

## Food Security and Sociopolitical Stability

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## What Do We Know About the Climate of the Next Decade?

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### Abstract and Keywords

The climate of the next decade will not fully determine crop yields, food prices, food security, or sociopolitical stability, but it will be influential. Over the next ten years, climate variations will be dominated by natural climate variability with anthropogenic climate change being secondary. For this next decade, the greatest climate concerns for agriculture are not secular trends but extreme events, including droughts, floods, and heat waves, as well as catastrophic events such as tropical cyclones. Climate science has shown that large-scale climate patterns alter the probability of these events. The climate system is chaotic and so predictability is intrinsically limited, and thus far decadal climate prediction is largely limited to the response to anthropogenic forcings.

*Keywords:* climate variability, climate change, decadal climate prediction, anthropogenic climate change

The years from 1876 to 1879 were a time of global catastrophe. Severe drought in China, India, Ethiopia, the Nordeste region of Brazil, and low Nile flow in Egypt led to widespread famine and disease, resulting in at least 17 million deaths worldwide—and perhaps twice that number (Davis 2001, 7). Based on excellent British records, it is fairly certain that rainfall in India in 1877 was less than at any time in the past 150 years. Although the droughts were especially severe, climate variations were not solely responsible for the appalling loss of life. Acknowledging the role of climate does not exonerate the Raj. During this period grain continued to be exported from India. British policy relied on railroads to distribute food in time of famine, and then only to those who worked. People were herded into camps in order to facilitate this policy, and malaria spread. The greatest loss of life was due to malaria and other diseases, rather than starvation (Whitcombe 1993).

In India, the drought precipitated a food shortage, leading to famine and epidemics among a weakened population. The variation in climate also had a direct influence on the malaria cycle by changing temperature and water-related factors, including rainfall, standing water, and stream flow. The malaria epidemic was worst after the drought was over because mosquitoes recover more rapidly from the drought than their predators, so the vector population was likely to have been larger than normal (Bouma and van der Kayy 1994, 1996). British interests

favored a cash crop economy, reducing the flexibility of a society previously able to respond to drought by growing food for local use and by foraging in nearby forests. The immediate response of the Raj to the crisis—creating camps—made things worse. In complex ways, climate variability can substantially impact the resilience of a social system.

Many authors have argued for a connection between climate and the collapse of civilizations or less calamitous but still important historical events. **(p.65)** The books of Brian Fagan offer copious examples; in *Floods, Famines, and Emperors: El Niño and the Fate of Civilizations* he discusses the fall of the Old Kingdom in ancient Egypt, the Moche society of Peru, and the Maya of lowland Central America among others. While Fagan is perhaps overly generous in labeling all the climate changes in question as “El Niño,” there is no doubt that these collapses coincided with strong climate changes. The most common explanation by Fagan and others for the link is a drought leading to food shortages and famine that place an unsupportable stress on an already weakened sociopolitical entity. Drought is the usual culprit, but catastrophic flooding destroyed Moche infrastructure and agriculture. Climate doubters emphasize the pre-existing weaknesses in these civilizations and tend to regard the concurrent climate changes as mere coincidence.

There is scholarly and other literature championing the impact of climate on food security and sociopolitical stability in contemporary times. Sahelian drought has been invoked as a cause of the conflict in Darfur. Hsiang et al. (2011) present quantitative evidence that over the past 60 years conflicts worldwide increase in an El Niño year. They do not establish a clear mechanistic linkage from El Niño to conflict, but offer a number of possible routes, food security prominent among them. They also point out that agricultural workers idled by droughts or other conditions are more susceptible to a call to arms as a means of redressing long-standing grievances, or simply as a chance to improve their lot with the spoils of war.

There is another lesson to be learned from the events of the 1870s and other instances of climate impacts on human affairs. Quite often, local climatic disasters are embedded in shifts of the global patterns of climate variation. The El Niño and its associated Southern Oscillation (ENSO) are the largest and best-known examples of such shifts. Though smaller in amplitude than the regular seasonal cycle, the unpredictable interannual variability is far more difficult for societies to cope with. ENSO influences the frequency of forest fires, hurricanes, severe winter storms, and other localized climatic events. The exceptionally strong El Niño in 1877 was undoubtedly a cause of the globally dispersed regional droughts mentioned above, all of which are typical occurrences in an El Niño year. Yancheva et al. (2007) find simultaneous changes in the Caribbean and in China of the position of the Intertropical Convergence Zone in the eighth through the tenth centuries AD. The droughts brought on by these changes coincide with the simultaneous rise and falls of the Classic Mayan civilizations and the Tang dynasty. At that time, these two sophisticated societies were unaware of each other’s existence. In today’s interconnected world, however, the impact of simultaneous global climate change could prove explosive.

The question at hand is the climate of the next decade, especially as it might impact food security and sociopolitical stability. The foregoing should make **(p.66)** it plain that this will involve natural climate variations as much or more than anthropogenic climate change.

Even though natural variability will dominate the climate of the next decade, there are regions where the trends induced by anthropogenic climate change will have a detectable impact. The most prominent climate signals already evident in observational data and clearly attributable to anthropogenic climate change are the rise in mean global temperature and the amplification of the warming signal in Northern Hemisphere polar regions (IPCC 2007). These are clear warning signs of global problems to come, but neither is terribly relevant to food security issues in the next decade. The changes that are relevant are subtler, but no less real.

Extreme events—droughts, pluvials, heat waves, frosts, tropical cyclones, and severe storms in midlatitudes—are also unquestionably important for food security. It is virtually impossible to attribute a single event, such as Hurricane Katrina or the Russian summer heat wave of 2010, to anthropogenic climate change, but anthropogenic climate change does shift the odds of occurrence for extreme events.

There is no reason to doubt that anthropogenic climate change will entail changes in the mean climate state. IPCC models indicate that the Hadley Cell will expand (Lu et al. 2007), the amount of moisture in the atmosphere will increase, and the jet streams will be displaced (IPCC WG1 2007; Lu et al. 2008). Such changes in the mean may result in changes in the characteristic patterns of natural variability. Remote effects (“teleconnections”) of natural modes like ENSO are transmitted via atmospheric wave-guides that will change when the mean state changes, so these remote influences might be altered. For example, the influence of the North Atlantic Oscillation (NAO) on the Mediterranean might be weakened, or the intensity of ENSO-related floods might change.

“Natural variability” can be broadly divided into variability internal to the climate system and variability generated by external forcing, which includes changes in solar radiance and in natural aerosol from volcanic eruptions.<sup>1</sup> There is some skill in predicting solar cycles a decade ahead, but we have no ability to predict volcanic eruptions, and at their historical worst they make the anthropogenic climate change expected in the next decade seem trivial. The Tambora eruption of 1815 caused the crop failures of the “year without a summer” (Stommel and Stommel 1983) and the eruption of 1258 was far stronger (Stothers 2000). Such powerful eruptions are highly unlikely in the next—or

any—decade, but they cannot be ruled out, and far weaker but still potent events, such as the 1991 Pinatubo eruption, would be enough to alter aspects of the world’s climate and put a temporary halt to global warming. We cannot foresee the volcanic eruptions of the next decade, but we could use the observational record of the past millennium to estimate the probability of eruptions and their consequences.

The question of whether there are distinct physics determining decadal variability has some bearing on how much accuracy we might expect from (p.67) decadal predictions. Decadal climate prediction is a field in its infancy, forced into the world somewhat prematurely by the needs of policymakers. It aims to cover the gap between seasonal to interannual prediction with lead times of two years or less and projections of climate change a century ahead.

Because natural variability as well as greenhouse gases and aerosols will influence future decades, predictions must start from a specification of the current state of the climate system in addition to accounting for the effects of anthropogenic forcing. The hope is that the extra information provided by a good enough estimate of the initial state will allow the models to track natural variability, resulting in more accurate forecasts of the next decade or two. This hope is more likely to be realized if rather than being random, decadal variability arises from physical modes evolving deterministically over a decade.

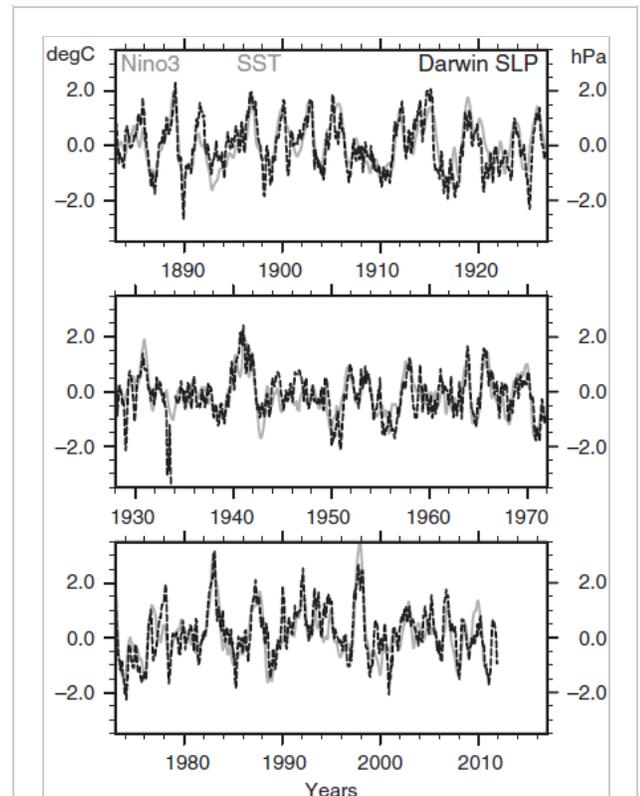
The climate of the next decade will not fully determine crop yields, food prices, food security, or sociopolitical stability, but it will be influential. Over the next ten years, climate variations will be dominated by natural climate variability, with anthropogenic climate change having a secondary effect. For this next decade, the greatest climate concerns for agriculture are not secular trends but extreme events, including droughts, floods, and extended periods of extreme temperatures, as well as catastrophic events such as tropical cyclones. The climate system is chaotic, and to some degree extreme events are effectively random and hence unpredictable. However, in recent decades climate science has shown that large-scale climate patterns alter the probability of these events in many regions.

