMO Index (K). (**g**) Modeled JJAS Sahel rainfall anomalies. (**h**) Modeled JJAS west central India rainfall anomalies. (**i**) Modeled PC 1 of LF JJAS rainfall anomalies. (**j**) Modeled Hurricane Shear Index (m/s) (Source: From [30])

Decadal Prediction: Prediction Experiments

Experimental decadal prediction has only recently begun. Decadal prediction differs from climate change projections in the initialization of the climate system, with particular emphasis on initialization of the oceans. The first paper demonstrating actual retrospective, decade-long, initialized forecasts was published in 2007 [3]. They showed improvements in prediction of globally averaged temperatures relative to the un-initialized climate change projections from the same model. However, it was not clear how much predictive information is available at the regional scale from these predictions, and it is not obvious what the main drivers are behind any predictive information they may yield.

The prediction systems for decadal prediction are essentially the same as for seasonal-to-interannual prediction. They require observations, models, and their connection through data assimilation systems. One of the main differences is the requirements on the observations: seasonal-to-interannual predictions mainly need information about the upper several hundred meters of the tropical oceans; decadal predictions require information about the global oceans, including the middle and high latitudes and also to much greater depths to capture information on the lower branch of the AMOC.

Observations needed to produce initial ocean conditions are incomplete. The creation of retrospective forecasts of decadal variability at least several decades into the past requires information on salinity fields that just do not exist. This has tested the limits of ocean state estimation with limited data, and the estimates even for large-scale averages, such as the average salinity anomaly in the upper 700 m of the midlatitudes of the Atlantic Ocean, can vary greatly. The uncertainty among datasets for upper ocean salinity anomalies on basin scales is larger than the variability within a single dataset [89]. Since the beginning of the twenty-first century, however, the Argo program of drifting buoys has provided unprecedented measurements of the upper 2 km of the global ocean. The floats measure temperature and salinity profiles as they descend and ascend the water column about every 10 days. There are currently over 3,000 floats reporting data through satellites (Fig. 11.11). Even with good observational data coverage of the global oceans there will still be challenges in merging those data efficiently with models through data assimilation systems to account for both mean biases and biases in space-time variability.

The first step in exploring decadal prediction has been through perfect model studies. In perfect model studies, a free-running integration of the model is taken as truth; this integration assumes the role of the “observations.” Ensemble members are set up to start from a particular point in the free-running integration with small perturbations to the initial state, representing the uncertainty in initial conditions. The ensemble members are then integrated forward to see how well they can track the “truth” of the free-running integration. In this experimental setup, the “observations” are perfect because since they are taken from the model they are known everywhere, and the model is perfect, because it is dynamically consistent

