CURRENT APPROACHES TO SEASONAL-TO-INTERANNUAL CLIMATE PREDICTIONS

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ABSTRACT

This review paper presents an assessment of the current state of knowledge and capability in seasonal climate prediction at the end of the 20th century. The discussion covers the full range of issues involved in climate forecasting, including (1) the theory and empirical evidence for predictability; (2) predictions of surface boundary conditions, such as sea surface temperatures (SSTs) that drive the predictable part of the climate; (3) predictions of the climate; and (4) a brief consideration of the application of climate forecasts. Within this context, the research of the coming decades that seeks to address shortcomings in each area is described. Copyright © 2001 Royal Meteorological Society.

1. INTRODUCTION

Research over the last century, and particularly in the last couple of decades, has shown that, in many regions of the world, the seasonal climate is potentially predictable. Useable predictions are possible under certain conditions: when the boundary conditions that force the atmosphere (e.g. sea-surface temperatures (SSTs) and land surface characteristics) are strongly perturbed, significant shifts are produced in the probabilities of different weather regimes that occur over a season (Palmer and Anderson, 1994). To the extent that the relevant boundary conditions and their associated climate impacts are predictable, skilful seasonal forecasts are possible.

Climate prediction efforts have existed for many hundreds of years. Very early approaches sought to identify environmental indicators that could suggest likely shifts in next season's climate (Inwards, 1994). Certain plants or animals may be sensitive to evolving climate patterns, for example, and the appearance of a flowering plant or the tendency of birds to build nests on a particular side of the tree may indicate that the next rainy season will be good or bad. Within some villages of Andean South America, predictions of summer rainfall and autumn harvests are based on changes in the visibility of stars in the *Pleiades* constellation. Recently, such changes in visibility have been attributed to changes in cloud cover over the tropical Pacific as a result of developing El Niño conditions (Orlove *et al*., 2000). Today, the physics behind such climate–environment relationships are better understood, and the tools for predicting them are more sophisticated. Similarly, our recognition of which elements of the climate system greatly affect future seasonal climate has grown considerably through the 20th century, as modelling and observational studies continue to add to our understanding.

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Progress in diagnosing, modelling and predicting seasonal climate variability represents a major scientific advancement of the 20th century; however, progress in the effective utilization of forecasts has lagged behind. Until recently, the burden rested on the user community to learn what prediction information was available, and how it might be applied. While this is still largely the case, there are now increasing efforts to engage systematically the user communities in actively voicing their needs, and participating in the development of forecast products and applications. For example, certain users might be interested more in the prediction of the duration of dry spells than the standard average 3-month rainfall anomaly. The prediction community is increasingly considering user requests when planning its research. At the other end of the prediction spectrum, the requirements for observations become better defined when users identify what prediction information they find most useful. This is an exciting time, as the view of climate variability across the disciplines becomes more coherent, and researchers from seemingly disparate disciplines begin to understand each other better.

The primary objective of this paper is to offer a comprehensive view of seasonal to interannual climate prediction—what methods are currently used, what information they provide, how they are typically judged, and their generally recognized advantages and disadvantages. No one approach is endorsed. In fact, benefits are likely gained from considering a variety of approaches. In practice, the method chosen will vary according to the type and use of information desired from the prediction, and also according to the resources available to produce the prediction. Much, but not all, attention is given to El Niño–Southern Oscillation (ENSO) because it has such a large global impact, and because so much of our forecasting efforts and skill derive from it. Given the rapid evolution during the recent few years in the understanding and techniques behind climate forecasting, it seems appropriate to stand back and assess what we know and what we need to know at this time, as society prepares to put this information to use.

2. THEORY OF PREDICTABILITY OF SEASONAL-TO-INTERANNUAL CLIMATE

2.1. Sources of predictability

Boundary conditions versus initial conditions. In the atmosphere, memory is short. An instantaneous realization of the weather will exert influence on future realizations only 5–10 days into the future. It has long been recognized that accurate observations of the initial atmospheric state are crucial for short and medium-range weather forecasts (Thompson, 1957; Lorenz, 1963, 1984, 1990; Shukla, 1981; Reinhold, 1987; Somerville, 1987; Murphy, 1988; Palmer *et al.*, 1990; Mureau *et al.*, 1993; Palmer and Anderson, 1994). For seasonal time scales, although atmospheric initial conditions do have a detectable influence, their importance is considerably weakened (Brankovic *et al.*, 1990; Barnett, 1995; Brankovic and Palmer, 2000). The relatively longer time scales of variability in the surface boundary layer allows for predictability of climate that potentially extends for many seasons—far beyond the predictability limit for the atmosphere alone (Charney and Shukla, 1981). Even simple thermal inertia of the upper ocean and persistence of land surface characteristics provide a degree of predictability out to a few months (Frankignoul, 1985). When other elements of the climate system, such as the upper ocean or the land surface, are dynamically coupled to the atmosphere and are allowed to evolve, even longer time scales of predictability are attainable (Rosati *et al.*, 1997; Zeng *et al.*, 1999). However, because these elements have differing intrinsic time scales, the issue of initialization in each of the air–sea–land components becomes far more complex (Larow and Krishnamurti, 1998; Pielke, 1998). At this time, most dynamical climate prediction involves only the atmosphere (as is discussed in Subsection 3.2), and it is assumed that atmospheric initial conditions are secondary to predictions of land and sea surface conditions.

Sea surface versus land surface boundary conditions. The decorrelation time scale of SST variability is about 1 year over much of the tropical Pacific Ocean, where El Niño and La Niña events dominate the variability. These events are extreme phases in the SST manifestation of the coupled ocean–atmosphere phenomenon, ENSO, which represents the single most prominent mode of climate variability at seasonal

to interannual time scales. These slowly evolving boundary conditions exert an influence on the tropical atmosphere by redistributing the surface heating, and thus, the low level wind fields, tropical convection and subsequent atmospheric heating that drives the global atmospheric circulation.

The land surface potentially provides additional sources of extended predictability for climate. The intrinsic time scales for land surface processes, though considerably longer than those of atmosphere-only processes, are typically less than the time scales of the ocean. Land surface variability is also fundamentally less dynamic than the atmosphere or ocean. Accordingly, much less research has focused on the impacts of land–atmosphere interactions, or the role of land surface initialization in forecasting. This is now changing, as recent studies (Fennessey and Shukla, 1999, and references therein; Zeng *et al.*, 1999; Douville and Chauvin, 2000; Koster *et al.*, 2000) are highlighting a potentially important role for the land surface.

2.2. ENSO predictability

The current understanding of ENSO has developed substantially over the past two decades (Neelin *et al.*, 1998), but rests heavily on earlier contributions. During an El Niño event (see Figure 1), the central and eastern tropical Pacific warms as the warm upper ocean waters of the western Pacific extend eastward. This reduces the equatorial SST gradient, and results in an eastward migration of active convection and rainfall, a slackening or even reversal in near-surface easterly winds, and a decrease (increase) in atmospheric surface pressure in the eastern (western) Pacific (the Southern Oscillation (SO) proper) (McPhaden *et al.*, 1998). The changes in near-equatorial winds allow even more of the warm western Pacific waters to move eastward. As the changes in the ocean lead to changes in the atmosphere, and *vice versa*, positive feedback is established. During the opposite extreme, now commonly called La Niña, anomalies of the opposite sign are observed to grow through analogous positive feedback. The period for a complete El Niño/La Niña cycle is typically 3–7 years.

In the 1960s, Bjerknes (1966, 1969, 1972) postulated that variability in ocean surface temperatures, and in tropical Pacific surface winds, were fundamentally coupled, and mutually reinforcing. He highlighted the role of equatorial oceanic upwelling and of SST gradients in modulating the meridional (Hadley) and zonal (Walker) overturning atmospheric circulations. These ideas have proven substantially correct, though incomplete as a theory for the quasi-oscillatory nature of ENSO.