### El Niño and the Southern Oscillation (ENSO)

The term “El Niño” was used long ago by Peruvian fishermen for the annual warming of coastal waters that occurs around Christmas time. We now use the term for a broad warming of the eastern equatorial Pacific, though there is no accepted definition of how much of a warming over exactly what region it takes to qualify as an “El Niño.” Figure 3.1 shows two widely used indices for ENSO over the past century and a half. NINO3, which refers to the sea surface temperature (SST) anomaly in the NINO3 region (90W–150W, 5S–5N) of the eastern equatorial Pacific, is a commonly used index of El Niño. The “Southern Oscillation” is a seesawing of atmospheric mass, and hence of sea-level pressure (SLP), between the eastern and western Pacific. It is most often indexed by the Southern Oscillation Index (SOI), a normalized SLP difference between Darwin, Australia and Tahiti. Figure 3.1 simply uses SLP at Darwin, which is almost the same because the anti-correlation between Tahiti and Darwin is so high. There is a striking similarity between the SLP and SST measures, one atmospheric and one oceanic, widely separated in space. Clearly, they (p.68)

index the same phenomenon. Some periods such as the last decades of the nineteenth or twentieth centuries are marked by numerous high amplitude oscillations, while others, such as the 1930s, are rather quiet. The strong positive swings (El Niño events) in 1877, and in the years around 1890, and again around 1900 were times of widespread drought and famine.

Our understanding of the ENSO cycle is built upon Jacob Bjerknes’ (1969, 1972) brilliant insights from his studies of the scant observational data then available.<sup>2</sup> Bjerknes did more than point out the empirical relation between the oceanic El Niño and the atmospheric Southern Oscillation. In Bjerknes’ (p.69) account of the connection between the ocean and atmosphere, the fishermen’s coastal El Niño is incidental to the important oceanic change, the warming of the tropical Pacific over a quarter of the circumference of the Earth. ENSO is generated and maintained by two-way interactions between the ocean and atmosphere in the equatorial Pacific, according to Bjerknes. Work in the 1970s and 1980s, especially under the auspices of the international Tropical Ocean Global Atmosphere (TOGA) Programme, provided theoretical and observational support for Bjerknes’ concept. Bjerknes’ theory accounted for the existence of extreme warm (El Niño) states and cold (normal, or in the extreme, La Niña) states, but stopped short of explaining the oscillations between states. The required addition, equatorial ocean dynamics, was made by Klaus Wyrtki (1975, 1979) based on data from a network of Pacific island tide gauges. The first model



to successfully simulate ENSO, and, soon afterwards, to predict ENSO, that of Zebiak and Cane (1987), was based explicitly on the Bjerknes-Wyrtki hypothesis.

The Zebiak-Cane numerical ENSO model depicts in a simplified manner the evolution of the tropical Pacific Ocean and overlying atmosphere. It is a dynamic model derived from the governing physical equations, in contrast to a statistical model built from a sequence of observations. Analysis of the model helped in developing a now widely accepted theory that treats ENSO as an internal mode of oscillation of the coupled atmosphere-ocean system, perpetuated by a continuous imbalance between the tightly coupled surface winds and temperatures on the one hand, and the more sluggish subsurface heat reservoir on the other.<sup>3</sup> One of the most significant results of the model simulations was the recurrence of ENSO at irregular intervals due solely to internal processes. This shows that solar variations or volcanic eruptions or other forcings external to the climate system are not required to drive the ENSO cycle, but it does not rule out the possibility that such external factors might influence it. Indeed, it turns out that they do (see Mann et al. 2005; Emile-Geay et al. 2007, 2008).

Bjerknes located the source of ENSO in a tropical Pacific coupling between El Niño and the Southern Oscillation, but he also proposed that the changes in atmospheric heating associated with tropical Pacific SST anomalies cause changes in midlatitude circulation patterns. Figure 3.2 is a version of a well-known diagram of the global influence of an ENSO warm event, an El Niño (after Ropelewski and Halpert 1987; all of the relationships discussed below may be found in that paper or Ropelewski and Halpert 1996). As a first approximation, one may say that ENSO cold events, often called “La Niña,” have the opposite effects, but there are significant exceptions. Typically, the effects of ENSO events are strongest and most reliable in the tropical Pacific genesis region and contiguous continents. When there is a warm event one can be fairly certain of heavy rains in Peru, drought in Indonesia and New Guinea, and drought and fewer typhoons in Australia. Typical consequences

(p.70) are somewhat less reliable in the global tropics, but still highly likely. Thus, there is frequent concurrence of ENSO warm events and a poor monsoon in India, below normal rains in southern Africa, resulting in poor maize yield in Zimbabwe (Cane et al. 1994), flooding in East Africa, drought in the Nordeste of Brazil, and reduced numbers of hurricanes in the Atlantic.

(p.71) ENSO influence beyond the tropics is less certain. Outside of the tropics an ENSO event should be thought of as biasing the system toward certain preferred outcomes rather than as a certain cause. Many of the more reliable midlatitude effects occur in the Americas. With warm (El Niño) events heavy rains in the Great Basin region of the United States are more likely, and with cold (La Niña) events, midwestern drought (e.g., 1988) and lower corn yields (Phillips et al. 1999) are more likely. It is more likely still that the southwestern United States and northern Mexico will experience drought with a La Niña, and above average rainfall with an El Niño. Similarly, an El Niño is likely to bring heavy rains to Uruguay, southern Brazil, and northern Argentina, while a La Niña brings below average rainfall. Certain patterns become more likely to persist, altering the paths of hurricanes, typhoons, and winter storms. For example, typhoons are more likely to make landfall near Shanghai in an El Niño year.

Another way to say that not all ENSO connections are equally strong and reliable is the more general statement that the global impacts of each ENSO event are different. The differences are not related in any obvious way to the magnitude of the events. For example, the Indian monsoon was normal in 1997 despite the very strong El Niño, while in 2002 the monsoon was very poor although the 2002 El Niño was quite moderate. Understanding of these differences is limited: they have hardly been classified satisfactorily, let alone explained in physical

Fig. 3.1 . Measures of El Niño and of the Southern Oscillation, 1866–2003

Note: The grey curve is a commonly used index of El Niño, the sea-surface temperature (SST) anomaly in the NINO3 region of the eastern equatorial Pacific (90°W–150°W, 5°S–5°N). The black curve is the sea-level pressure (SLP) at Darwin, Australia, an index of the atmospheric Southern Oscillation. Both are 3-month running mean anomalies from the long-term average. The close relationship between the two indices is evident. (Departures in the earliest part of the record are more likely due to data quality problems than to real structural changes in ENSO.)

Source: Drawn from Kaplan SST and Darwin SLP data at <http://iridl.ldeo.columbia.edu> (accessed April 21, 2013).

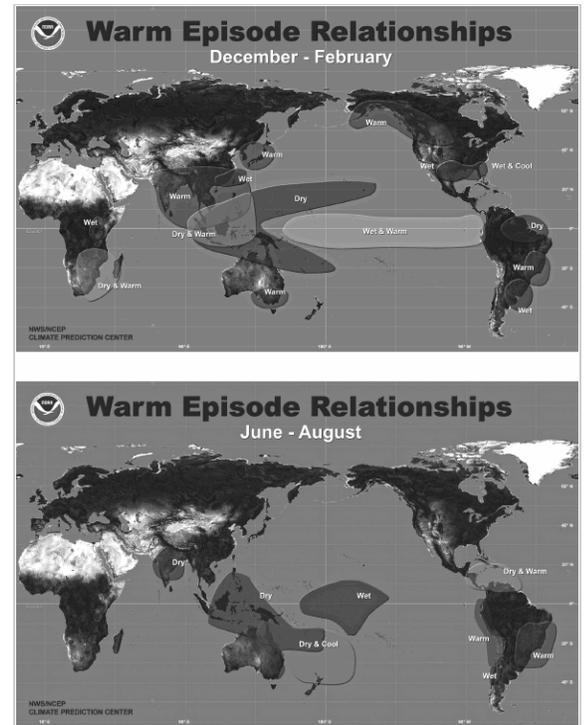


Fig. 3.2 . Warm event (El Niño) relationships

Source: Ropelewski and Halpert (1987). Available at [http://www.cpc.ncep.noaa.gov/products/analysis\\_monitoring/](http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/) (accessed April 21, 2013).

terms. However, it is known that the global response is sensitive to the location and strength of the atmospheric heating in the tropics (e.g., Hoerling et al. 1997).

A second reason that the global impacts of each ENSO event are unique is that the atmosphere is a chaotic, dynamic system, which means that small changes in boundary and initial conditions can be amplified to give very large differences in the future state of the atmosphere. One result of this chaos is “weather”—that is, variability on a timescale much shorter than the timescale of what we call “climate variations.” We may think of weather (and other short-time variability) as random “noise” in the climate system that makes the system unpredictable: even with SST and other boundary conditions fixed, the atmosphere may evolve into very different states if started with only slight differences in its initial state. The higher level of weather “noise” in the extratropics is a reason why ENSO impacts are more reliable in the tropics.

### Predicting ENSO Impacts

ENSO theory has a number of implications for prediction. First, since the essential interactions take place in the tropical Pacific, data from that region alone may be sufficient for forecasting. Second, the memory of the coupled system resides in the ocean. Anomalies in the atmosphere are dissipated far **(p.72)** too quickly to persist from one El Niño event to the next. The surface layers of the ocean are also too transitory. Hence the memory must be in the subsurface ocean thermal structure. The crucial set of information for El Niño forecasts is the spatial variation of the depth of the thermocline in the tropical Pacific Ocean. The thermocline is the thin region of rapid temperature change separating the warm waters of the upper ocean from the cold waters of the abyssal ocean.