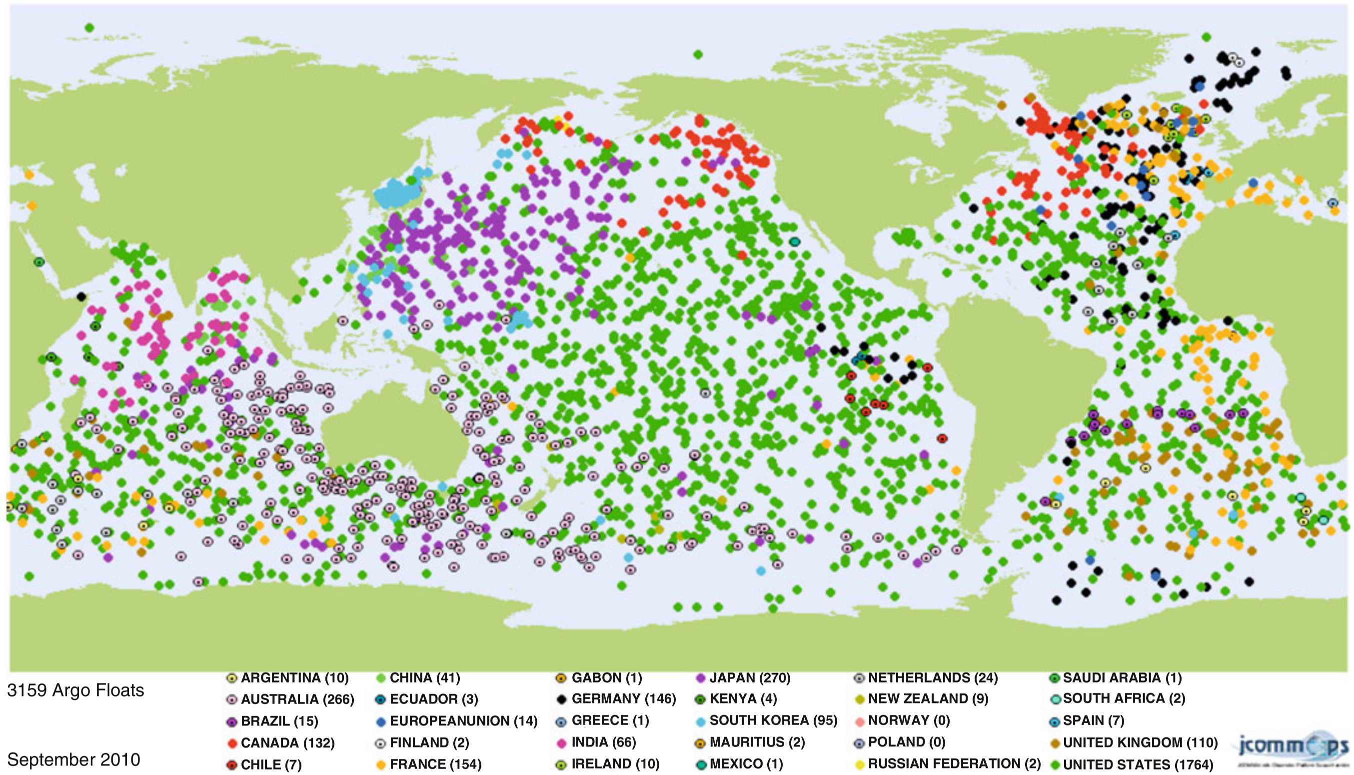

Fig. 11.11 Map of location of Argo floats and the countries that deployed them, as of September 2010. Note that *dot* size is greatly exaggerated relative to size of floats (Source: http://wo.jcommops.org/cgi-bin/WebObjects/Argo.woa)

with the “observations,” which are just a snapshot from the model. Similar experiments toward the design of assimilation systems test the insertion of these perfect “observations” but sampled only at locations that the actual observing network could provide data. The idea is to see if in this most idealized of circumstances – perfect observations and perfect model – the model is able to predict the evolution of the “observed” variability taken from the free-running integration. If not, it implies that in the particular model, too much noise exists to extract a predictable signal. The situation will only be worse in a real forecast setting with imperfect observations in the model that is also not perfect.

A number of these perfect model prediction experiments have been carried out since the early part of the twenty-first century. In a coordinated experiment of five European modeling centers, called PREDICATE, two to three experiments were carried out by each group starting their ensemble predictions at different points in time to explore the prediction dependence on the variability of the AMOC. In all cases there was some skill in predicting the evolution of the AMOC (Fig. 11.12). The experiments also demonstrated conditional predictability much like is seen with El Niño predictions. The perfect model predictions started when the AMOC was stronger than average yielded predictability of the AMOC to about 10–15 years into the future; predictions started with a weak AMOC predicted the future evolution of the AMOC only 2–5 years into the future [90]. The PREDICATE experiments were based on model control runs, meaning that atmospheric composition was held fixed. More recent perfect model studies explore the relative predictive signal due to the initial conditions versus due to radiative forcing from increasing greenhouse gases [91]. Several common lessons are beginning to emerge from these studies. One is that the predictable time horizon, when the signal in the ensemble of predictions is larger than the uncertainty across ensemble members, is longer for midlatitudes than for the tropics due to the dominance of year-to-year variability in the tropical oceans. Another lesson is that upper ocean heat content is more predictable than sea surface temperature due to the impact of weather noise on surface temperatures, while the upper ocean temperatures are more reflective of the slow changes in the atmospheric circulation. Thus even if the AMOC is predictable, the surface temperatures connected with that feature will be less so, but it is this surface expression that is necessary for predicting the terrestrial climate impacts. Finally, it appears that the external forcing due to increasing greenhouse gases becomes comparable to the information from ocean initial conditions by 10 years out for the midlatitudes and less in the tropics. Again, these are perfect model results. However, such results only indicate the upper limit of predictability for a particular model, and even though the similar results have been found across several of the current models, it is not to say that different results might be possible from better models.

To date, only a few pioneering attempts have been documented of “retrospective forecasts,” which are decadal predictions initialized with real observed initial conditions from some time ago. These prediction experiments not only used different models, they also used very different methods to obtain the initial conditions: one initialized with only sea surface temperatures [4], one initialized the