Theory behind ENSO's cyclic behaviour developed during the 1970s and early 1980s as substantial progress was made in understanding the dynamics of the equatorial oceans. Of particular importance to current understanding was the description of how wind-forced equatorial Kelvin and Rossby waves, together with meridional boundary reflections, determine much of the observed variability in sea level and upper ocean circulation (Godfrey, 1975; Wyrtki, 1975; McCreary, 1976; Hurlburt *et al.*, 1976; Cane and Sarachik, 1977, 1981; Busalacchi and O'Brien, 1980, 1981; Philander and Pacanowski, 1981). In parallel, Gill (1980) proposed a simple mechanistic model for describing the heat-induced overturning circulations of the tropical atmosphere, which was then used to describe equatorial wind changes in response to SST variations associated with El Niño (Zebiak, 1982, 1986; Lindzen and Nigam, 1987; Harrison and Larkin, 1998). These complementary theories of how the ocean and atmosphere affect each other provided the essential elements for the first coupled models of ENSO (McCreary, 1983; Cane and Zebiak, 1985; Philander and Seigel, 1985; Zebiak and Cane, 1987).

The Zebiak and Cane (1987; hereafter ZC) model was the first to describe self-sustained, continuously coupled oscillations arguably like the real ENSO. ZC also produced the first successful prediction of El Niño by forecasting the 1986–1987 event 12 months in advance (Cane *et al.*, 1986). ZC argued for the role of oceanic heat content, and in turn, equatorial ocean dynamics, in setting the intrinsic time lags that could sustain an oscillation. Independent analyses (Battisti, 1988; Suarez and Schopf, 1988; Battisti and Hirst, 1989) presented a more complete theory, known as the 'delayed-oscillator' theory, which ascribes a critical role for oceanic adjustment (in the form of equatorial waves) in the evolution of the ENSO cycle. Elaboration and variations of this theory have been proposed more recently (e.g. Jin and Neelin, 1993a,b; Neelin and Jin, 1993; Jin, 1997a,b; Picaut *et al.*, 1997; Neelin *et al.*, 1998; Wang and Weisberg, 2000), although the essential contributions of oceanic wave dynamics and strong air–sea coupling remain.

Normal Conditions
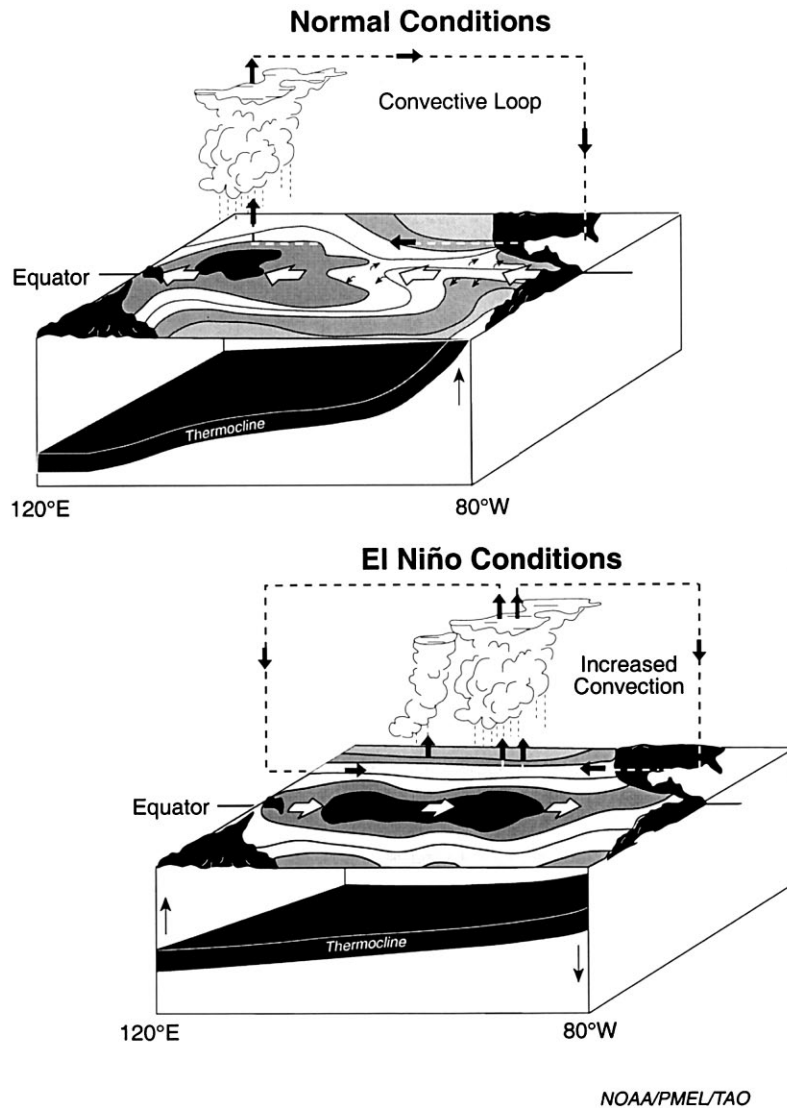
El Niño Conditions

NOAA/PMEL/TAO

Figure 1. Schematic of normal and El Niño conditions in the equatorial Pacific, illustrating the important components of the coupled air–sea system. Under normal conditions, the thermocline, which separates the warm upper ocean from the colder abyssal ocean, is drawn towards the surface in the east, as the zonal winds blowing from east to west cause divergence in the oceanic surface currents away from the equator and colder sub-surface water is brought to the surface. This creates a zonal gradient in SSTs, colder in the east and warmer in the west, that reinforces the easterly winds. The atmospheric circulation, together with the pattern of SSTs places the deep convection over the western Pacific. Significant perturbations to any one of these components can potentially lead to a chain-reaction of positive feedback, developing into an ENSO event. See Subsection 2.2 for more details (reproduced from MJ McPhaden, AJ Busalacchi, R Cheney, RW Reynolds, N Smith and K Takeuchi, The Tropical Ocean–Global Atmosphere observing system: a decade of progress, in *Journal of Geophysical Research*, **103**: 14169–14240, 1998, copyright (1998) by the American Geophysical Union)

Over the past 10 years numerous groups have developed increasingly complex and comprehensive general circulation models in an attempt to simulate ENSO better (e.g. Lau *et al*., 1992; Nagai *et al*., 1992; Latif *et al*., 1993; Roeckner *et al*., 1996; Frey *et al*., 1997; Shukla, 1998). Although important challenges still exist (Latif *et al*., 1998), notable progress has been made in simulating ENSO in many models (Stockdale *et al*., 1998a). These new results substantiate the theories derived from the simpler predecessors that indicate a degree of determinism, and thus, potential predictability, in the coupled climate system that extends to several seasons.

2.3. Climate predictability

2.3.1. ENSO teleconnections. Progress in collecting routine weather observations and the growth of scientific curiosity converged at the beginning of the 20th century, allowing scientists to perform the first investigations of the global climate and its year-to-year variability (Allan *et al.*, 1996). Through investigations of the Indian Summer Monsoon rainfall, Sir Gilbert Walker and colleagues documented various modes of seasonal climate variability (Walker, 1924; Walker and Bliss, 1932). Walker is credited with discovering and naming the SO, the vacillation of sea level pressure spanning the tropical Pacific basin that is associated with the changes in tropical Pacific SST during El Niño and La Niña extremes. However, other researchers had also discovered and discussed this tropical Pacific variability (Hildebrandson, 1897; Lockyer and Lockyer, 1902, 1904; Brooks and Braby, 1921). Their early studies were able to link some modes of climate variability, principally the SO, with seasonal rainfall patterns. These statistical relationships between regional rainfall or temperature patterns with larger scale modes of climate variability are often called 'teleconnections'.