Since 1985, our group at Lamont has used the Zebiak–Cane model (known as the Lamont model in the forecasting realm) to predict El Niño (Cane et al. 1986). The only data going into our first forecasts were observations of surface winds over the ocean. Using the wind data as a forcing field, we ran the ocean component of the model to generate currents, thermocline depths, and sea surface temperatures that served as initial conditions for forecasts, a step made necessary by the lack of direct observations of oceanic variables. Each forecast then consisted of choosing the conditions corresponding to a particular time, and running the coupled model ahead to predict the evolution of the combined ocean–atmosphere system. By making predictions for past times—“hindcasts” or “retrospective forecasts”—we could compare forecasts directly with reality. The results clearly demonstrated predictive skill, setting the stage for the first predictions of the future, made in early 1986, which called unambiguously for an El Niño occurrence later that year (Cane et al. 1986). The moderate El Niño that developed later in 1986 matched the forecast well enough to score it a success, although differences in timing and other details show that the prediction scheme was far from perfect.

In the 1980s the Lamont model was the only physically based forecasting system with this level of accuracy, but now several dozen models with varying degrees of complexity make routine ENSO forecasts.<sup>4</sup> These models can be divided into three categories: purely statistical models, physical ocean–statistical atmosphere hybrid models, and fully physical ocean–atmosphere coupled models. There have been a number of reviews of ENSO forecast skill over the years; Barnston et al. (2012) is the most recent. The general conclusions are that the predictions have useful skill at least two seasons ahead, and that the skills of the physical and statistical models are comparable, though there is a suggestion that the physical models have greater skill at longer leads. The ensemble mean forecast across all prediction systems has markedly greater skill than any single forecast (Tippett and Barnston 2008).

Most modelers believe that only for the past few decades is the observational data adequate for model initialization. Thus, the periods of retrospective forecasting are too short to distinguish among the skill scores of different prediction systems or to allow a confident estimate of our overall ability to predict ENSO. However, Chen et al. (2004) performed a retrospective forecast experiment spanning the past one and a half centuries that uses only reconstructed SST data for model initialization. Each month all other initial fields **(p.73)** (winds, thermocline depth, etc.) are created by the model from these SSTs and the model’s state at the previous month. At a six-month lead, the model is able to predict most of the warm and cold events that occurred during this long period, especially the larger El Niño and La Niña events, though the model had difficulty with small events and no-shows (see Chen et al. 2004, Fig. 1).

If the reaction to the 1986 forecasts was surprise that it could be done at all, the question now is why we aren’t doing better. The factors now limiting the accuracy of forecasts are inherent limits to predictability, flaws in the models, gaps in the observing system, and flaws in the data assimilation systems used to introduce the data into the models.

ENSO is surely predictable, but how predictable is it? Is there much more room for improvement of our predictive skill? One cause of uncertainty is in the ways we estimate ENSO’s predictability. In weather forecasting, predictability is estimated using twin-model experiments in which initial conditions are perturbed slightly from one run to the next, and the separation of the evolved atmospheric states tells us how fast small initial errors grow. This is error growth in the *model*, but weather-forecasting models are realistic enough to make it a reliable measure for error growth in nature. ENSO models however, have not been shown to be realistic enough for this purpose and the

answer is model dependent. Estimates of El Niño’s predictability based on the retrospective predictions over one to three decades available for most models encompass a relatively small number of events and so are quite uncertain. The uncertainty is increased by the fact that ENSO predictability varies from decade to decade (Chen et al. 1995; Balmaseda et al. 1995; Kirtman and Schopf 1998).

As evident in Figure 3.3, the predictive skill of the Lamont model varies substantially, especially at longer lead times. The periods with the highest overall scores, 1876 to 1895 and 1976 to 1995, are dominated by strong and regular ENSO events. The periods of lower skill have fewer and smaller events to predict. For example, during the 1936 to 1955 period, when the predictability was the lowest by all measures, the only strong El Niño is the prolonged warm event in 1940–42 (see Figure 3.1). Though data coverage was reduced in the years of the Great Depression and Second World War, it was not worse than in the nineteenth century, so for the results shown here we may conclude that temporal variations in predictability outweigh variations in data availability. This is only one model and one data assimilation method, and it does not rule out the likely possibility that observations of the subsurface ocean would improve forecasts, especially in the less active periods. Regardless, the predictability of ENSO is limited in principle by the chaotic and noisy nature of the climate system, so forecasts are most correctly presented as a probability distribution of possible future states.

Uncertainties as to the inherent limits to predictability notwithstanding, it appears that our current level of predictive skill is far from those limits. Our (p.74)

task then is to improve our observing systems, models, and data assimilation methods. Tremendous efforts have been made in all these areas in the last two decades. Observation networks such as Tropical Atmosphere Ocean (TAO) array and satellite altimetry and scatterometry missions have proven invaluable for ENSO monitoring and forecasting. The current observing system does not seem to be the principal limitation on our skill (Stockdale et al. 2011), though constant vigilance is needed to ensure that it does not deteriorate. (p.75) Regional and global models with different degrees of complexity have been significantly improved in terms of both physics and computational capability, but these models are still notably imperfect, and their ability to simulate ENSO is not among their stronger points.<sup>5</sup>

The area with the greatest near-term potential for improving skill is data assimilation, the process of creating an initial state for the forecast by combining observational data with a model-generated first guess. While there is 60 years of data assimilation experience for weather forecasting, application from seasonal to interannual forecasting presents new challenges because of the necessity of initializing the ocean state as well as the atmosphere (Chen and Cane 2008). In addition to the new technical questions the ocean adds, there is the fact that observations of the subsurface ocean are few and far between, especially if one would like to “practice” forecasting by going back earlier than the last two decades. Even in the hypothetical case that data coverage is so good that the state of the atmosphere and ocean is very well known, it would still be a challenge to determine the initial state that yields the best forecast. The problem is that the model is not perfect, so that even if the data were so good that we could start it in the same place as nature, it would insist on evolving differently. One telltale of model imperfection is that the average state of a model over a long time—its climatology—differs from nature’s climatology. In other words, the model has systematic biases. Unfortunately, it is not easy to characterize model bias in ways that lend themselves to improved data assimilation, and only a few studies have addressed this issue for ENSO forecasting (Chen and Cane 2008). More research is needed in the analysis of the pattern, nature, and statistics of the biases, and in the implementation of proper bias correction schemes for coupled General Circulation Models (GCMs).

Predicting the state of the tropical Pacific is only the beginning for predicting socially relevant climate variations, such as those affecting agriculture. Given the correct SSTs in the tropical Pacific, atmospheric models are quite good at capturing the “teleconnections” to land areas depicted in Figure 3.2. Figure 3.2 derives from a statistical analysis of data, so statistical models also capture these relations. Yet these teleconnections are not certain consequences of an ENSO event; rather the ENSO cycle shifts their probability of occurrence. In an El Niño

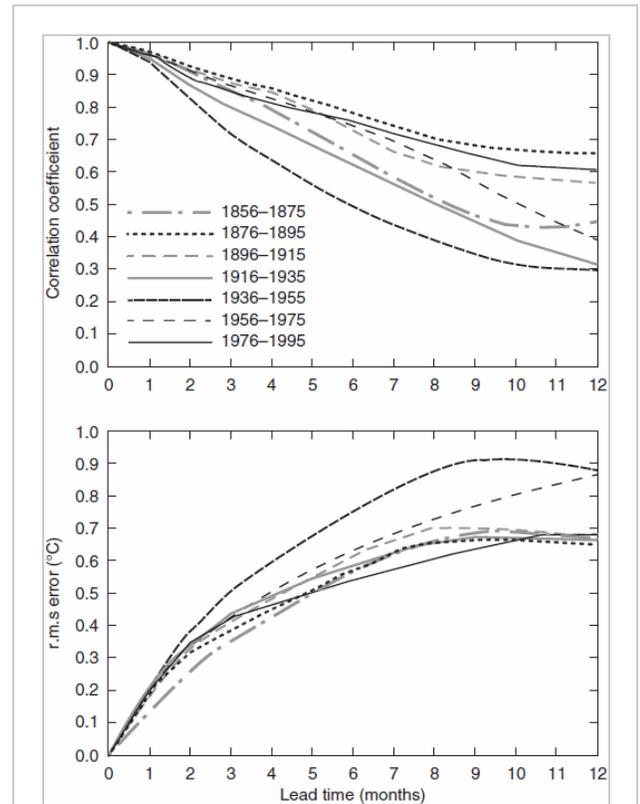


Fig. 3.3. Anomaly correlations (top) and rms (root-mean-square) errors (bottom) between observed and predicted NINO3.4 index

Note: Recorded as a function of lead-time, for seven consecutive 20-year periods since 1856.

Source: Chen et al. 2005.

year there is a very high probability of drought in Indonesia, while in India, the mean prediction would also be below average monsoon rainfall, but the distribution would be wider, reflecting the reality that in almost 40 percent of El Niño events rainfall is close to the average. Finally, not all seasonal to interannual predictability stems from ENSO. SST patterns in the other tropical oceans contribute, especially to regions adjacent to these oceans (Goddard et al. 2001). Insofar as these SSTs are predictable, however, it is primarily because of the influence of ENSO.

**(p.76) Decadal Variability**

There are many contrasts between decadal variability and ENSO in addition to the obvious one of timescale. Most telling, we have no accepted theories for decadal variability and no evidence that socially useful predictions are possible. In fact, it is not firmly established that there is such a thing as variations in climate with particular physical mechanisms that favor a decadal timescale. Perhaps we have identified certain variations as decadal because the short instrumental record does not allow us to see that the same patterns occur at longer intervals. On the other hand, there is value in describing these modes and their associated impacts, and we have not ruled out the possibility that they are predictable.