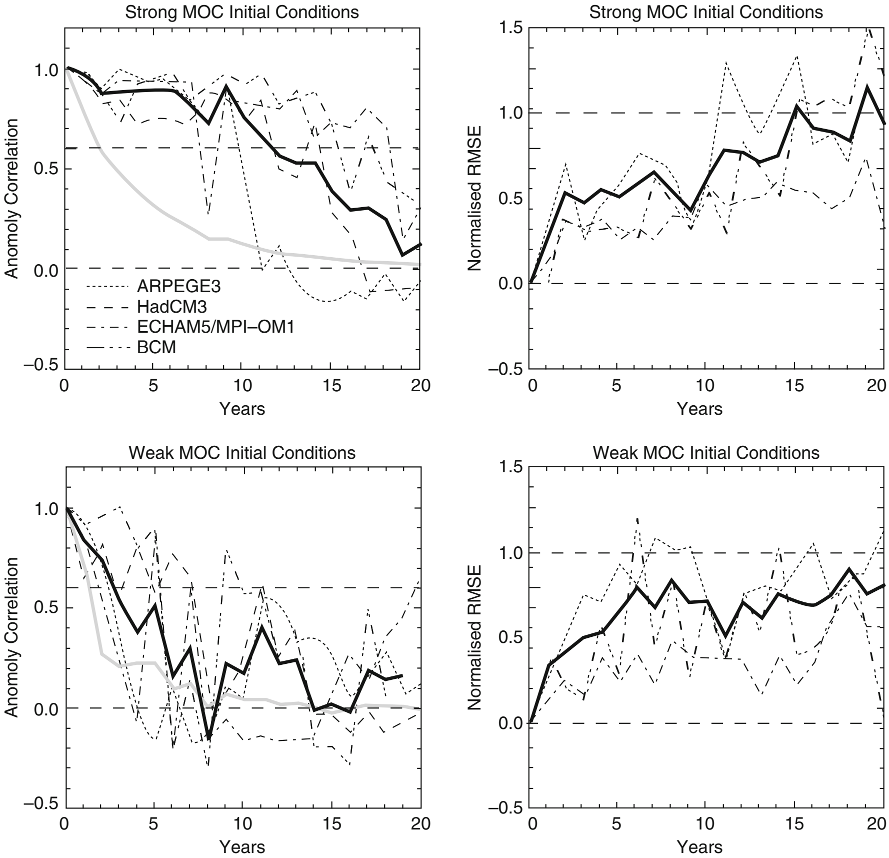

Fig. 11.12 Measures of the potential predictability of variations in the strength of the Atlantic Meridional Overturning Circulation from four of the five coupled models (see legend). (*left*) The anomaly correlation coefficient (ACC: unity for perfect potential predictability; zero for no potential predictability) for (*top*) strong and (*bottom*) weak MOC initial conditions (*right*). The normalized root mean squared error (rmse: zero for perfect potential predictability; unity for no potential predictability) in the same order. Also shown in the figures are the multi-model average ACC and rmse (*thick black line*) and the multi-model average ACC for a simple damped persistence (*thick gray line*) (Source: From [90])

observed data for ocean temperature and salinity anomalies as well as atmospheric anomalies [3], the third nudges their model toward the observational analysis using a different procedure [5].

The results are mixed. All claim to gain benefit from initialization of the climate system compared to the climate change projections that consider only changes in the atmospheric composition. Two of the studies [3, 5] show improvement in global mean temperatures compared to the un-initialized climate change projections; the other study [4] slightly degrades their prediction of global mean temperatures with initialization. All claim, or at least imply, that much of the decadal variability that is captured is due to initialization of the AMOC. Two of the studies [4, 5] demonstrate improved temperature predictions over the eastern North Atlantic region, but for the study that also quantifies the impact of initialization on prediction errors [4] shows larger errors for North Atlantic sea surface temperature in the initialized predictions. The same two studies that show improved correlations for North Atlantic temperature predictions claim that it is due to improved prediction of the AMOC. Since there are no observations of this circulation feature in the twentieth century, the conclusions are based on comparison with the analysis responsible for the initial conditions, which constitutes something like a semi-perfect model result rather than a verified prediction.

Two of the early prediction experiments [3, 4] do show some improvement in regional temperature predictions over land, but how much improvement is not easily discerned, and is difficult to compare across the experiments. There are also some regions where the temperature predictions are less skillful. Maps of skill, or differences in skill, are not provided for precipitation in these studies. These papers are only the beginning of assessment decadal prediction skill.

What these results do or do not show must be viewed with caution though. Several difficulties stand in the way of more conclusive estimates of predictability and prediction skill for decadal climate variability. One difficulty is that the current sets of experiments, and even those that will soon be available (see Decadal Prediction: Internationally Coordinated Efforts) have very few ensemble members. Small ensemble size leads to uncertainty in the predicted signal, and provides very little information about the uncertainty due to uncertain initial conditions in a particular model. Multi-model ensembles will likely be more problematic for decadal predictions given the wide range of approaches to initial conditions; the prediction skill can also be compromised by the data assimilation component, even if the models are of equally high quality. Data assimilation and the development of initialization techniques for current and retrospective decadal predictions require considerable research investment. What experiments do exist and are likely to exist in the next several years will have limited realizations of decadal-scale variability, complicated with the evolution of that variability against a changing background climate due to increasing greenhouse gases. That combined with limited observations, not only of the subsurface ocean but also of terrestrial climate for much of the world, makes verification of retrospective forecasts extremely challenging.

Decadal Prediction: Internationally Coordinated Efforts

Several international efforts have been organized since the beginning of the twenty-first century to ascertain the predictability and prediction skill of decadal climate variability by systematizing the investigation across many models. The PREDICATE project, which was referred to above, provided a systematic comparison of the “perfect model” predictability in five European coupled models. They found potential predictability in the AMOC (Fig. 11.12), and also to some extent in surface air temperatures, that exceeded damped persistence [90]. The PREDICATE project examined the potential predictability of the response of atmospheric models to prescribed sea surface temperatures, such as those associated with the AMV, and found good consistency across the models suggesting potential predictability if the pattern of SST was itself predictable [92].

A more recent activity, also drawing on the European modeling and prediction community is ENSEMBLES ([75]; http://ensembles-eu.metoffice.com/). This was a 5-year climate change research project begun in 2004, and involving 66 research partners across Europe. The project generated retrospective climate forecasts from seasonal to multi-decadal scales, provided local interpolation and/or downscaling, and sought to apply that information to sectoral outlooks, such as agriculture, health, and energy, across Europe.

The most extensive collaboration on decadal prediction experiments is the coordinated experiments designed and being run for the IPCC Fifth Assessment Report [93]. Together with the climate change projections for the next IPCC report, these decadal prediction experiments will be part of the Coupled Model Intercomparison Project-5 (CMIP5). There is a minimal set of runs at the core of the experimental design that requires hindcasts initialized for near the end of 1960 and every 5 years after that to 2005, in each case predicting 10 years past the initialization. Of those 10 sets of experimental start dates, a subset – those initialized at 1960, 1980, and 2005 – will be run out for 30 years. These experiments are to be run with a nominal ensemble size of 3. Of the dozen or more international modeling and prediction centers that will participate in the decadal prediction experiments of CMIP5, several will run with larger ensemble sizes and more start dates.