Much of the early work by Walker and others fell from favour from the late 1920s to the 1950s, largely because many of the teleconnections failed to hold during this period. Many present-day researchers suspect that decadal and longer-term climate variability, which Walker's limited data could not take into account, can affect ENSO teleconnections (Rodo *et al.*, 1997; Gershunov and Barnett, 1998; Krishna Kumar *et al.*, 1999a,b; Power *et al.*, 1999; Rajagopalan *et al.*, 2000). After World War II, a network of weather stations was fostered by the World Meteorological Organization (WMO), and continues to form the backbone of weather and climate observations into the present. Much of the more recent empirical work documenting the relationships between ENSO and precipitation and temperature are based on these data.

With increased understanding of ENSO in recent decades came a renewed interest in ENSO teleconnections. Several studies since the 1980s documented the large-scale patterns of rainfall associated with ENSO based on observed data. Ropelewski and Halpert (1987, 1989) highlighted broad regions in which precipitation anomalies exhibited a discernible response to the phase of ENSO. Correlation-based analyses (e.g. Lau and Sheu, 1988; Kiladis and Diaz, 1989) also show patterns of relatively strong relationships between ENSO and rainfall. The composite relationships between ENSO and regional rainfall or temperature variability do not occur in every ENSO event, however. As discussed in Subsection 3.3, the changes in SST boundary forcing shift the distribution of possible climate outcomes, making certain scenarios (such as above-normal rainfall) more likely, but not guaranteed. Rainfall or air temperature anomalies of the opposite sign to the most typical ENSO response can occur in even the strongest teleconnection regions (Figure 2). The degree to which ENSO events shift the range of climate outcomes locally depends on the region, season, and also the strength and spatial distribution of the ENSO-related SST anomalies. Two examples of how the rainfall anomalies expected during an El Niño event might be presented are shown for South America in Figure 3. The upper panel gives the information as a composite category (wetter or drier than average for December, January and February (DJF)); whereas, the lower panel indicates how frequently the 'expected outcome' occurred in previous El Niño events, also known as conditional probabilities. The conditioned probabilistic climate anomalies suggest the relative robustness of regional teleconnections associated with ENSO (Mason and Goddard, 2001). In addition to differences between events in tropical Pacific SST forcing and internal variability of the atmosphere, some studies suggest that extra-tropical SST anomalies may influence (Gershunov and Barnett, 1998) or be influenced by (Bladé, 1999) ENSO teleconnections. ENSO teleconnections are also affected by SST anomalies in the tropical Indian and Atlantic Oceans that produce their own regional climate variations.

2.3.2. The influence of other ocean basins. Atlantic Ocean influence. Despite ENSO's widespread influence, the importance of the tropical Atlantic sector in affecting regional climate variability has been recognized since the 1970s. Relatively small changes in tropical Atlantic SSTs, particularly changes in the meridional gradient of SST, can shift the seasonal position of the Inter-Tropical Convergence Zone (ITCZ), directly impacting local climate. The average position of the ITCZ over the tropical Atlantic
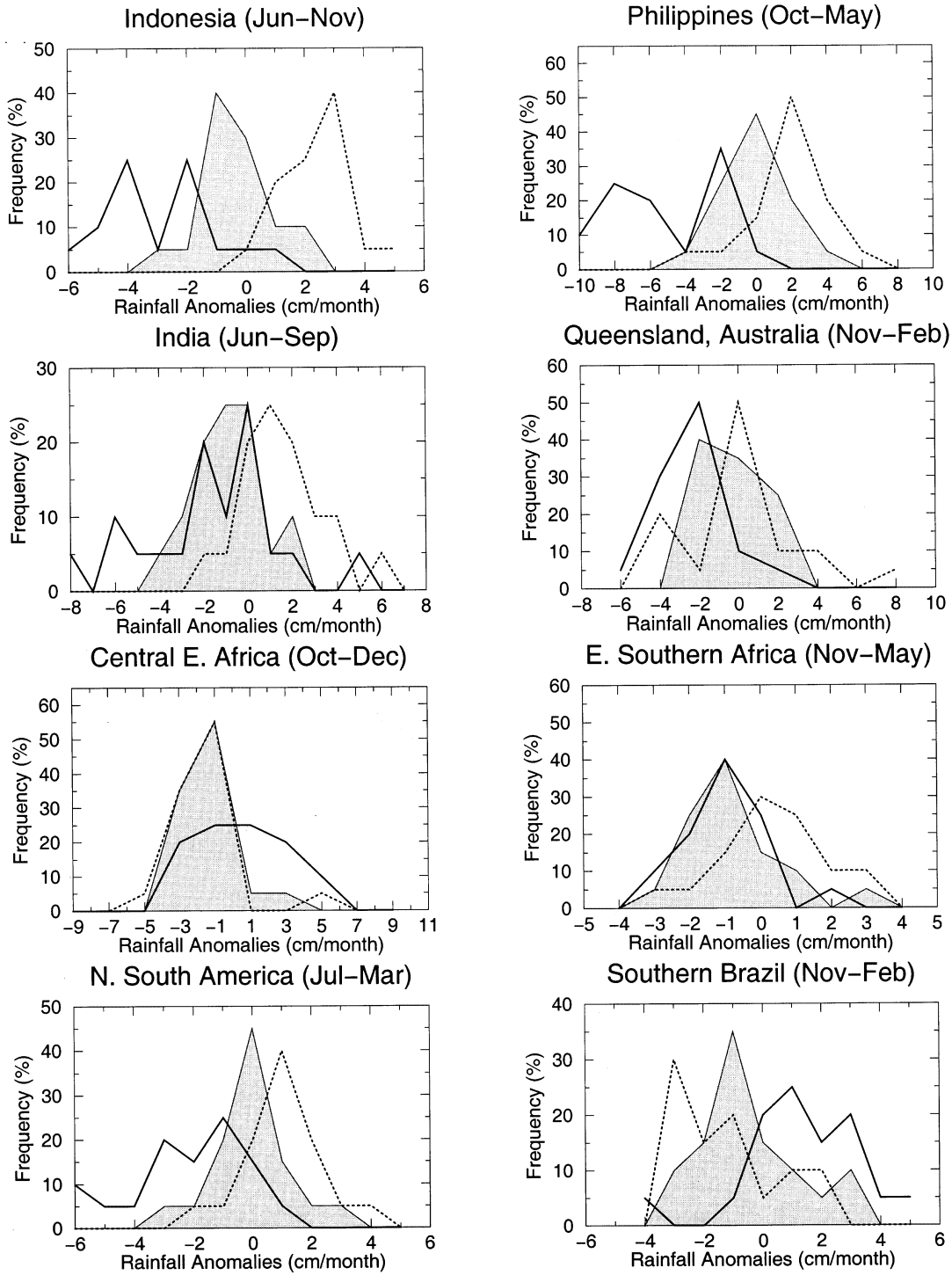
Figure 2. PDFs based on observed precipitation during the period 1890–1989. Three distributions are shown in each plot: 20 warmest El Niño events (heavy solid line); 20 coldest La Niña events (dashed line), and 20 years for which NINO3.4 was closest to zero anomaly (light solid line, with light gray shading), based on ranked anomalies for the season indicated at the top of each panel. Regions and associated seasons are based on identified ENSO teleconnection patterns from Ropelewski and Halpert (1987)
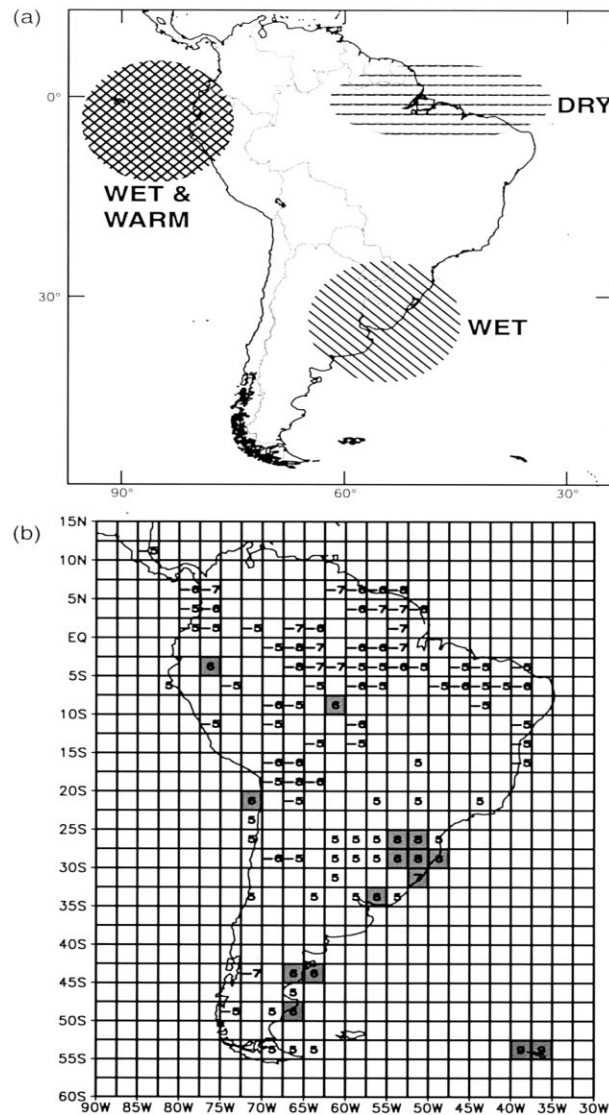
Figure 3. Expectations of anomalous rainfall during El Niño events for the December, January and February season, based on historical observations. (a) Composite expectations (reproduced from Global and regional scale precipitation patterns associated with eth El Niño/Southern Oscillation, *Monthly Weather Review*, **115**: 1606–1626, by CF Ropelewski and M Halpert, 1987, by permission of the American Meteorological Society); (b) Conditional probabilities of rainfall being in the wettest (dark shading, positive numbers) or driest (light shading, negative numbers) tercile during the 10 strongest El Niño events since 1950