Surface temperature anomalies on decadal timescales are no larger than a few tenths of a degree Celsius. It might seem that such puny anomalies could not matter, but there is ample evidence that they do. Figure 3.4, adapted from Seager et al. (2005) shows that the Dust Bowl drought can be simulated by an atmospheric model forced by SSTs of this amplitude—though they must have the right pattern.<sup>6</sup> The anomalies that matter most are the La Niña-like pattern in the tropical Pacific; the lower right panel shows how much of the drought over North America is captured when the model is forced by anomalies in that region only. Next in importance is the warming in the North Atlantic, which resembles a positive Atlantic Multidecadal Oscillation, which is discussed below.

The literature on low-frequency climate variability is typically organized around a small set of variously named patterns with acronyms: El Niño–Southern Oscillation (ENSO); North Atlantic Oscillation (NAO), which for some is equivalent to the Arctic Oscillation (AO) or the Northern Annular Mode (NAM); Pacific Decadal Oscillation (PDO), Pacific Decadal Variability (PDV), or Interdecadal Pacific Oscillation (IPO); Atlantic Multidecadal Oscillation (AMO) or Atlantic Multidecadal Variability (AMV); Southern Annular Mode (SAM); and more. A few low-frequency climate variations, such as monsoon variability, have been studied extensively despite lacking the grace note of an acronym.

The PDO patterns of SST, SLP, and winds are compared with ENSO in Figure 3.5 (Mantua et al. 1997; Mantua and Hare 2002). The PDO amplitude is relatively greater in the North Pacific and smaller in the tropics, but the overall similarity in pattern suggests dynamic similarities (Alexander et al. 2002). When temperatures are colder in the central North Pacific, they are warmer in the eastern tropical Pacific and along the coast of North America. The time series are quite distinct: the PDO is dominated by variability at timescales longer than a decade and ENSO is interannual. In the twentieth century, PDO variability is greatest at periodicities of 15 to 25 years and 50 to 70 years, so we cannot say that the PDO has a single characteristic frequency. One view **(p.77)**

of Figure 3.5 sees only two full PDO cycles: cool tropical phases from 1890 to 1924 and again from 1947 to 1976, with switches to warm phases in about 1925 and 1977. A “climate regime shift,” particularly in the Pacific, is often said to have occurred from 1976 to 1977 (e.g., Trenberth 1990). This shift has been observed in Pacific marine ecosystems; Alaskan salmon production is something of a poster child for the PDO (see Mantua and Hare 2002 and references **(p.78)** **(p.79)** therein). The warm phase of the PDO depicted in Figure 3.5 is usually accompanied by winter season (October to March) anomalies reminiscent of El Niño anomalies. These include warmer air temperatures and below average snow pack and stream flow in northwestern North America, cooler temperatures in the southeastern United States, above average precipitation in the southern United States and northern Mexico, and below average rainfall in eastern Australia (Power et al. 1999).

The NAO has been known far longer than the PDO and has a far larger literature. The climatic patterns over the North Atlantic are shown in Figure 3.6 along with a time series of a standard NAO index (Figure 3.6b), the SLP difference between the Azores and Iceland. Pressure at these two places tends to fluctuate

**(p.80)** out of phase: when the Icelandic low is anomalously low and the Azores high is anomalously high, the winds over the Atlantic tend to be stronger than

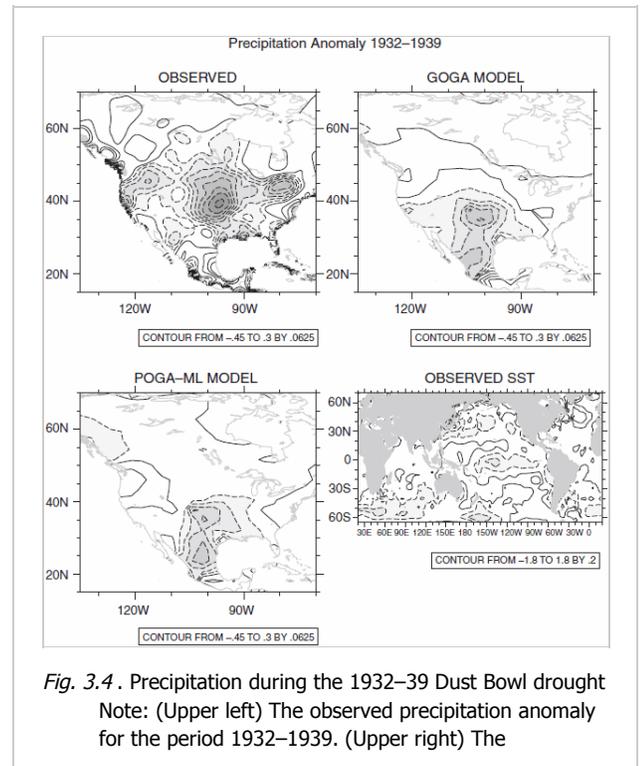


Fig. 3.4. Precipitation during the 1932–39 Dust Bowl drought  
Note: (Upper left) The observed precipitation anomaly for the period 1932–1939. (Upper right) The

normal and the enhanced southwest to northeast flow brings warm wet weather to northern Europe. In this positive phase of the NAO the Mediterranean region tends to be dry because the storm tracks are diverted away from it. Recent droughts and forest fires on the Iberian Peninsula are consistent with the positive NAO pattern. Positive NAO winters on the east coast of the United States are relatively mild and wet, while in the negative phase the east coast of the United States has more cold air outbreaks. This is because the storm tracks take a more southerly route, which also brings more precipitation to the Mediterranean. Mediterranean harvest yields of grapes and olives have been shown to depend significantly on the NAO. More generally, an upward trend in the NAO brings drought conditions to the Middle East.

While its intraseasonal variability has been attributed to weather “noise,” the origin of the NAO’s interannual persistence, which leads to an apparent decadal fluctuation, remains unclear (Kushnir et al. 2006). Over a considerable time there were many attempts to show that North Atlantic SST anomalies are essential in creating this enhanced persistence or even an oscillation in atmospheric pressure; they have largely failed. Barsugli and Battisti (1998) argue that the North Atlantic SSTs do matter in that the NAO SST pattern is the one that least damps what is in essence an *atmospheric* mode (also see the discussion in Kushnir et al. 2006). The variability in an index of the NAO is not different from a power law distribution; its spectrum has no significant peaks suggestive of an oscillatory process (Wunsch 1999). This fact supports the notion that the NAO is a consequence of a favored atmospheric pattern generated by synoptic weather “noise.”

The AMO is a mode in which North Atlantic SSTs are warmer than normal almost everywhere or colder than normal almost everywhere. When the North Atlantic is warm, northern Europe tends to be warmer and wetter, and there is typically less rain over the United States, especially the eastern half of the country (Enfield et al. 2001; Sutton and Hodson 2005). Note the similarities to the positive phase of the NAO. A warmer tropical North Atlantic (as occurs with a positive AMO) results in more rainfall in the Sahel (Giannini et al. 2003; Biasutti and Giannini 2006). A weaker Indian monsoon has been linked to colder temperatures in the North Atlantic related to both NAO and AMO negative phases; Goswami et al. (2006) propose that the link is via changes in tropospheric temperatures over Eurasia.

A positive AMO has been shown to be strongly associated with an increase in Atlantic hurricane activity (Kerr 2005), which has created an intense debate over whether or not the current warm AMO is part of the global man-made warming signal (Mann and Emanuel 2006) or whether it is a internal mode of climate variability (Goldenberg et al. 2001). This attribution question requires separating the internal AMO mode from the climate response forced by solar (p.81) variations, aerosols, or greenhouse gases (Trenberth and Shea 2006; Zhang et al. 2007; Knight 2009). Approaches range from simply removing the linear trend from SSTs averaged over the North Atlantic Basin (Enfield et al. 2001) to sophisticated statistical methods (Schneider and Held 2001; Ting et al. 2009; Del Sole et al. 2011). The issue has arisen again very recently in the assertion of Booth et al. (2012) that the low frequency variability in the Atlantic sector during the twentieth century was a consequence of variations in radiative properties of clouds induced by aerosols. This conclusion, which is drawn from simulations with a model using a new and very strong representation of this “indirect effect” of aerosols on the Earth’s heat budget, will surely be challenged.

precipitation anomaly from the GOGA ensemble of Atmospheric GCM simulations forced by the global SST anomaly pattern shown in the lower right hand panel. (Lower left) the precipitation anomaly from the POGA-ML ensemble of atmospheric simulations forced by the SST pattern in the tropical Pacific between 20N and 20S. Ocean temperatures elsewhere are calculated from a simple mixed layer model. (Lower right) The observed SST anomaly. Precipitation in mm/month; SST in °C.

Source: After Seager et al. 2005; data courtesy of Naomi Henderson and Richard Seager; the observational precipitation data used is CRU-TS3.1.

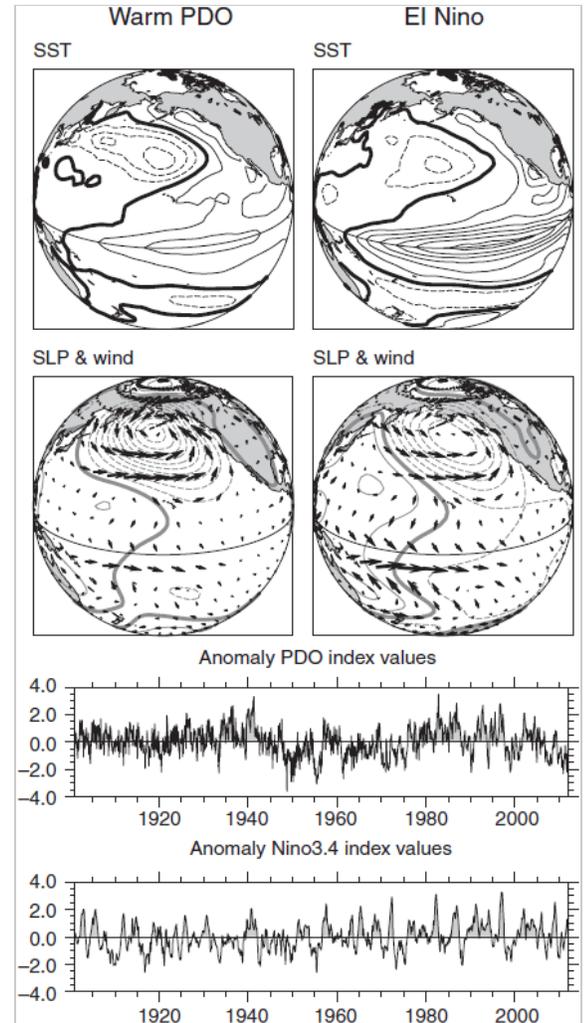


Fig. 3.5. The sea surface temperature (SST), sea level pressure (SLP), and wind patterns associated with the PDO (Pacific Decadal Oscillation) positive phase (left) and the ENSO warm phase (right).