What is not being coordinated for the CMIP5 decadal prediction experiments is the data assimilation or initialization strategy. The guidelines only require that the predictions begin with a state of the climate system representative of the observations at that time. Thus, although there will likely be prediction systems that perform better than others, considerable analyses and further research will be required to assess which part of various prediction systems are responsible for their relative success or failure.

Future Directions

Although seasonal prediction is a relatively mature activity, considerable room for further improvement exists in the production, provision, and application of seasonal climate forecasts [9]. Dynamical models have many recognized biases in their tropical climate, such as tropical upper ocean structure and mixing, a tendency to produce a double intertropical convergence zone in the Pacific, and poor simulation of the stratus clouds that sit near the coasts along the eastern subtropical oceans.

These problems are probably not unrelated, but they have proved difficult to solve. These tropical biases impact the realism of predicted El Niño events, which introduces biases into the associated teleconnections. Although much of the discussion in this chapter has focused on the climate predictability that arises from tropical SSTs, and especially El Niño, other factors in the climate system that are not well represented of initialized in models may carry additional prediction skill. Such processes include land characteristics [36] such as soil moisture, snow, and vegetation, as well as sea ice, variability in the stratosphere [94], and intra-seasonal variability such as the Madden–Julian Oscillation [95]. The provision of seasonal forecasts has improved since the 1990s; it has become common practice for operational centers to provide probabilistic information. However, that information is not sufficient for many decision makers if it is not accompanied by information on how the forecast is constructed, the past skill of the system, and more flexible or varied information that would allow sophisticated users to incorporate the data into quantitative decision systems. These types of best practices are much easier to address than model biases. Also, if addressed they would allow for broader use of past forecasts for research to underpin the use of current forecasts for decisions.

Decadal prediction is still in the phase of research and experimentation. Thus, decadal prediction itself should be considered a future direction of climate prediction. Although there have been some pioneering studies that present results from decadal prediction systems, there is no community-wide agreement on how decadal prediction systems should be constructed, what information can be provided, with what accuracy, and even how best to verify the information that is predicted [2]. The internationally coordinated set of experiments under CMIP5 should contribute to a better understanding of these prediction systems and their potential. These experimental predictions will build on the current limited understanding to illuminate the relative information provided by initial conditions, in a real forecast setting, compared to the radiative forcing from current and future atmospheric greenhouse gas increases. The prediction experiments taken together should also help identify model biases that are of particular concern to decadal variability and set priorities on the future development and maintenance of the ocean observing system. Also, the added complexities of data assimilation for decadal prediction that will encompass longer timescales, greater depths in the ocean, and more need for salinity information, which was not available for most of the ocean prior to the twenty-first century, will lead to innovations in data assimilation systems (e.g., [96]).

The seasonal and decadal prediction systems share many common elements. In particular, they use the same type of dynamical models, and they both rely heavily on ocean initial conditions interpreted through data assimilation systems. They are both potentially impacted by external forcings such as solar variability and volcanoes. The same model biases that affect seasonal prediction skill will impact decadal predictions also. As the research community develops improved dynamical models, that better represent the Earth system in all its complexity, it will benefit climate predictions at all timescales. The additional observational data and more sophisticated data assimilation systems that are required for initialization of decadal predictions will provide more information of the ocean state that could be relevant for seasonal predictions as well. Already, some efforts to create retrospective seasonal predictions are being run farther into the future to investigate the ability of those systems to predict interannual-to-decadal climate variability. On the other side, retrospective decadal predictions that will contribute to the CMIP5 database already predict through the seasonal timescale.

The larger vision for the future direction of seasonal and decadal prediction is the union of the two efforts. This has been called "seamless prediction" [97, 98], which seeks the seasonal predictions to both the longer-term decadal predictions as well as the shorter-term weather forecasts. Initial steps in bridging the weather and seasonal timescales have been made (e.g., [97]), and since the observational and data assimilation systems are in place and have been well tested for these timescales, it is a sensible starting point. The joining of seasonal and decadal prediction scales would appear to be developing naturally as part of the evolving research into climate variability, predictability, and prediction on these timescales.

Bibliography

Primary Literature

1. Stockdale TN, Alves O, Boer G, Deque M, Ding Y, Kumar A, Kumar K, Landman W, Mason S, Nobre P (2010) Understanding and predicting seasonal-to-interannual climate variability – the producer perspective. Procedia Environ Sci 1:55–80
2. Meehl GA, Goddard L, Murphy J, Stouffer RJ, Boer G, Danabasoglu G, Dixon K, Giorgetta MA, Greene AM, Hawkins E, Hegerl G, Karoly D, Keenlyside N, Kimoto M, Kirtman B, Navarra A, Pulwarty RS, Smith D, Stammer D, Stockdale T (2009) Decadal prediction: can it be skillful? Bull Am Meteorol Soc 90:1467–1485
3. Smith D, Cusack S, Colman A, Folland C, Harris G, Murphy J (2007) Improved surface temperature prediction for the coming decade from a global circulation model. Science 317:796–799
4. Keenlyside NS, Latif M, Jungclaus J, Kornblueh L, Roeckner E (2008) Advancing decadal-scale climate prediction in the North Atlantic sector. Nature 453:84–88
5. Pohlmann H, Jungclaus JH, Köhl A, Stammer D, Marotzke J (2009) Initializing decadal climate predictions with the GECCO oceanic synthesis: effects on the North Atlantic. J Clim 22:3926–3938
6. Seager R, Ting M, Held I, Kushnir Y, Lu J, Vecchi G, Huang H-P, Harnik N, Leetmaa A, Lau N-C, Li C, Velez J, Naik N (2007) Model projections of an imminent transition to a more arid climate in southwestern North America. Science 316:1181–1184
7. Stott PA, Stone DA, Allen MR (2004) Human contribution to the European heatwave of 2003. Nature 432:610–614
8. Trenberth KE, Shea DJ (2006) Atlantic hurricanes and natural variability in 2005. Geophys Res Lett 33:L12704
9. NRC (2010) Assessment of intraseasonal to interannual climate prediction and predictability. The National Academies, Washington, DC
10. Orlove B, Chiang J, Cane M (2000) Forecasting Andean rainfall and crop yield from the influence of El Nino on Pleiades visibility. Nature 403:68–71
11. Walker GS (1923) Correlations in seasonal variations of weather, VIII: a preliminary study of world weather. Mem India Meteorol Dep 24:75–131