Ocean basin is oriented west–southwest to east–northeast, and typically, spans the deep tropics from northeastern Brazil to western Africa. The annual cycle of rainfall from northern Brazil to western Africa reflects the annual north and south excursions of the ITCZ. Thus, SST anomalies in the equatorial Atlantic Ocean, by varying the seasonal mean position of the Atlantic ITCZ, lead to interannual variability of rainfall over northern Brazil (Hastenrath and Lamb, 1977; Markham and McLain, 1977; Moura and Shukla, 1981; Hastenrath, 1984) and western Africa (Folland *et al*., 1986; Semazzi *et al*., 1988; Lamb and Peppler, 1991; Rowell *et al*., 1995; Ward, 1998).

The anomalous meridional SST gradient, which is sometimes referred to as the Atlantic Dipole (Weare, 1977; Hastenrath, 1978; Moura and Shukla, 1981), although perhaps erroneously (Houghton and Tourre, 1992; Enfield *et al*., 1999), is not independent of ENSO (Penland and Matrovosa, 1998; Latif and Grötzner, 2000). In the months following the peak of an El Niño event, it is common for the northeast

trade winds over the Atlantic to weaken, and warm SST anomalies to develop in the Caribbean and northern tropical Atlantic Ocean (e.g. Folland *et al.*, 1986; Wolter 1987; Aceituno, 1988; Marengo and Hastenrath, 1993; Enfield and Mayer, 1997). Because of this relationship between tropical Atlantic SST variability and ENSO events, it may be difficult to separate ENSO teleconnections from the local tropical Atlantic teleconnections. Over the past decade, however, a number of studies have identified the relative influence of the eastern Pacific (ENSO) and equatorial Atlantic SSTs on rainfall over the Caribbean and northern South America (Hastenrath, 1995; Enfield, 1996; Enfield and Mayer, 1997; Enfield and Alfaro, 1999; Giannini *et al.*, 2000).

A second mode of variability exists in the tropical Atlantic, which appears to be independent of the variability in the northern tropical Atlantic described above. This mode evolves similarly to ENSO with SST variability focused along the equator and coupling between the SST and wind stress anomalies (Hirst and Hastenrath, 1983; Philander and Pacanowski, 1986; Reverdin and McPhaden, 1986; Richardson and Walsh, 1986; Servain and Legler, 1986; Colin and Garzoli, 1987; Zebiak, 1993). However, direct connection between this equatorial Atlantic variability and ENSO has not been established. This mode, which is most pronounced in boreal summer, can affect rainfall anomalies in the Gulf of Guinea region (Wagner and da Silva, 1994), and parts of central (Hirst and Hastenrath, 1983; Nicholson and Entekhabi, 1987) and southern Africa (Jury, 1996).

Indian Ocean influence. It is even more difficult to separate Indian Ocean teleconnections from tropical Pacific teleconnections than is the case for the Atlantic sector. SST variability in the Indian Ocean correlates highly with that of the tropical Pacific, with the tropical Pacific leading by approximately 3 months (e.g. Nicholson and Nyenzi, 1990; McCreary *et al.*, 1993; Nicholson, 1997; Tourre and White, 1997; Goddard and Graham, 1999; Klein *et al.*, 1999; Reason *et al.*, 2000). Modelling studies show evidence that the atmospheric changes induced by ENSO events are capable of affecting the Indian Ocean as observed (Lau and Nath, 1996; Venzke *et al.*, 2000).

The strong relationship between the Indian Ocean and the Pacific raises questions about which ocean's SST variability is actually responsible for the observed ENSO teleconnections in the Indian Ocean sector. Over southern and eastern equatorial Africa, where rainfall variability is correlated significantly with ENSO events (Figure 4(a)–(c)), attempts have been made to identify the relative contribution of the Pacific and Indian Ocean, and results suggest that the Indian Ocean contributes more to the regional variability (Tennant, 1996; Rocha and Simmonds, 1997; Goddard and Graham, 1999). Thus, many statistical approaches to forecasting seasonal rainfall over southern and eastern Africa consider conditions in the Indian Ocean (Hastenrath *et al.*, 1995; Mason, 1998; Landman and Mason, 1999a; Thiaw *et al.*, 1999). Modelling studies have demonstrated that the Indian Ocean drives the climate variability over eastern Africa (Figure 4(d); Goddard and Graham, 1999). Tropical Pacific forcing, applied in isolation, actually produces rainfall variability opposite to that observed over eastern equatorial Africa (Figure 4(e); Goddard and Graham, 1999). In contrast, rainfall variability over the Indian sub-continent correlates better to tropical Pacific variability than to local Indian Ocean variability (Shukla and Misra, 1977; Weare, 1979; Pant and Parthasarathy, 1981; Ropelewski and Halpert, 1987).