Note: The contour interval (CI) is 0.2°C for SST and 0.4 hPa for SLP. The time series is based on monthly means.

Source: Top figure is ERSSTv3 SST; SLP and winds from NCEP Reanalysis; all available at <http://iridl.ldeo.columbia.edu> (accessed March 21, 2013). The time series data is from

## Anthropogenic Climate Change

Disputes about whether recent warming trends in the North Atlantic are attributable to natural or human causes notwithstanding, few would disagree with the anemic but correct claim that both are active. There is no doubt that the world has warmed over the past century, especially during the past few decades. No one should doubt that human activity is largely responsible: the evidence is too abundant and too pertinent (e.g., in IPCC 2007). Though models do not agree on the precise regional distribution of temperature changes, certain robust projections appear in observational data by the end of the twentieth century (Table SPM.2 in the Working Group I Report of IPCC 2007). Over most land areas these include warmer and fewer cold days and nights; more frequent hot days and nights; more frequent heat waves.

Unlike temperature, anthropogenic influences on precipitation are not obvious. As the air warms, the amount of water vapor the air holds goes up 7 percent per °C, but precipitation does not increase nearly as fast. Since the atmosphere stores very little water, the amount of global precipitation must equal the amount of evaporation. Global evaporation at the surface is constrained by the Earth's energy budget and is estimated to be about 2 percent per °C (Allen and Ingram 2002; Held and Soden 2006). One consequence of the far more rapid increase of water held by the atmosphere is that individual rain events will become more intense. While this trend is already seen in twentieth-century observational records (Table SPM.2 in the Working Group I Report of IPCC 2007), there is little else conclusive to be said about precipitation changes. The IPCC WG 1 report (2007, 23) says: "Significantly increased precipitation has been observed in the eastern parts of North and South America, northern Europe and northern and central Asia. Drying has been observed in the Sahel, the Mediterranean, southern Africa and parts of southern Asia. Precipitation is highly variable spatially and temporally, and robust (p.82) long-term trends have not been established for other large regions." Even the cited trends cannot be firmly attributed to anthropogenic influences: natural causes cannot be ruled out. For example, Sahel rainfall is closely related to the position of the Intertropical Convergence Zone (ITCZ) in the Atlantic, and this in turn is strongly affected by the SST distribution in the Atlantic, including the AMO (Giannini et al. 2003; Zhang and Delworth 2006).

We can make a few general statements about the likely changes in precipitation. It is likely that the "wet places get wetter and the dry places get dryer" (Held and Soden 2006). This follows if, as expected with anthropogenic climate change, the amount of moisture in the atmosphere increases markedly while the circulation changes only slightly (Allen and Ingram 2002; Held and Soden 2006). The places where it rains are places where moisture converges in the atmosphere, and more moisture and about the same convergence means more convergence of moisture and hence more rain. Similarly, the dry places, which are the places where moisture diverges away, stand to lose more heavily.

A relatively robust result in IPCC AR4 models is the expansion of the circulation poleward, so that the midlatitude storm tracks move poleward, and the subtropical belt where air sinks expands as well as moving poleward. These subtropical regions contain most of the world's deserts and semi-arid regions. This, together with the "dry places get dryer" argument, leads one to expect increased droughts in, among other places, the Mediterranean region, the southwestern United States and northern Mexico, and much of Australia. Allen et al. (2012) summarize the observational evidence that the expansion is already occurring, but also show that it may be more a consequence of changes in tropospheric ozone and black carbon than greenhouse gases. Biasutti and Giannini (2006) present evidence that the late twentieth-century drying is more a response to aerosols than to greenhouse gases. These culprits are all anthropogenic in origin, though not the usual suspects.

## Predicting Decadal Climate

Forecasting the climate of the next decade will demand some skill at forecasting interannual and decadal natural variability, as well as changes due to anthropogenic influences. Natural variability includes changes in external radiative forcing due to solar variations and volcanic eruptions as well as changes internal to the climate system. Anthropogenic influences include activities that alter atmospheric ozone and aerosols, as well as greenhouse gases. Other human influences include land-use changes, though additional changes in the next decade

<http://jisao.washington.edu/pdo/PDO.latest> (accessed March 21, 2013).

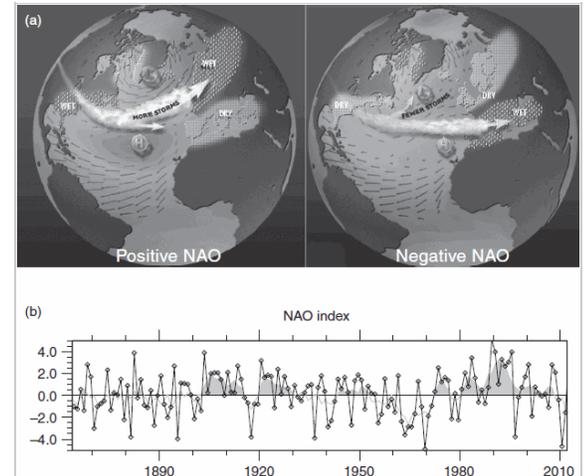


Fig. 3.6. The sea surface temperature (SST), sea level pressure (SLP), and storm track locations associated with positive (top left) and negative (top right) phases of the North Atlantic Oscillation (NAO). The time series (bot) is an NAO index.

Note: Wet and dry anomalies are labeled. The NAO index is the winter (December thru March) difference of normalized sea level pressure (SLP) between Lisbon, Portugal, and Stykkisholmur/Reykjavik, Iceland. The black curve is the DJFM average for every year; the gray curve is a 5-year running average.

Source: (top) <http://www.ldeo.columbia.edu/res/pi/NAO/> (accessed March 21, 2013). (bottom)

<http://climatedataguide.ucar.edu/guidance/hurrell-north-atlantic-oscillation-nao-index-station-based> (accessed March 21, 2013).

seem unlikely to have an appreciable effect on large regions.

Most skill in predicting interannual climate variability stems from our ability to predict ENSO. Prediction of ENSO a year or two ahead rests on a good **(p.83)** theoretical understanding of ENSO dynamics. In particular, the upper levels of the tropical Pacific Ocean provide the “inertia” so that the ENSO cycle continues into the future. However, there is no demonstrated skill in predicting ENSO up to a decade ahead, and our limited understanding of the intrinsic predictability of ENSO does not rule out the possibility that this is impossible in theory as well as in our now primitive practice. We lack a decent theoretical understanding of decadal and multidecadal variations such as the PDO and AMO, so we do not know if their past behavior determines their future evolution. The leading view at present is that they are not self-sustained oscillations, but perhaps damped ocean modes driven by atmospheric noise, a view that would seem to limit hopes for predictability. That they do not exhibit a preferred timescale is another blow to optimism. Still, it may be that once one of these noise-driven modes is set decisively in motion, it will follow through in a predictable pattern. The greatest hope lies in the North Atlantic, where the meridional overturning circulation (AMOC), which models simulate with apparent success, might be the internal ocean mode that provides the inertia to impart predictability to the AMO.

As with ENSO, decadal predictions can be made with statistical models, dynamical models, or hybrids. Lean and Rind (2009) use linear regression models trained on historical data to predict surface temperature at each  $5^{\circ}\times 5^{\circ}$  square on the Earth’s surface, as well as the mean global temperature. The predictors are ENSO, solar and volcanic activity, and a measure of anthropogenic influence that attempts to account for greenhouse gases, land use, snow albedo changes, and tropospheric aerosols (Hansen et al. 2007).

The Lean and Rind statistical model pays no attention to decadal modes of variability, whereas forecasts with two dynamical models that greatly stimulated enthusiasm for decadal forecasting were looking to the AMOC/AMO mode as a source of skill (Smith et al. 2007; Keenlyside et al. 2008). The retrospective forecasts they report do show skill relative to the most basic forecasts, ones that either assume the persistence of existing conditions, or forecast climatological conditions. It is noteworthy that Smith et al. (2007) predict that the next five years will be warmer than the past decade, while Keenlyside et al. (2008) predict the opposite. Moreover, neither study is persuasive in showing that using information about the present state of the climate provides skill beyond that attributable to anthropogenic forcing.

The forecasts of Smith et al. (2007), for example, use the data assimilation system DePreSys to incorporate the observed state of the atmosphere and ocean in order to predict internal variability. They also estimate changes in anthropogenic sources of greenhouse gases and aerosol concentrations, as well as forecasts of changes in solar irradiance and volcanic aerosol. Their NoAssim forecasts differ from the DePreSys forecasts in that they do not assimilate the observed state of the atmosphere or ocean. Results from the two sets of forecasts offer just the slightest hint that assimilation might be helpful (see Smith et al. 2007, Fig. 3).<sup>7</sup>

**(p.84)** Why isn’t assimilation more beneficial? The reasons are similar to the ones that limit ENSO prediction. Starting from an observed initial state is essential to predicting the evolution of natural variability internal to the climate system such as the AMO or PDO, but it is not at all established that much predictability is even theoretically possible. Capturing the current state of these decadal modes requires knowledge of the ocean’s state, and observations of the subsurface ocean are very sparse. The deployment of a global network of Argos floats within the past decade has vastly improved matters, but that still leaves us without much knowledge of earlier times to practice our hindcasts. Initializing the ocean state for prediction purposes is a very new endeavor, and current efforts are surely far from optimal. Finally, and perhaps most important, climate models are imperfect and have their own climate, biased away from nature’s climate. When started from an initial state that is realistic they may evolve natural anomalies somewhat correctly, but they will also be moving away from nature’s climate toward their own. That error may overwhelm any gains from starting with correct climate anomalies.