12. Ropelewski CF, Halpert MS (1987) Global and regional scale precipitation patterns associated with the El Niño/Southern Oscillation. Mon Weather Rev 115:1606–1626
13. Ropelewski CF, Halpert MS (1989) Precipitation patterns associated with the high index phase of the southern oscillation. J Clim 2:268–284
14. Mason SJ, Goddard L (2001) Probabilistic precipitation anomalies associated with ENSO. Bull Am Meteorol Soc 82:619–638
15. Bjerknes J (1969) Atmospheric teleconnections from the equatorial Pacific. Mon Weather Rev 97:163–172
16. Wyrtki K (1975) El Niño – the dynamic response of the equatorial Pacific Ocean to atmospheric forcing. J Phys Oceanogr 5:572–584
17. Zebiak S, Cane MA (1987) A model of El Nino-Southern Oscillation. Mon Weather Rev 115:2262–2278
18. Battisti DS (1988) Dynamics and thermodynamics of a warming event in a coupled tropical atmosphere–ocean model. J Atmos Sci 45:2889–2919
19. Suarez Max J, Schopf Paul S (1988) A delayed action oscillator for ENSO. J Atmos Sci 45:3283–3287
20. Cane MA, Zebiak SE, Dolan SC (1986) Experimental forecasts of El Niño. Nature 321:827–832
21. Graham NE (1994) Decadal-scale climate variability in the tropical and North Pacific during the 1970s and 1980s: observations and model results. Clim Dyn 10:135–162
22. Mantua NJ, Hare SR, Zhang Y, Wallace JM, Francis RC (1997) A Pacific interdecadal climate oscillation with impacts on Salmon production. Bull Am Meteorol Soc 78:1069–1079
23. Hurrell JW, Van Loon H (1997) Decadal variations in climate associated with the North Atlantic Oscillation. Clim Change 36:301–326
24. Goldenberg SB, Landsea CW, Mestas-Nunez AM, Gray WM (2001) The recent increase in Atlantic hurricane activity: causes and implications. Science 293:474–479
25. Latif M, Barnett TP (1994) Causes of decadal climate variability over the North Pacific and North America. Science 266:634–637
26. Griffies SM, Bryan K (1997) Predictability of North Atlantic multidecadal climate variability. Science 275:181–184
27. IPCC (2007) Contribution of working group 1 to the fourth assessment report of the intergovernmental panel on climate change; Solomon S, Qin D, Manning M, Chen Z, Marquis M, Averyt KB, Tignor M, Miller HL (eds). Cambridge University Press, Cambridge
28. Vera C, Barange M, Dube OP, Goddard L, Griggs D, Kobysheva N, Odada E, Parey S, Polovina J, Poveda G (2010) Needs assessment for climate information on decadal timescales and longer. Procedia Environ Sci 1:275–286
29. Knight JR, Folland CK, Scaife AA (2006) Climate impacts of the atlantic multidecadal oscillation. Geophys Res Lett 33:L17706
30. Zhang R, Delworth TL (2006) Impact of Atlantic multidecadal oscillations on India/Sahel rainfall and Atlantic hurricanes. Geophys Res Lett 33:L17712
31. Schubert S, Gutzler D, Wang H, Dai A, Delworth T, Deser C, Findell K, Fu R, Higgins W, Hoerling M, Kirtman B, Koster R, Kumar A, Legler D, Lettenmaier D, Lyon B, Magana V, Mo K, Nigam S, Pegion P, Phillips A, Pulwarty R, Rind D, Ruiz-Barradas A, Schemm J, Seager R, Stewart R, Suarez M, Syktus J, Ting M, Wang C, Weaver S, Zeng N (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 Clim 22:5251–5272
32. Lau N-C, Nath MJ (2003) Atmosphere–ocean variations in the Indo-Pacific sector during ENSO episodes. J Clim 16:3–20
33. Xie S-P, Carton JA (2004) Tropical Atlantic variability: patterns, mechanisms, and impacts. Geophys Monogr 147:121–142
34. Giannini A, Chiang JCH, Cane MA, Kushnir Y, Seager R (2001) The ENSO teleconnection to the Tropical Atlantic Ocean: contributions of the remote and local SSTs to rainfall variability in the Tropical Americas. J Clim 14:4530–4544