Figure 4. Results from GCM experiments showing the importance of the Indian Ocean for simulating observed precipitation response over eastern and southern Africa during the November, December and January season (reproduced from Goddard and Graham, 1999, courtesy of the American Meteorological Society). The top panel (a) shows the 1st mode of SST (homogeneous predictor maps) from CCA analysis between the Indian Ocean SSTs and observed African precipitation anomalies and between the Pacific Ocean SSTs and African precipitation anomalies. Shading indicates positive temperature anomalies, with 0.2°C contour levels. The subsequent panels show the African precipitation anomalies (heterogeneous predictand maps) related to Indian Ocean SSTs (left column: b1, c1, d) and those related to Pacific Ocean SSTs (right column: b2, c2, e), using rainfall anomalies from observations (b1, b2); a GCM forced with global observed SSTs (GOGA) (c1, c2); a GCM forced with observed SSTs only in the Indian Ocean (IOGA) and annual cycle of SSTs elsewhere (d); and a GCM forced with observed SSTs only in the tropical Pacific Ocean (POGA) and annual cycle of SSTs elsewhere. Shading and solid contours imply positive rainfall anomalies, with contours at starting at ±0.5 mm/day and an interval of 1.0 mm/day above magnitudes of 1.0. Notice that the IOGA experiment (d) replicates the rainfall pattern seen in the analysis of the observations (b1, b2) and the GOGA experiments (c1, c2), but the pattern of rainfall anomalies in the POGA experiment (e) is quite different. (Figure modified from L Goddard and NE Graham, The importance of the Indian Ocean for simulating rainfall anomalies over eastern and southern Africa, *Journal of Geophysical Research*, **104**: 6335–6352, 1999, copyright (1999) by the American Geophysical Union)
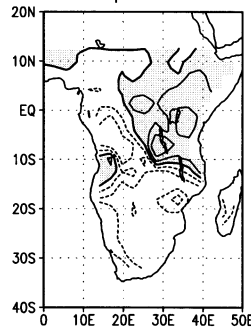
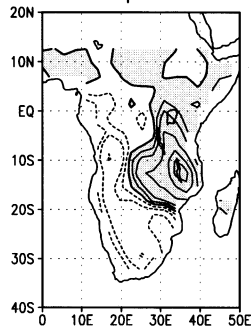## (a) SST Anomalies (Mode 1) : NDJ 1970-1992
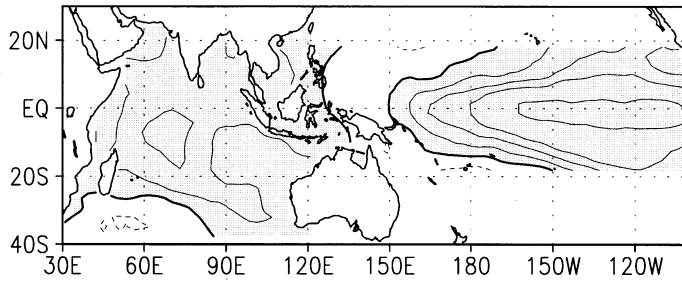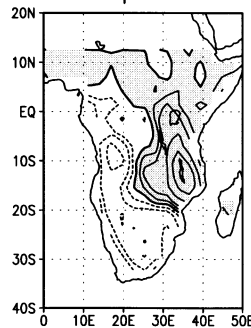
(b1) OBS Precip. v. IO SSTa
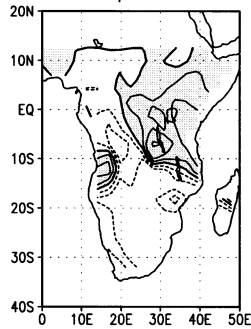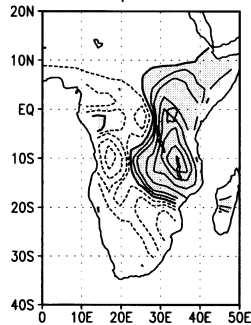
(b2) OBS Precip. v. PO SSTa
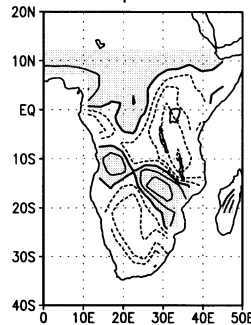
(c1) GOGA Precip. v. IO SSTa

(c2) GOGA Precip. v. PO SSTa

(d) IOGA Precip. v. IO SSTa

(e) POGA Precip. v. PO SSTa

The physical mechanisms associated with SST variability in the tropical Atlantic and Indian Oceans are not as well understood as those of ENSO. Most of the Atlantic SST forecast methods in common use are statistical. Similarly, whether the Indian Ocean's response to ENSO results from dynamics or thermodynamics is currently in debate (Saji *et al.*, 1999; Venzke *et al.*, 2000). The PIRATA program (Servain *et al.*, 1998) may provide the observational data necessary for better understanding of Atlantic Ocean variability. A similar observing system in the Indian Ocean is clearly needed. In addition, a newly launched global system of 'sounding buoys' under the ARGO program (Argo Science Team, 1999) may eventually contribute to further understanding and improved modelling for all the global tropical oceans. Until then, prediction of Indian and Atlantic SST is likely to remain in the realm of statistical/empirical techniques.

3. PREDICTING THE OCEAN-ATMOSPHERE SYSTEM

3.1. *Predicting boundary conditions*

3.1.1. SST prediction. Observations. Current predictions of the ocean boundary layer depend on several key observations that have been available in real-time since the 1980s. By far, the most developed observing system for the global oceans is the Tropical Atmosphere–Ocean (TAO) buoy array, which consists of more than 70 moorings in the tropical Pacific (8°N–8°S, 137°E–95°W; see Hayes *et al.*, 1991 and McPhaden *et al.*, 1998 for comprehensive summaries). These buoys make detailed measurements of surface winds, humidity, and temperature, and subsurface temperature and salinity, and continuously relay the information via satellites. The establishment of this observing system has allowed a more detailed understanding of processes surrounding ENSO, and it has provided critical information to initialize ocean models for seasonal predictions (Latif *et al.*, 1998; Stockdale *et al.*, 1998a; Wallace *et al.*, 1998). Another important data source for subsurface thermal conditions, particularly outside the tropical Pacific, is measurements from merchant ships that measure depth profiles of temperature and sea surface salinity. Observing ships also contribute to data sets of surface wind stress and surface air pressure. Other *in situ* measurements include a network of tide gauge stations that have been in place for decades (Wyrtki, 1985; Mitchum *et al.*, 1994). Relatively recently, satellite-based data for SST, winds, and sea level topography have become available (e.g. Fu *et al.*, 1994; Liu *et al.*, 1996). The potential usefulness of this data is great, as satellite products have the capability to offer higher resolution and more uniform coverage in both space and time than other systems.

The best observed oceanic field is SST. Quality SST observations are important for all aspects of prediction. First, having access to such data provides the ability to monitor closely ENSO and other variability. Second, timely access to SST data allows for continuous verification of SST predictions that are used to forecast climate (see Subsection 3.2). Third, having reliable SST observations may reduce uncertainty in predictions of climate that are based on observed SSTs. And finally, some climate-based decisions are tied directly to these oceanic observations, such as for the fishery industry (Lehodey *et al.*, 1997; Carr and Broad, 2000), in which case high resolution, accurate, and current observations are crucial (GOOS, 1998). The most commonly used products are obtained from a blending of *in situ* observations from ships of opportunity and buoys, and satellite observations (Reynolds and Smith, 1994). The relatively uniform coverage of the satellite measurements, and the large-scale bias correction of the satellite signal based on *in situ* measurements, provides for a high-quality analysis on weekly time scales. Prior to the satellite era (early 1980s) SST data are acceptably good in many areas since the mid-1950s.

For prediction of SSTs, especially through the use of dynamical models, other physical components of the air–sea system must be well measured and easily accessible. Crucial to all ocean model simulations or forecast initializations are surface fluxes, especially momentum fluxes. The first ENSO prediction schemes used only surface wind stress to generate oceanic initial conditions, and even in the presence of considerable ocean data, wind forcing remains an extremely important quantity for initializing ocean models. Sea-surface elevation is increasingly being considered in prediction, although in the initialization

of the more complex models, the use of sea level data remains exploratory (Chen *et al*., 1998; Ji *et al*., 2000; Segschneider *et al*., 2000). A current, major problem is the decomposition of sea level into the separate contributions from temperature and salinity. In the absence of significant subsurface salinity measurements, the decomposition requires statistical estimates of inherently limited accuracy. Oceanic velocity data are also valuable, particularly as sources of validation for ocean models. Such data are provided routinely by drifting buoys and moored current meters, although the latter are available only at a very few sites.