As part of the IPCC AR5 there will soon be a large number of studies in the same vein as Smith et al. (2007). For now, there are two actual forecasts in the literature in very different styles. Seager et al. (2004) used the Zebiak–Cane intermediate complexity ENSO model to make the prediction that an ENSO index averaged for the period 1998 to 2013 would be colder than in the previous 15 years.<sup>8</sup> The prediction is based solely on projecting internal variability: it does not explicitly account for anthropogenic or other external forcing. This work followed up on a theoretical study of decadal predictability in the Zebiak–Cane model (Karspeck et al. 2004). That study used an “identical twin” methodology in which a model simulation substitutes for reality. Karspeck et al. (2004) found some predictability, but even in this idealized setting it was only slightly better than chance—too small an advantage to be of much practical use.

Hoerling et al. (2011) predicted the mean decadal climate over North America for 2011 through 2020 in response to anthropogenic greenhouse gases. The methodology is complex, involving an ensemble of runs with a number of different models and corrections of model biases using several observational data sets for the twentieth century. SSTs from existing IPCC coupled model runs (CMIP3) together with two bias corrected versions of SST for 2011 to 2020 are used as boundary forcing for a multimodel set of Atmospheric General Circulation Model runs. Temperatures are warmer almost everywhere, markedly so in Alaska and northern Canada. The latter is largely a response to

reduced summer sea ice in the Arctic. Precipitation generally increases over Canada and Alaska, and is reduced over much of the United States. In this study, the internal variability of the climate system is regarded not as something to be predicted, but as noise that moves the actual (p.85)

climate away from the forced response. Figure 3.7 shows distributions of possible states obtained by adding this internal noise to the forced response together with the distributions from simulations of a preindustrial world lacking anthropogenic forcing. There is a high probability of warmer temperatures in the United States (94 percent probability) and Canada (98 percent) and of above average precipitation in Canada (99 percent), while dryer conditions over the United States are likely (75 percent). In other words, the forced signal is sufficiently greater than the decadal climate variability (p.86) to give a highly significant probability of climate change for all but United States precipitation. Note that these are forecasts for decadal averages, not for the individual years of a decade. Any given year would have a large component of internal variability. While there is some predictability for a year or two ahead due largely to ENSO, at longer leads there is no demonstrated predictive skill.

In all regions and globally, almost all predictive skill for the next decade derives from the anthropogenically forced trend. There could be some additional skill from extrapolating solar activity forward in time, but there is nothing to be done for volcanic aerosol—except to let it add to the uncertainty of the forecast. The internal variability of the climate system in modes such as ENSO, AMO, and PDO is also primarily a source of climate noise, adding uncertainty to forecasts, though there is some reason for optimism, especially for the North Atlantic sector.

### Three Recent Droughts: the Southwestern United States, the Mediterranean, and East Africa

None of these extended droughts was predicted, and we cannot say if any of them might have been predictable. Since 1998 there has been a serious drought in the southwestern United States and northern Mexico. On the one hand, this might be taken as confirmation of the global warming projections that the subtropical zones will expand and become more arid. Seager et al. (2007) show precipitation minus evaporation in the southwestern United States as projected by four different IPCC models. Remarkably, all indicate a shift to a more arid regime circa 1998. On the other hand, there has been a prevalent La Niña pattern in the equatorial Pacific since the end of the 1997–98 El Niño, and southwestern drought is an expected consequence of this SST configuration. We do not know if the drought should be attributed solely to natural decadal variations resulting in the La Niña-like pattern of tropical Pacific SSTs—a pattern unlike the one predicted by IPCC climate projections—or whether it is at least in part due to anthropogenic climate change.

The Mediterranean has also been gripped by drought in recent years, raising the question of whether this drought might have contributed to the Arab Spring uprisings, including the ongoing conflict in Syria. The Mediterranean is another subtropical region expected to become drier under the influence of anthropogenic climate change. However, it is also a region prone to drought when a positive phase of the NAO prevails. If anthropogenic climate change is the cause, then the drought may be expected to persist, but if the NAO is controlling, the Mediterranean would become wetter again as the NAO cycle (p.87) shifts toward a negative state. Two recent studies (Hoerling et al. 2011; Kelley et al. 2011) used models to address this attribution question. These studies show that the larger share of Mediterranean drying in recent decades is associated with natural variability, especially the NAO, but that in a few regions—southern Spain, the Atlas Mountains, and the Middle East—human influence is at least comparable. This suggests that current drought conditions in Syria are attributable to anthropogenic climate change, and that future droughts will be a common occurrence in the Middle East.

East Africa has also suffered a decade-long drought, with disastrous consequences for food security in the region. Widespread famine in Somalia has led to a migration populating what is now the world's largest refugee camp in Kenya. According to the IPCC (2007) assessment,

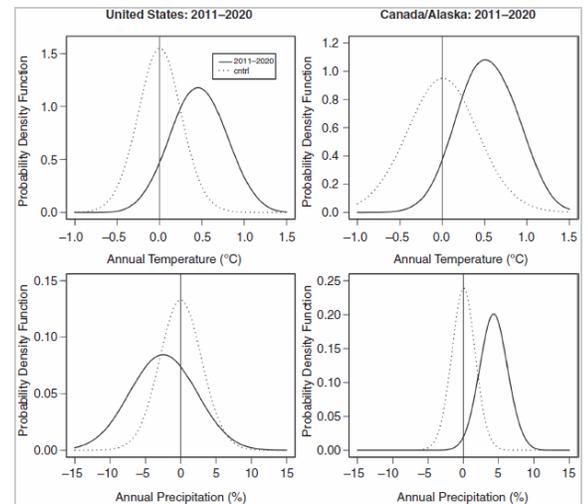


Fig. 3.7. Probabilistic forecasts (solid lines) for the 2011–20 decadal anomalies of (left) contiguous U.S. (top) surface temperature and (bottom) precipitation and (right) Canada/Alaska (top) surface temperature and (bottom) precipitation. Preindustrial climatologies are shown as dotted lines.

Note: The curves are based on commingling the PDFs of the forced responses to our scenarios of anthropogenic changes in ocean boundary conditions and the decadal climate conditions resulting from natural, internal decadal SST variability during the twentieth century. It is assumed that the North American anomalies resulting from natural decadal SST conditions and those from the anthropogenic change component are linearly additive. All departures are relative to the 1971–2000 reference. Dotted-line PDFs illustrate the statistics of decadal climate anomalies derived from the roughly 8,000 independent samples of 10-yr averages calculated from preindustrial CMIP3 simulations.

Source: Hoerling et al. 2011, Figure 4, © American Meteorological Society. Used with permission.

the expected consequence of anthropogenic climate change is above average rainfall in this region. Since 1998 the equatorial Pacific has been dominated by a pattern that resembles La Niña in having a strengthened zonal SST gradient, and one expected consequence of a La Niña event would be reduced rainfall in East Africa. Complicating the picture is the fact that the established link to La Niña and ENSO is with the short (October–December) rains, but in the current drought the long (March–May) rains have also been poor, failing disastrously in 2010 and 2011 (Lyon and DeWitt 2012 and references therein). Moreover, the ENSO link to the short rains is not directly with the Pacific but via ENSO-induced changes in Indian Ocean SSTs (Goddard and Graham 1999), whereas Lyon and DeWitt (2012) show that the long rains are linked to changes in western Pacific SSTs. At present we cannot say whether the East African drought is a consequence of natural variability overwhelming the response to greenhouse gas forcing, or whether the IPCC models, which tend to weaken the zonal SST gradient in the Pacific, are failing to capture the correct response to human influences on the climate system. If we attain some skill in decadal prediction of SSTs in the tropical Pacific and the North Atlantic, then perhaps droughts like these might prove to be predictable.

### Climate and Food Security: Looking Forward

A number of historical cases and some quantitative studies strongly suggest that sociopolitical stability can be influenced by climate changes, but the mechanistic links between them are far from clear. The most frequently cited is food security, as there is no doubt that food production is affected by variations in climate. Of course, food security is important in itself, regardless of whether or not its loss leads to sociopolitical instability. The same may be said for a number of other possible links that can connect climate to sociopolitical instability, including increased disease burdens, increased unemployment (of **(p.88)** agricultural workers when a drought ruins crops, for example), destruction of transportation and other infrastructure by flooding, and elevated temperatures causing more crime and conflict and decreasing industrial productivity (Hsiang 2010).

Climate alone is not sufficient to generate food insecurity or sociopolitical instability. Other conditions must be met. Amartya Sen has taught us that famines are not so much a consequence of climatological drought as they are a consequence of entitlement, of access to resources. The most disastrous climate event of the past 150 years was probably the 1877 El Niño, which triggered widespread famines. The meteorological drought in India caused food shortages, but the policies of the British Raj transformed a climate event into the loss of millions of lives. The current famine in Somalia is a stark example. The 2012 drought has caused crop failure and food shortages, but it is the anarchic warlordism that is blocking relief efforts that could prevent starvation. The summer of 2012 brought extreme drought to the midwestern United States, but no one expects the crop failure to lead to food shortages there: prices will rise, but Americans will not starve.

Global impacts are more difficult to foresee and will depend on how crops fare elsewhere. The Middle East has come to rely on the Russian and Ukrainian wheat crops, and it is plausible though unproven that the failure of these crops in the Russian heat wave of 2010 had some influence on the Arab Spring in 2011. One of the lessons of climate science is that many climate anomalies have widespread impacts, so strong effects will rarely be confined to a single region. While climate events will lead to the worst outcomes in places where the society is internally vulnerable, external climate variations can also push such societies over the edge. For example, although conflicts occur in places that are conflict-prone for societal reasons, Hsiang et al. (2011) have shown that the number of civil conflicts in the world increase in an El Niño year.