35. Goddard L, Graham NE (1999) Importance of the Indian Ocean for simulating rainfall anomalies over eastern and southern Africa. J Geophys Res 104:19099–19116
36. Koster RD, Mahanama SPP, Yamada TJ, Balsamo G, Berg AA, Boisserie M, Dirmeyer PA, Doblas-Reyes FJ, Drewitt G, Gordon CT, Guo Z, Jeong J-H, Lawrence DM, Lee W-S, Li Z, Luo L, Malyshev S, Merryfield WJ, Seneviratne SI, Stanelle T, van den Hurk BJJM, Vitart F, Wood EF (2010) Contribution of land surface initialization to subseasonal forecast skill: first results from a multi-model experiment. Geophys Res Lett 37:L02402
37. Fischer EM, Seneviratne SI, Lüthi D, Schär C (2007) Contribution of land-atmosphere coupling to recent European summer heat waves. Geophys Res Lett 34:L06707
38. Cohen J, Fletcher C (2007) Improved skill of northern hemisphere winter surface temperature predictions based on land–atmosphere fall anomalies. J Clim 20:4118–4132
39. Jhun J-G, Lee E-J (2004) A New East Asian Winter Monsoon Index and associated characteristics of the winter monsoon. J Clim 17:711–726
40. Goddard L, Mason S (2002) Sensitivity of seasonal climate forecasts to persisted SST anomalies. Clim Dyn 19:619–632
41. Alexander MA, Bladé I, Newman M, Lanzante JR, Lau N-C, Scott JD (2002) The atmospheric bridge: the influence of ENSO teleconnections on air–sea interaction over the global oceans. J Clim 15:2205–2231
42. Jin F-F (1997) An equatorial ocean recharge paradigm for ENSO. Part I: conceptual model. J Atmos Sci 54:811–829
43. McPhaden MJ, Busalacchi AJ, Cheney R, Donguy J-R, Gage KS, Halpern D, Ji M, Julian P, Meyers G, Mitchum GT, Niiler PP, Picaut J, Reynolds RW, Smith N, Takeuchi K (1998) The tropical ocean-global atmosphere observing system: a decade of progress. J Geophys Res 103:14169–14240
44. Saha S, Nadiga S, Thiaw C, Wang J, Wang W, Zhang Q, Van den Dool HM, Pan H-L, Moorthi S, Behringer D, Stokes D, Peña M, Lord S, White G, Ebisuzaki W, Peng P, Xie P (2006) The NCEP climate forecast system. J Clim 19:3483–3517
45. Barnston AG, Chelliah M, Goldenberg SB (1997) Documentation of a highly ENSO-related SST region in the equatorial pacific. Atmos–Ocean 35:367–383
46. Larkin NK, Harrison DE (2005) On the definition of El Niño and associated seasonal average U.S. weather anomalies. Geophys Res Lett 32:L13705
47. Chen D, Cane MA, Kaplan A, Zebiak SE, Huang D (2004) Predictability of El Niño over the past 148 years. Nature 428:733–736
48. Kirtman Ben P, Shukla J, Huang B, Zhu Z, Schneider Edwin K (1997) Multiseasonal predictions with a coupled tropical ocean global atmosphere system. Mon Weather Rev 125:789–808
49. Barnston AG, He Y, Glantz MH (1999) Predictive skill of statistical and dynamical climate models in SST forecasts during the 1997–98 El Niño Episode and the 1998 La Niña Onset. Bull Am Meteorol Soc 80:217–243
50. Goddard L, DeWitt DG (2005) Seeking progress. In: El Niño Prediction, vol 3. US CLIVAR Variations
51. Davey M, Huddleston M, Sperber K, Braconnot P, Bryan F, Chen D, Colman R, Cooper C, Cubasch U, Delecluse P, DeWitt D, Fairhead L, Flato G, Gordon C, Hogan T, Ji M, Kimoto M, Kitoh A, Knutson T, Latif M, Le Treut H, Li T, Manabe S, Mechoso C, Power S, Roeckner E, Terray L, Vintzileos A, Voss R, Wang B, Washington W, Yoshikawa I, Yu J, Yukimoto S, Zebiak S, Meehl G (2002) STOIC: a study of coupled model climatology and variability in tropical ocean regions. Clim Dyn 18:403–420
52. Zhang S, Harrison MJ, Rosati A, Wittenberg A (2007) System design and evaluation of coupled ensemble data assimilation for global oceanic climate studies. Mon Weather Rev 135:3541–3564
53. Balmaseda MA, Fujii Y, Alves O, Awaji T, Behringer D, Ferry N, Lee T, Rienecker M, Rosati T, Stammer D, Smith D, Molteni F (2009) Initialization for seasonal and decadal forecasts. http://www.oceanobs09.net/blog/?p=57