Statistical forecasting methods. Most statistical forecasts of SSTs focus on the ENSO phenomenon and involve prediction of a field of tropical Pacific SSTs, or a simple area-average over representative regions of the equatorial Pacific, such as the NINO3 (SST anomaly (SSTa) averaged over the region 5°S–5°N; 150°–90°W), NINO3.4 (5°S–5°N; 170°–120°W), or NINO4 (5°S–5°N; 160°E–150°W) areas. These ENSO predictions are frequently derived from previously observed *in situ* sea temperatures, surface pressure, and/or wind stress anomalies, although relationships with atmospheric anomalies outside of the tropical Pacific sector are sometimes considered (Xu and von Storch, 1990; Barnett *et al*., 1991). The most commonly used statistical methods describe linear deterministic relationships between the predictor and a single predictand index, and include regression (Knaff and Landsea, 1997), method of analogues (Van den Dool, 1994), and singular spectrum analysis (Keppenne and Ghil, 1992). Linear multivariate methods for forecasting ENSO in which the predictand is a field, most often SST, are widely used also. One class of such models keys on autoregression, either through Markov modelling (Xue *et al*., 1994, 2000) or through linear inverse methods optimized to fixed lead-times (Penland and Magorian, 1993; Penland and Sardeshmukh, 1995). The second class of models uses covariance or correlation between multiple fields, at fixed lead-times. The most commonly used algorithm is canonical correlation analysis (CCA) (Barnston and Ropelewski, 1992; Graham *et al*., 1997a,b), although other methods such as singular value decomposition (SVD), and combined empirical orthogonal functions (EOFs) have also been used (Bretherton *et al*., 1992). Recent attempts to use non-linear methods have been made (Tangang *et al*., 1997, 1998a,b; Hsieh and Tang, 1998), but do not provide significant improvements in skill over linear methods (Tang *et al*., 2000). Although probabilistic methods of statistical prediction have been used in climate forecasts (as discussed in Subsection 3.2), their application in forecasting SSTs has been minimal.

Outside the tropical Pacific, there are fewer examples of statistical forecasts of SSTs. However, some recent attention has been given to forecasts of global SSTs using autoregressive models (Navarra *et al*., 1998) and CCA (Mason *et al*., 1999; Landman and Mason, 2001). Also, tropical Atlantic temperatures are now regularly forecast using linear inverse modelling (Penland and Matrovosa 1998) and CCA (Pezzi *et al*., 1998; Repelli and Nobre, 2001).

Dynamical forecasting methods. A spectrum of dynamical models, ranging from the relatively simple (so-called intermediate) models initially used to predict ENSO, to comprehensive coupled general circulation models, are used routinely for SST prediction (Latif *et al*., 1994, 1998; Stockdale *et al*., 1998a). Intermediate models currently are run only in a regional context, focusing on the tropical Pacific and ENSO (e.g. Kleeman *et al*., 1995; Chen *et al*., 1999, 2000). Both atmospheric and oceanic components are represented dynamically, but simplified to the level of equatorial, linear, shallow-water equations. Parameterizations of the thermodynamics of both atmosphere and ocean are more complex, and non-linear. Outputs are predicted winds and SST over the coupled domain.

The commonly used hybrid models involve a statistical atmosphere model, coupled to either an intermediate ocean model (Kang and Kug, 2000) or to an ocean general circulation model (GCM) (Barnett *et al*., 1993). In all cases, the atmosphere model is derived from either SVD or CCA, based on observed SST and surface wind (stress). Outputs are surface wind stress and SST predictions over the coupled domain, typically, the tropical Pacific.

In recent years, development efforts have been focused towards relatively comprehensive coupled models for SST prediction. One approach employs a full ocean GCM and a global atmospheric GCM, but air–sea coupling occurs only in the limited domain of the tropical Pacific, and either climatology or persistence of SST anomalies is prescribed elsewhere (Ji *et al*., 1996, 1998; Kirtman *et al*., 1997). The additional assumption of so-called anomaly coupling is often made; that is, the coupling fields (i.e. heat

fluxes and wind stress) are computed from the simulated *anomalies* of each component model (relative to a forced, uncoupled climatology), and added to the appropriate observed climatology. Anomaly coupling minimizes errors associated with simulating aspects of the observed mean climate or mean annual cycle, but at the possible expense of introducing incorrect parameter sensitivities under certain conditions (Neelin and Dijkstra, 1995).

The outputs of fully coupled, and global domain GCMs (e.g. Rosati *et al.*, 1997; Stockdale *et al.*, 1998a,b; Segschneider *et al.*, 2000) include the full state space of both atmosphere and ocean (and land surface). Varying approaches are taken for the treatment of sea-ice in the polar regions: in some cases, sea-ice is simply specified, in others, an interactive sea-ice model is included. Sometimes, the models are used in a one-tier approach, directly forecasting climate, as well as SST (Stockdale *et al.*, 1998b), but more typically, the coupled GCMs are used to forecast SST only. In that case, the coupled models are configured at a moderate resolution of 3–4° (adequate to resolve many of the critical tropical air–sea interactions), and then higher resolution atmosphere-only AGCMs (AGCMs) are used with the predicted SSTs to forecast climate (see Subsection 3.2 below), an example of the two-tiered approach.

Apart from these global ocean modelling efforts, dynamical modelling of the Atlantic Ocean has received increasing attention over recent years (Philander, 1986; Zebiak, 1993; Chang *et al.*, 1997). Very recently, some studies have been directed towards the Indian Ocean sector as well (Saji *et al.*, 1999; Webster *et al.*, 1999). Yet the level of understanding of coupled climate variability in these oceans is extremely limited in comparison with that of the Pacific (i.e. ENSO). Central to the problem is the fact that the variability is weaker in these sectors, and most likely, impacted remotely by ENSO, and perhaps other factors. Additional basic research is needed, with continuing efforts to improve model simulations and predictions. In the extratropics, the situation is also very uncertain. To date, there has been no convincing demonstration of significant local air–sea coupling in the extra-tropics operating at seasonal time scales, and involving the sub-mixed layer ocean. This too continues as an area of active research.

Forecast performance. Since the first prediction of the 1986–1987 El Niño (Cane *et al.*, 1986), steadily intensifying efforts in statistical, dynamical, and hybrid model prediction have led to more than a dozen forecast systems that are currently being used to make regular predictions (many available through the Experimental Long Lead Forecast Bulletin: http://www.iges.org/ellfb; Kirtman, 2000). Owing to the known dominance of ENSO in global climate variability, forecast skill for ENSO indices such as NINO3, NINO3.4, NINO4 are important measures of performance. Comparisons among different forecast methods have been made for different ENSO events over the past decades (Barnett *et al.*, 1988; Barnston *et al.*, 1994, 1999a; Landsea and Knaff, 2000). Figure 5 shows forecasts for the period covering mid-1996 to late 1998 from three dynamical and three statistical models; this is a subset of models from an extensive comparison study by Barnston *et al.* (1999a). It must be noted that the period shown is very limited, and the apparent skill of any one tool may not be representative of its true ability. However, the magnitude of the 1997–1998 El Niño event, and its associated climate impacts, make it an important case study for ENSO prediction tools. This comparison, shown in Figure 5, reveals that, at present, forecasting methods of all types are generally competitive. During the 1997–1998 El Niño event, the GCM-based forecasts with active ocean data assimilation did perform better than simpler models without ocean data assimilation (for example, compare NCEP coupled model against the COLA coupled model, Figure 5). However, some statistical forecasts did as well as any dynamical model in predicting NINO3 (Barnston *et al.*, 1999a; Landsea and Knaff, 2000). The approximately equal skill of the different forecast methods is not too surprising: the deterministic processes that the dynamical models describe explicitly lead to systematic patterns in the data, extractable and useful for statistical prediction. However, dynamical models have an inherent, but yet unrealized advantage; namely, that with improved and more comprehensive representations of the real physics, there is room for further improvements in prediction skill. The only comparable means to improve statistical models is to increase the volume of observational data, a task fundamentally more limited. Thus, considerable energy is now being invested in improved dynamical prediction at many centres worldwide.