What can be said about the climate of the next decade, about its impacts on agriculture and other human activities, and about the implications for food security and sociopolitical stability? Far less than we would like.

We wish we could predict the climate variations of the next decade with some certainty. Unfortunately, our ability to do this is quite limited, because our knowledge and prediction tools are limited, but more importantly, because the climate system is chaotic. The climate of the next decade will be a combination of natural interannual variability, natural variability on decadal and other long time scales, and the response to anthropogenic forcing. The last includes industrial aerosols and land use changes in addition to the main actor, greenhouse gases. Natural changes may be internal to the climate system or forced by external factors, specifically solar radiation and volcanic aerosols. These external factors do matter for the climate of the next decade, and while we can probably extrapolate solar activity a decade ahead, we have no ability to predict volcanic eruptions.

**(p.89)** The main factor in interannual variability is ENSO, which is reasonably well understood and can be predicted. Current predictive skill extends for a year or two ahead at best, and although ENSO forecasting may improve, it is unlikely that there is even the theoretical possibility of predictability a decade ahead. The best hope seems to lie in the North Atlantic, where models simulate variability with some realism, and where there is a plausible role for the ocean, with its long memory. Anthropogenic influences do appear to be predictable a decade ahead, and the climate response over this time is nearly invariant under different scenarios of greenhouse gas emissions. Over much of the globe this predictable effect dominates over internal variability in decadal averages, though not for year-to-year variations. It does introduce a bias that alters the probability of occurrence of extreme events like warm spells and droughts. One of the more likely influences is the expansion and intensification of drying in subtropical regions, including the Mediterranean and the southwestern United States/northern

Mexico.

The expansion of the subtropical dry belt is one of the more certain changes to be expected in the next decade, but in order to assess potential climate impacts on agriculture and other sectors we would like to have a globally complete, quantitative set of regional climate changes. Most important would be extreme events: extended heat waves, droughts, floods, severe storms, and tropical cyclones. We know it is impossible to predict such events very far ahead, but by knowing the influences of anthropogenic climate change, of interannual variations (ENSO, primarily), and longer period climate variations such as the AMO or PDO, we can estimate the expected changes in the probability of occurrence of extreme events.

The next years will bring a substantial increase in the number of decadal forecasts. A deeper understanding and some improvement in forecast skill is a likely outcome, although we will probably not gain a useful ability to predict decadal variations internal to the climate system, such as the AMO. At a minimum, we can expect a better depiction of the regional characteristics of climate noise and a better accounting of the probabilities of extreme events. This climate information may improve assessment of the climate risk for food security and could be used as input to crop models, hydrologic models, and other sectoral models to provide a best assessment of the climate risk for food security and other factors that influence sociopolitical stability.

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## Notes

### References

#### Bibliography references:

- Alexander, M. A., I. Bladé, M. Newman, J. R. Lanzante, N.-C. Lau, and J. D. Scott. 2002. The atmospheric bridge: The influence of ENSO teleconnections on air–sea interaction over the global oceans. *Journal of Climate* 15: 2205–31.
- Allen, M. R., and W. J. Ingram. 2002. Constraints on future changes in climate and the hydrologic cycle. *Nature* 419: 224–32.
- Allen, R. J., S. C. Sherwood, J. R. Norris, and C. S. Zender. 2012. Recent Northern Hemisphere tropical expansion primarily driven by black carbon and tropospheric ozone. *Nature* 485: 350–4. doi:10.1038/nature11097.
- Balmaseda, M. A., M. K. Davey, and D. L. T. Anderson. 1995. Decadal and seasonal dependence of ENSO prediction skill. *Journal of Climate* 8: 2705–15.
- Barnston, A. G., M. K. Tippett, M. L. L'Heureux, S. Li, and D. G. DeWitt. 2012. Skill of real-time seasonal ENSO Model predictions during 2002–11: Is our capability increasing? *Bulletin of the American Meteorological Society* 93: 631–51.
- Barsugli, J. J., and D. S. Battisti. 1998. The basic effects of atmosphere–ocean thermal coupling on midlatitude variability. *Journal of the Atmospheric Sciences* 55: 477–93. (p.91)
- Biasutti, M., and A. Giannini. 2006. Robust Sahel drying in response to late 20th century forcings. *Geophysical Research Letters* 33:L11706. doi:10.1029/2006GL026067.
- Bjerknes, J. 1969. Atmospheric teleconnections from the equatorial Pacific. *Monthly Weather Review* 97: 163–72.
- . 1972. Large-scale atmospheric response to the 1964–65 Pacific equatorial warming. *Journal of Physical Oceanography* 15: 1255–73.
- Booth, B. B. B., N. J. Dunstone, P. R. Halloran, T. Andrews, and N. Bellouin. 2012. Aerosols implicated as a prime driver of twentieth-century North Atlantic climate variability. *Nature* 484: 228–32. doi:10.1038/nature10946.
- Bouma, M. J., and J. J. van der Kuy. 1994. Epidemic malaria in India and the El Niño Southern Oscillation: Health and climate change. *Lancet* 344: 1389.
- . 1996. The El Niño Southern Oscillation and the historic malaria epidemics on the Indian subcontinent and Sri Lanka: An early

warning system for future epidemics? *Tropical Medicine and International Health* 1: 86–96.

Cane, M. A. 1986. El Niño. *Annual Review of Earth and Planetary Sciences* 14: 43–70.

———. 2005. The evolution of El Niño, past and future. *Earth and Planetary Science Letters* 104: 1–10.

———, G. Eshel, and R. W. Buckland. 1994. Forecasting maize yield in Zimbabwe with Eastern equatorial Pacific sea surface temperature. *Nature* 370: 204–205.

———, S. E. Zebiak, and S. C. Dolan. 1986. Experimental forecasts of El-Niño. *Nature* 321(6073): 827–32.

Chen, D., and M. A. Cane. 2008. El Niño prediction and predictability. *Journal of Computational Physics* 227(7): 3625–40. doi:10.1016/j.jcp.2007.05.014.

———, A. Kaplan, S. E. Zebiak, and D. Huang. 2004. Predictability of El Niño over the past 148 years. *Nature* 42: 733–36.

———, S. E. Zebiak, A. J. Busalacchi, and M. A. Cane. 1995. An improved procedure for El Niño forecasting: Implications for predictability. *Science* 269: 1699–702.

Cook, B. I., R. L. Miller, and R. Seager. 2008. Dust and sea surface temperature forcing of the 1930s “Dust Bowl” drought. *Geophysical Research Letters* 35: L08710. doi:10.1029/2008GL033486.

Davis, M. 2001. *Late Victorian holocausts: El Niño famines and the making of the Third World*. London: Verso.

Del Sole, T., M. K. Tippett, and J. Shukla. 2011. A significant component of unforced multidecadal variability in twentieth century global warming. *Journal of Climate* 24: 909–25

Emile-Geay, J., M. A. Cane, R. Seager, A. Kaplan, and P. Almasi. 2007 El Niño as a mediator of the solar influence on climate. *Paleoceanography* 22: PA3210. doi:10.1029/2006PA001304.

Emile-Geay, J., R. Seager, M. A. Cane, E. R. Cook, and G. H. Haug. 2008. Volcanoes and ENSO over the last millennium. *Journal of Climate* 21: 3134–48.

Enfield, D. B., A. M. Mestas-Núñez, and P. J. Trimble. 2001 The Atlantic multidecadal oscillation and its relation to rainfall and river flows in the continental U.S. *Journal of Geophysical Research* 28: 2077–80.

Giannini, A., R. Saravanan, and P. Chang. 2003. Oceanic forcing of Sahel rainfall on interannual to interdecadal time scales. *Science* 302: 1027–30. **(p.92)**

Goddard, L., and N. E. Graham. 1999. The importance of the Indian Ocean for simulating precipitation anomalies over eastern and southern Africa. *Journal of Geophysical Research* 104: 19099–116.

Goddard, L., S. J. Mason, S. E. Zebiak, C. F. Ropelewski, R. Basher, and M. A. Cane. 2001. Current approaches to seasonal to interannual climate predictions. *International Journal of Climatology* 21: 1111–52.

Goldenberg, S. B., C. W. Landsea, A. M. Mestas-Núñez, and W. M. Gray. 2001. The recent increase in Atlantic hurricane activity: Causes and implications. *Science* 293: 474–49.

Goswami, B. N., M. S. Madhusoodanan, C. P. Neema, and D. Sengupta. 2006. A physical mechanism for North Atlantic SST influence on the Indian summer monsoon. *Geophysical Research Letters* 33: L02706. doi:10.1029/2005GLO24803.

Hansen, J., M. Sato, R. Ruedy, P. Kharecha, A. Lacis, R. L. Miller, L. Nazarenko et al. 2007. Climate simulations for 1880–2003 with GISS model E. *Climate Dynamics* 29: 661–96. doi:10.1007/s00382-007-0255-8.

Held, I. M. and B. J. Soden. 2006. Robust responses of the hydrological cycle to global warming. *Journal of Climate* 19: 5686–99.

Hoerling, M., J. Hurrell, A. Kumar, L. Terray, J. Eischeid, P. Pegion, T. Zhang, X. Quan, T. Xu. 2011. On North American decadal climate for 2011–20. *Journal of Climate* 24: 4519–28. doi:10.1175/2011JCLI4137.1.