54. Stockdale T, Anderson DLT, Balmaseda M, Doblas-Reyes FJ, Ferranti L, Mogensen K, Palmer TN, Molteni F, Vitart F (2011) ECMWF System 3 and its prediction of sea surface temperature. Clim Dyn. doi:s00382-010-0947-3/s00382-010-0947-3
55. Toth Z, Kalnay E (1993) Ensemble forecasting at NMC: the generation of perturbations. Bull Am Meteorol Soc 74:2317–2330
56. Molteni F, Buizza R, Palmer TN, Petroliagis T (1996) The ECMWF ensemble prediction system: methodology and validation. Q J R Meteorol Soc 122:73–119
57. Wilks DS (2006) Statistical methods in the atmospheric sciences, vol 59, International geophysics series. Academic, San Diego
58. Goddard L, Hoerling MP (2006) Practices for seasonal-to-interannual climate prediction. US CLIVAR variations, vol 4
59. Jin EK, Kinter JL, Wang B, Park C-K, Kang I-S, Kirtman BP, Kug J-S, Kumar A, Luo J-J, Schemm J, Shukla J, Yamagata T (2008) Current status of ENSO prediction skill in coupled ocean–atmosphere models. Clim Dyn 31:647–664
60. Hagedorn R, Doblas-Reyes FJ, Palmer TN (2005) The rationale behind the success of multi-model ensembles in seasonal forecasting – I. Basic concept. Tellus A 57:219–233
61. Rajagopalan B, Lall U, Zebiak SE (2002) Categorical climate forecasts through regularization and optimal combination of multiple GCM ensembles*. Mon Weather Rev 130:1792–1811
62. Robertson AW, Lall U, Zebiak SE, Goddard L (2004) Improved combination of multiple atmospheric GCM ensembles for seasonal prediction. Mon Weather Rev 132:2732–2744
63. Weigel AP, Liniger MA, Appenzeller C (2009) Seasonal ensemble forecasts: are recalibrated single models better than multimodels? Mon Weather Rev 137:1460–1479
64. NRC (ed) (2008) Review of CCSP draft synthesis and assessment product 5.3: decision-support experiments and evaluations using seasonal to interannual forecasts and observational data. The National Academies, Washington, DC
65. Robertson AW, Moron V, Swarinoto Y (2009) Seasonal predictability of daily rainfall statistics over Indramayu district, Indonesia. Int J Climatol 29:1449–1462
66. Gershunov A, Barnett TP (1998) ENSO influence on intraseasonal extreme rainfall and temperature frequencies in the contiguous United States: observations and model results. J Clim 11:1575–1586
67. Higgins RW, Leetmaa A, Kousky VE (2002) Relationships between climate variability and winter temperature extremes in the United States. J Clim 15:1555–1572
68. Joliffe IT, Stephenson DB (2003) Forecast verification: a practitioner's guide in atmospheric sciences. Wiley, Chicester
69. WMO (2002) World Meteorological Organization (WMO) Standardized verification system (SVS) for long-range forecasts (LRF) In: New attachment II-9 to the manual on the GDPS (WMO-N. 485), vol 1, Geneva
70. Livezey RE, Timofeyeva MM (2008) The first decade of long-lead U.S. seasonal forecasts. Bull Am Meteorol Soc 89:843–854
71. Goddard L, Dilley M (2005) El Niño: catastrophe or opportunity. J Clim 18:651–665
72. Gates WL (1992) AMIP: the atmospheric model intercomparison project. Bull Am Meteorol Soc 73:1962–1970
73. Palmer TN, Shukla J (2000) DSP/PROVOST. Q J R Meteorol Soc 126:1989–2350, Special Issue
74. Palmer TN, Doblas-Reyes FJ, Hagedorn R, Alessandri A, Gualdi S, Andersen U, Feddersen H, Cantelaube P, Terres J-M, Davey M, Graham R, Délécluse P, Lazar A, Déqué M, Guérémy J-F, Díez E, Orfila B, Hoshen M, Morse AP, Keenlyside N, Latif M, Maisonnave E, Rogel P, Marletto V, Thomson MC (2004) Development of a European multimodel ensemble prediction system for seasonal-to-interannual prediction (DEMETER). Bull Am Meteorol Soc 85:853–872
75. Hewitt CD, Griggs DJ (2004) Ensembles-based predictions of climate changes and their impacts. EOS 85:566