High skill in forecasting ENSO events with lead-times of 12 months or more has been claimed (Cane *et al.*, 1986; Latif *et al.*, 1998). However, operational skill estimates, which provide the only truly unbiased
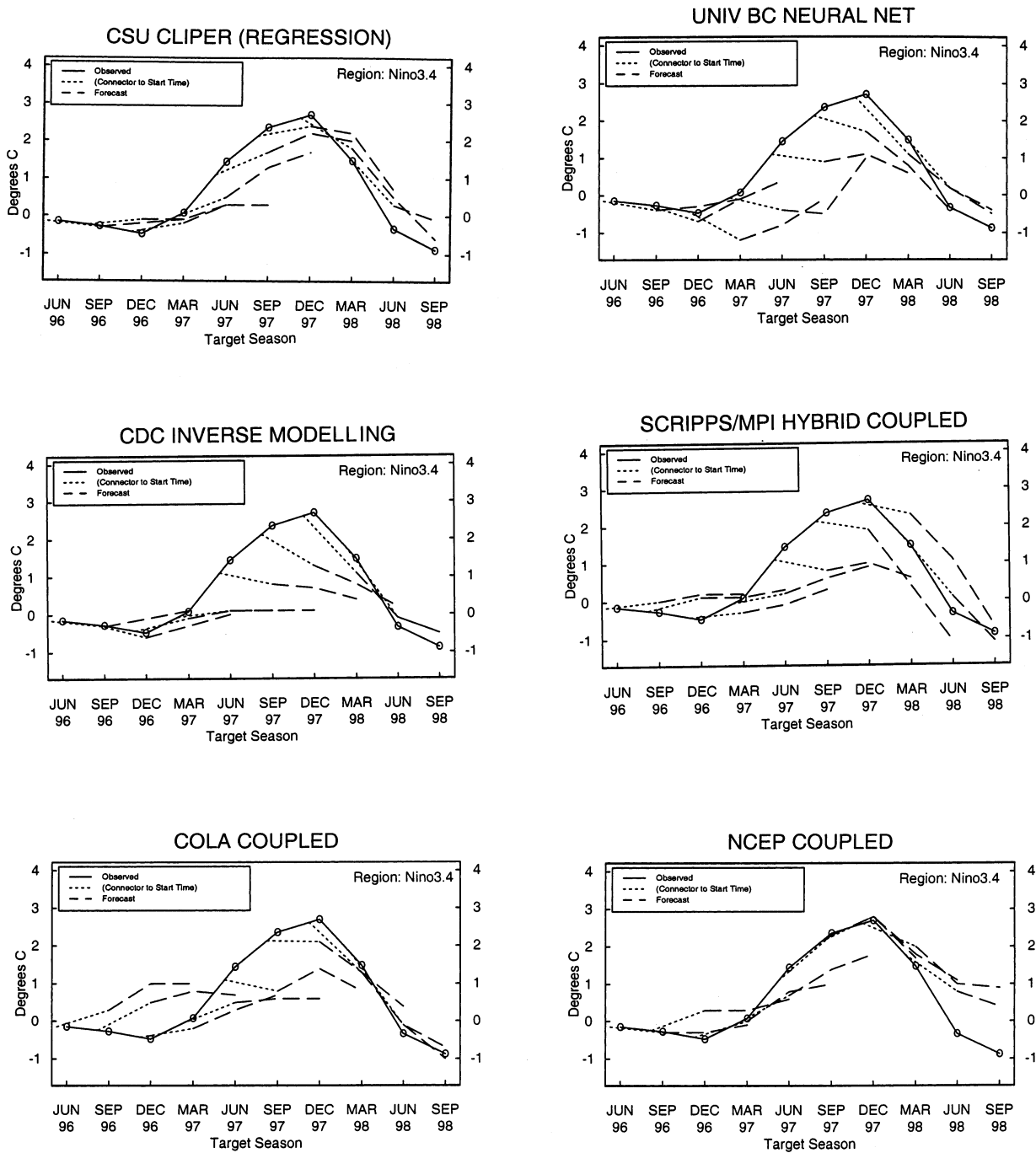
Figure 5. Plots of tropical Pacific SST forecasts (dashed lines) and observations (solid lines) over the June 1996–September 1998 period for six models projecting the state of ENSO at lead times of 3.5, 6.5, and 9.55 months. The specific predicted regions and SST units vary by model as shown in the upper-right corner, and by the vertical axis label, respectively. Dotted lines connect the observation centred at the approximate start time to the earliest (3.5 month lead) forecast. This is done for the readers' convenience only; the beginning of the dotted line does not represent the model's actual initialization, nor its forecast at very short lead times. The 3-month periods shown on the abscissa are denoted by their middle month. The first three panels show the performance of the statistical models (indicated above each panel), the next three the dynamical models. Figure reproduced by permission of the American Meteorological Society from, Predictive skill of statistical and dynamical climate models in forecasts of SST during the 1997–98 El Niño episode and the 1998 La Niña onset, by AF Barnston, MH Glantz and Y He, 1999, *Bulletin of the American Meteorological Society*, **80**, 217–244

indications of forecast skill, suggest that some ENSO events can be forecast qualitatively only a few months in advance (Barnston *et al.*, 1999a; Landsea and Knaff, 2000), and occasionally, only after an event has begun (Chen *et al.*, 1997). The difficulty in predicting ENSO phase-changes has been attributed to seasonal variability in the predictability of the equatorial Pacific. A 'springtime barrier' has been noted, as lower skill is generally observed for predictions that extend through boreal spring. (Blumenthal, 1991; Goswami and Shukla, 1991; Latif and Flügel, 1991; Latif and Graham, 1992; Webster and Yang, 1992; Balmaseda *et al.*, 1995; Webster, 1995; Davey *et al.*, 1996; Moore and Kleeman, 1996; Flügel and Chang, 1998; Latif *et al.*, 1998). The assumed reason for such a barrier is that the ENSO signal (year-to-year variance in SST anomalies) is a minimum in March–May, but the noise of the tropical Pacific air–sea system is nearly constant (Xue *et al.*, 1994). Thus the signal-to-noise ratio in the equatorial Pacific is small during boreal spring, and causes the forecast evolution through this season to be more sensitive to random variability. The spring barrier is most well defined during decades of relatively poor predictability (Balmaseda *et al.*, 1995), but is not evident in all ENSO-prediction models, and so, may not be an inherent feature of the ENSO phenomenon (Chen *et al.*, 1995).

In addition to being a function of the ENSO phase, skill levels have varied inter-decadally, with relatively higher skill in the 1980s, and lower skill in the 1970s and 1990s (Balmaseda *et al.*, 1995; Chen *et al.*, 1995; Ji *et al.*, 1996; Kirtman and Schopf, 1998). This low-frequency variability in the predictability of ENSO events may be a reflection of changes in the role of the delayed-oscillator mechanism in equatorial Pacific ocean-atmosphere dynamics (Goddard and Graham 1997).