- Hoerling, M. P., A. Kumar, and M. Zhong. 1997. El Niño, La Niña, and the nonlinearity of their teleconnections. *Journal of Climate* 10: 1769–86.
- Hsiang, S. 2010. Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America. *Proceedings of the National Academy of Sciences* 107: 15367–72.
- , K. Meng, and M. A. Cane. 2011. Civil conflicts are associated with the global climate. *Nature* 476: 438–41. doi:10.1038/nature10311.
- IPCC. 2007. *Climate change 2007: The physical science basis*. Eds. S. Solomon, D. Qin, M. Manning, Z. Chen, M. Marquis, K. B. Averyt, M. Tignor, and H. L. Miller. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge and New York: Cambridge University Press.
- Karspeck, A., R. Seager, and M. A. Cane. 2004. Predictability of tropical Pacific decadal variability in an intermediate model. *Journal of Climate* 17: 2842–50.
- Keenlyside N. S., M. Latif, J. Jungclaus, L. Kornbluh, and E. Roeckner. 2008. Advancing decadal-scale climate prediction in the North Atlantic sector. *Nature* 453: 84–88. doi: 10.1038/nature06921.
- Kelley, C., M. Ting, R. Seager, and Y. Kushnir. 2011. The relative contributions of radiative forcing and internal climate variability to the late 20th century drying of the Mediterranean region. *Climate Dynamics*. doi: 10.1007/s00382-011-1221-z.
- Kerr, D. 2005. Atlantic climate pacemaker for millennia past, decades hence? *Science* 309: 41–42.
- Kirtman, B. P., and P. S. Schopf. 1998. Decadal variability in ENSO predictability and prediction. *Journal of Climate* 11: 2804–22.
- Knight, J. R. 2009. The Atlantic Multidecadal Oscillation inferred from the forced climate response in coupled general circulation models. *Journal of Climate* 22: 1610–25. **(p.93)**
- Kushnir, Y., W. A. Robinson, P. Chang, and A. W. Robertson. 2006. The physical basis for predicting Atlantic sector seasonal-to-interannual climate variability. *Journal of Climate* 19: 5949–70.
- Lean, J. L., and D. H. Rind. 2009. How will Earth's surface temperature change in future decades? *Geophysical Research Letters* 36: L15708. doi:10.1029/2009GL038932.
- Lu, J., G. Chen, and D. M. W. Frierson. 2008. Response of the Zonal Mean Atmospheric Circulation to El Niño versus global warming. *Journal of Climate* 21:5835–51.
- Lu, J., G. A. Vecchi, and T. Reichler. 2007. Expansion of the Hadley cell under global warming. *Geophysical Research Letters* 34: L06805. doi:10.1029/2006GL028443.
- Lyon, B., and D. G. DeWitt. 2012. A recent and abrupt decline in the East African long rains. *Geophysical Research Letters* 39: L02702. doi:10.1029/2011GL050337.
- Mann, M. E., M. A. Cane, S. E. Zebiak, and A. Clement. 2005. Volcanic and solar forcing of El Niño over the past 1000 years. *Journal of Climate*. 18: 447–56.
- , and K. A. Emanuel. 2006. Atlantic hurricane trends linked to climate change. *EOS, Transactions American Geophysical Union* 87: 233.
- Mantua, N. J., S. R. Hare, Y. Zhang, J. M. Wallace, and R. C. Francis. 1997. A Pacific interdecadal climate oscillation with impacts on salmon production. *Bulletin of the American Meteorological Society* 78:1069–79.
- Mantua, N. J., and S. R. Hare. 2002. The Pacific Decadal Oscillation. *Journal of Oceanography* 58: 35–44.
- Oldenborgh, G. J. van, F. J. Doblas-Reyes, B. Wouters, and W. Hazeleger. 2012. Skill in the trend and internal variability in a multi-model decadal prediction ensemble. *Climate Dynamics* 38(7): 1263–80. doi:10.1007/s00382-012-1313-4.
- Phillips, J., B. Rajagopalan, M. A. Cane, and C. Rosenzweig. 1999. The role of ENSO in determining climate and maize yield variability in the

U.S. cornbelt. *International Journal of Climatology* 19: 877–88.

Power, S., T. Casey, C. Folland, A. Colman, and V. Mehta. 1999. Inter-decadal modulation of the impact of ENSO on Australia. *Climate Dynamics* 15:319–24.

Ropelewski, C. F., and M. S. Halpert. 1987. Global and regional scale precipitation patterns associated with the El Niño/Southern Oscillation. *Monthly Weather Review* 115: 1606–26.

———. 1996. Quantifying Southern Oscillation–precipitation relationships. *Journal of Climate*. 9: 1043–59.

Sarachik, E. S., and M. A. Cane. 2010. *The El Niño-Southern Oscillation phenomenon*. London: Cambridge University Press.

Schneider, T., and I. M. Held. 2001. Discriminants of twentieth-century changes in earth surface temperatures. *Journal of Climate* 14: 249–54.

Seager, R., A. Karspeck, M.A. Cane, Y. Kushnir, A. Giannini, A. Kaplan, B. Kerman, and J. Velez. 2004. Predicting Pacific decadal variability. In *Earth's Climate: The Ocean–Atmosphere Interaction*, ed. C. Wang, S.-P. Xie, and J. A. Carton, 115–30. Washington DC: American Geophysical Union.

Seager, R., Y. Kushnir, C. Herweijer, N. Naik, and J. Miller. 2005. Modeling of tropical forcing of persistent droughts and pluvials over western North America: 1856–2000. *Journal of Climate*. 18: 4065–88.

Seager, R., M. Ting, I. M. Held, Y. Kushnir, J. Lu, G. Vecchi, H.-P. Huang et al. 2007. Model projections of an imminent transition to a more arid climate in southwestern North America. *Science* 316: 1181–84. **(p.94)**

Smith, D. M., S. Cusack, A. W. Colman, C. K. Folland, G. R. Harris, J. M. Murphy. 2007. Improved surface temperature prediction for the coming decade from a global climate model. *Science* 317: 796–99. doi: 10.1126/science.1139540.

Stockdale, T. N., D. L. T. Anderson, M. A. Balmaseda, F. Doblas-Reyes, L. Ferranti, K. Mogensen, T. N. Palmer, F. Molteni and F. Vitart. 2011. ECMWF Seasonal Forecast System 3 and its prediction of sea surface temperature. *Climate Dynamics* 37: 455–71. doi:10.1007/s00382-010-0947-3.

Stommel, H., and E. Stommel. 1983. *Volcano weather: The story of 1816, the year without a summer*. Newport: Seven Seas Press.

Stothers, R. B. 2000. Climatic and demographic consequences of the massive volcanic eruption of 1258. *Climatic Change*. 45: 36D374.

Sutton, R. T., and D. L. R. Hodson. 2005. Atlantic Ocean forcing of North American and European summer climate. *Science* 309: 115–18.

Ting, M., Y. Kushnir, R. Seager, and C. Li. 2009. Forced and internal 20th century SST trends in the North Atlantic. *Journal of Climate* 22: 1469–81.

Tippett, M. K., and A. G. Barnston. 2008. Skill of multimodel ENSO probability forecasts. *Monthly Weather Review* 136: 3933–46.

Trenberth, K. E. 1990. Recent observed interdecadal climate changes in the Northern Hemisphere. *Bulletin of the American Meteorological Society* 71: 988–93.

———, and D. J. Shea. 2006. Atlantic hurricanes and natural variability in 2005. *Geophysical Research Letters* 33: L12704. doi:10.1029/2006GL026894.

Whitcombe, E.1993. Famine mortality. *Economic and Political Weekly*. 28(23): 1169–84.

Wunsch, C. 1999. The interpretation of short climate records, with comments on the North Atlantic Oscillation and Southern Oscillation. *Bulletin of the American Meteorological Society* 80: 245–55.

Wyrtki, K. 1975. El Niño—the dynamic response of the equatorial Pacific Ocean to atmospheric forcing. *Journal of Physical Oceanography* 5: 572–74.

———. 1979. The response of sea surface topography to the 1976 El Niño. *Journal of Physical Oceanography* 9: 1223–31.

Yancheva, G., N. R. Nowaczyk, J. Mingram, P. Dulski, G. Schettler, J. F. W. Negendank, J. Liu, D. M. Sigman, L. C. Peterson, and G. H. Haug. 2007. Influence of the intertropical convergence zone on the East Asian monsoon. *Nature* 445: 74–77.

Zebiak, S. E., and M. A. Cane. 1987. A model El Niño–Southern Oscillation. *Monthly Weather Review* 115: 2262–78.

Zhang, R., and T. L. Delworth. 2006. Impact of the Atlantic Multidecadal Oscillation on North Pacific climate variability. *Geophysical Research Letters* 34. doi: 10.1029/2006GL028683.

#### Notes:

- (1) . It also includes the changes in Earth’s orbit that were responsible for the cycles of ice ages until human interference in the climate system rendered them obsolete. Orbital changes will continue to influence climate, but their timescales of tens of thousands of years are not relevant here.
- (2) . Cane (1986) gives a historical account of ENSO theory.
- (3) . Cane (2005) offers a relatively accessible description of the mechanism that maintains the ENSO cycle; Sarachik and Cane (2010) is a comprehensive account.
- (4) . Chen and Cane (2008) has a brief account; current forecast information is available at <http://iri.columbia.edu> (accessed March 21, 2013). See “Forecast Plume” for the individual predictions of the entire suite of models. Operational forecasts by many groups throughout the world can also be found in the quarterly Experimental Long Lead Forecast Bulletin at <http://www.iges.org/ellfb> (accessed March 21, 2013).
- (5) . See section 7.8 of Sarachik and Cane (2010) and references therein for a review covering the CMIP3 models used in the IPCC Fourth Assessment; similar evaluations of the CMIP5 models used in the Fifth Assessment will be available by the time this goes to press.
- (6) . Cook et al. (2008) show that including the dust of the Dust Bowl improves the simulation, especially over the northwestern US.
- (7) . Oldenborgh et al. (2012) carried out a similar study but with an ensemble of four forecast models. They too find that beyond the first year there is no skill in predictions of the variations of global mean temperature about the trend due to the increase in greenhouse gases and other anthropogenic influences.
- (8) . As of January 2013 we can say that this forecast has proven to be correct.

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