76. Kirtman B, Pirani A (2009) The state of the art of seasonal prediction: outcomes and recommendations from the First World Climate Research Program Workshop on seasonal prediction. Bull Am Meteorol Soc 90:455–458
77. Power S, Casey T, Folland C, Colman A, Mehta V (1999) Inter-decadal modulation of the impact of ENSO on Australia. Clim Dyn 15:319–324
78. Alexander MA, Deser C, Timlin MS (1999) The reemergence of SST anomalies in the North Pacific Ocean. J Clim 12:2419–2433
79. Schneider N, Miller AJ (2001) Predicting Western North Pacific Ocean Climate. J Clim 14:3997–4002
80. Di Lorenzo E, Schneider N, Cobb KM, Franks PJS, Chhak K, Miller AJ, McWilliams JC, Bograd SJ, Arango H, Curchitser E, Powell TM, Rivière P (2008) North Pacific Gyre oscillation links ocean climate and ecosystem change. Geophys Res Lett 35:L08607
81. Deser C, Phillips AS, Hurrell JW (2004) Pacific Interdecadal climate variability: linkages between the Tropics and the North Pacific during Boreal Winter since 1900. J Clim 17:3109–3124
82. Meehl GA, Hu A (2006) Megadroughts in the Indian Monsoon Region and Southwest North America and a mechanism for associated multidecadal Pacific Sea surface temperature anomalies. J Clim 19:1605–1623
83. Knight JR, Allan RJ, Folland CK, Vellinga M, Mann ME (2005) A signature of persistent natural thermohaline circulation cycles in observed climate. Geophys Res Lett 32:L20708
84. Vellinga M, Wu P (2004) Low-latitude freshwater influence on centennial variability of the Atlantic thermohaline circulation. J Clim 17:4498–4511
85. Latif M, Roeckner E, Botzet M, Esch M, Haak H, Hagemann S, Jungclaus J, Legutke S, Marsland S, Mikolajewicz U, Mitchell J (2004) Reconstructing, monitoring, and predicting multidecadal-scale changes in the North Atlantic thermohaline circulation with sea surface temperature. J Clim 17:1605–1614
86. Stoner AMK, Hayhoe K, Wuebbles DJ (2009) Assessing general circulation model simulations of atmospheric teleconnection patterns. J Clim 22:4348–4372
87. AchutaRao K, Sperber KR (2006) ENSO simulation in coupled ocean–atmosphere models: are the current models better? Clim Dyn 27:1–15
88. Gray ST, Graumlich LJ, Betancourt JL, Pederson GT (2004) A tree-ring based reconstruction of the Atlantic multidecadal oscillation since 1567 A.D. Geophys Res Lett 31:L12205
89. Davey M, and co-authors, 2006. Multi-model multi-method multi-decadal ocean analyses from the ENACT project. CLIVAR Exchanges, Vol 11, No. 3, pgs 22–25. http://eprints.soton.ac.uk/41286/1/Exchanges38.pdf
90. Collins M, Botzet M, Carril AF, Drange H, Jouzeau A, Latif M, Masina S, Otteraa OH, Pohlmann H, Sorteberg A, Sutton R, Terray L (2006) Interannual to decadal climate predictability in the North Atlantic: a multimodel-ensemble study. J Clim 19:1195–1203
91. Branstator G, Teng H (2010) Two limits of initial-value decadal predictability in a CGCM. J Clim 23:6292–6311. doi:10.1175/2010JCLI3678.1
92. Rodwell MJ, Drévillon M, Frankignoul C, Hurrell JW, Pohlmann H, Stendel M, Sutton RT (2004) North Atlantic forcing of climate and its uncertainty from a multi-model experiment. Q J R Meteorol Soc 130:2013–2032
93. Taylor KE, Stouffer RJ, Meehl GA (2011) Bulletin of the American Meteorological Society. http://dx.doi.org/10.1175/BAMS-D-11-00094.1
94. Baldwin MP, Dunkerton TJ (2001) Stratospheric harbingers of anomalous weather regimes. Science 294:581–584
95. Gottschalck J, Wheeler M, Weickmann K, Vitart F, Savage N, Lin H, Hendon H, Waliser D, Sperber K, Nakagawa M, Prestrelo C, Flatau M, Higgins W (2010) A framework for assessing operational Madden–Julian oscillation forecasts: a CLIVAR MJO Working Group Project. Bull Am Meteorol Soc 91:1247–1258
96. Zhang S, Rosati A (2010) An inflated ensemble filter for ocean data assimilation with a biased coupled GCM. Mon Weather Rev 138:3905–3931

97. Vitart F, Buizza R, Balmaseda M, Balsamo G, Bidlot J-R, Bonet A, Fuentes M, Hofstadler A, Molteni F, Palmer TN (2008) The new VarEPS-monthly forecasting system: a first step towards seamless prediction. Q J R Meteorol Soc 134:1789–1799
98. Hazeleger W, Severijns C, Semmler T, Ştefănescu S, Yang S, Wang X, Wyser K, Dutra E, Baldasano J, Bintanja R, Bougeault P, Caballero R, Ekman AML, Christensen JH, van den Hurk B, Jimenez P, Jones C, Kållberg P, Koenigk T, McGrath R, Miranda P, van Noije T, Palmer T, Parodi J, Schmith T, Selten F, Storelvmo T, Sterl A, Tapamo H, Vancoppenolle M, Viterbo P, Willén U (2010) EC-Earth: a seamless earth system prediction approach in action. Bull Am Meteorol Soc 91:1357–1363

Books and Reviews

Hurrell JW, Delworth T, Danabasoglu G, Drange H, Griffies S, Holbrook N, Kirtman B, Keenlyside N, Latif M, Marotzke J, Meehl G A, Palmer T, Pohlmann H, Rosati T, Seager, R, Smith D, Sutton R, Timmermann A, Trenberth KE, and Tribbia J (2010) Decadal climate prediction: opportunities and challenges. In: Hall J, Harrison DE, Stammer D (eds) Proceedings of OceanObs'09: sustained ocean observations and information for society, vol 2. ESA Publication WPP-306: Venice, 21–25 Sep 2009. Available at http://www.oceanobs09.net/blog/?p=97

Latif M, Delworth T, Dommenget D, Drange H, Hazeleger W, Hurrell J, Keenlyside N, Meehl GA, and Sutton R (2010) Dynamics of decadal climate variability and Implications for its prediction. In: Hall J, Harrison DE, Stammer D (eds) Proceedings of OceanObs'09: sustained ocean observations and information for society, vol 2. ESA Publication WPP-306: Venice, 21–25 Sep 2009. Available at http://www.oceanobs09.net/blog/?p=104

Mehta V, Meehl GA, Goddard L, Knight J, Kumar A, Latif M, Lee T, Rosati A, Stammer D (2010) The eighth workshop on decadal climate variability decadal climate predictability and prediction: where are we? Bull Am Meteorol Soc. doi:10.1175/2010BAMS3025.1

Murphy J, Kattsov V, Keenlyside N, Kimoto M, Meehl G, Mehta V, Pohlmann H, Scaife A, Smith D (2010) Towards prediction of decadal climate variability and change. Procedia Environ Sci 1:287–304. doi:10.1016/j.proenv.2010.09.018