Skill comparisons beyond the tropical Pacific and ENSO are few, as few predictions extend to the broader domain. Some statistical schemes target the tropical Atlantic and Indian Oceans (as discussed above), and near global domain coupled GCM forecasts exist already. Performance has been evaluated generally with temporal correlations between observed and forecast SST (Penland and Matrovosa, 1998; Repelli and Nobre, 2001), but robust validation of many of the current coupled GCM forecasts is presently limited by sample sizes. The expense of running these models often limits the number of retrospective forecasts conducted, and further work is needed. Those skill measures that are available indicate that forecast skill outside the tropical Pacific is distinctly lower than that for ENSO. As global SST forecasts are required for two-tiered forecasting systems (Hunt, 1997; Mason *et al.*, 1999), the need to improve skill beyond the tropical Pacific represents a major challenge for future forecast research.

3.1.2. Land-surface prediction. The land surface also serves as a boundary condition on the atmosphere, but it is often treated differently than SSTs. Prediction, or even persistence of anomalous conditions of the land surface, such as snow or soil moisture, are rarely incorporated into climate prediction. A major limitation is that there is no global observational analysis of soil moisture (wetness) with which to validate or initialize models. Even climatological soil moisture is generally estimated using a model (Mintz and Serafini, 1992). Currently, weather forecast models are typically run with interactive land surface parameterizations, and the atmospheric data assimilation process results in estimates of soil moisture that can be utilized for climate purposes (Fennessey and Shukla, 1999). However, land-surface analyses are not commonly used to initialize seasonal climate forecasts.

Until recently, the physics contained in the land surface component have been very crude and simplistic. The first interactive land surface models followed the so-called 'bucket' approach; i.e. a simple one-dimensional system that includes a reservoir, a precipitation source, and calculated fluxes at the surface (Manabe, 1969). A more recent class of models includes explicit vegetation, and its impacts on surface energy, water, and momentum transfer (Sellers *et al.*, 1986; Dickinson *et al.*, 1998). This class of model has been further developed, and can be considered state-of-the-art at present. A new class of model under development will go further in attempting to account for sub-grid scale variability, and the effects of topography on runoff (Koster *et al.*, 2000).

Numerous studies using these land surface models have investigated and identified important impacts of land surface processes on climate and its variability (see reviews in Dirmeyer and Shukla, 1993; Eltahir and Bras, 1996). Studies focusing on seasonal prediction impacts are suggestive of important land surface initialization impacts under some conditions (Fennessey and Shukla, 1999; Douville and Chauvin, 2000).

For example, the importance of initializing the soil moisture for simulations of drought and flood events at seasonal or longer time scales has been demonstrated (Brankovic *et al.*, 1990; Fennessey *et al.*, 1994). However, initializing a climate model with observations that are not dynamically consistent with that particular model may degrade rather than enhance the model's performance (Anderson and Ploshay, 2000). But given the potential importance of anomalous land surface conditions on the overlying climate, operational centres are beginning to assimilate land surface observations into dynamical climate models (Douville *et al.*, 2000). A number of new research initiatives under development will address this issue further, and can be expected to occupy an important position in the future research agenda.

3.2. Predicting climate

Observations. Routine observations of temperature and rainfall at selected locations have been taken for centuries. These observations are essential to diagnostics and process studies, for building statistical climate models, for understanding and improving dynamical climate models, and for validating both statistical and dynamical models. Routine real-time monitoring of the current climate, such as drought and flood conditions, is also important to provide the appropriate context for interpretation of climate forecasts.

Temperature measurements have been taken at sufficient spatial resolution to provide estimates of seasonal and annual global air temperatures over land from the mid-19th century to the present (Jones, 1994). While observations at less than 200 adequately spaced locations are sufficient for global temperature estimates, far more observations are necessary for the study and specification of regional and seasonal to interannual variability. Europe, North America and Australia have fairly good records extending back 100 years or more, but much of the remaining land areas of the world have had adequate regular temperature observations only from the 1950s onwards. The availability of good monthly station data in the latter half of the 20th century are partly owing to efforts of the World Meteorological Organization to coordinate the regular international exchange and archiving of monthly temperature and rainfall data. Some 1600 weather stations have been designated official climate stations and have agreed to exchange monthly climate summaries, called CLIMAT records, on a routine basis. However, the global observing network has thinned in the last two decades. A number of efforts are underway to arrest the recent decline in climate networks, such as the designation of a surface observing network of about 1000 stations under the Global Climate Observing System (GCOS). While these observing networks and the exchange of these data is an achievement, climate variability on decadal and longer temporal scales limit the use of this 50-year record in some seasonal climate prediction problems.

The observational record for precipitation generally parallels that of temperature. However, the smaller spatial and temporal scales of variability exhibited by precipitation make global seasonal patterns of rainfall more difficult to classify. As with temperature, some regions, again mainly Europe, Australia and parts of North America, have reasonable historical precipitation records back to the beginning of the 20th century. The advent of satellite precipitation estimates (Xie and Arkin, 1997) has provided high spatial resolution data sets for the study of global rainfall, including over the world's oceans, albeit with limitations in accuracy.

The simplest methods for seasonal climate prediction are based purely on local observations of past and current climate. The use of the climatological average as the 'prediction' is a valid starting point, or one can assume that a recent seasonal to multi-year climate anomaly will persist through the upcoming season(s) (Huang *et al.*, 1996). These methods have been used for centuries, and are used implicitly today by many people on a regular basis. The development of prediction methods that are superior to these simple approaches is the goal of most climate prediction research.

Statistical models. Implicit in any statistical model is that antecedent, current, or expected future values of predictor variables can be used to predict the future state or evolution of the predictand based upon historical observations of mathematical relationships between the predictors and predictands. With the development of global observing networks that measure air temperature, sea temperature, precipitation, and some aspects of the atmospheric circulation, statistical prediction methods have evolved considerably through the 20th century.

Regression models, including CCA, are the most commonly used statistical techniques for forecasting climate anomalies. Most models for the Indian monsoon use multiple linear regression, and this method, together with CCA, has been adopted extensively in Africa also. Auto-regressive approaches have received attention recently (Elfandy *et al.*, 1994; Chu *et al.*, 1995; Mentz *et al.*, 2000), as have probabilistic methods, most notably discriminant analysis (Ward and Folland, 1991; Casey, 1995; Carter and Elsner, 1997; Lehmiller *et al.*, 1997; Mason, 1998; Mattes and Mason, 1998; Mutai *et al.*, 1998; Mason and Mimmack, 2001).

In most cases, statistical forecasts of seasonal climate anomalies depend heavily upon the SST boundary forcing, which is the fundamental source of predictability in two-tiered dynamical modelling approaches. Antecedent or forecast SSTs form the sole, or at least dominant, predictors of models for the Sahel (Bah, 1987; Folland *et al.*, 1991; Barnston *et al.*, 1996; Ward, 1998; Thiaw *et al.*, 1999), eastern Africa (Mutai *et al.*, 1998), southern Africa (Klopper *et al.*, 1998; Landman and Klopper, 1998; Mason, 1998; Mattes and Mason, 1998; Landman and Mason, 1999a; Mason and Tyson, 2000), northeast Brazil (Ward and Folland, 1991; Uvo *et al.*, 1998), the Pacific Islands and Alaska (Barnston and He, 1996; Yu *et al.*, 1997), Australasia (Casey, 1998), Europe (Johansson *et al.*, 1998; Colman and Davey, 1999), the United States (Barnston, 1994), and Canada (Shabbar and Barnston, 1996). Most predictability is associated with the tropical Pacific. The skill of seasonal climate forecasts may be minimal in non-ENSO years (Barnston *et al.*, 1999b; Landman and Mason, 1999a), but important exceptions include central Africa and the Indian monsoon areas (Yang *et al.*, 1998). The simplest models include only a single ENSO index (Hutchinson, 1992), and simple average responses to ENSO events do provide seasonal forecasters with valuable initial guidance (Ropelewski and Halpert, 1996). A slightly more sophisticated approach, that relates seasonal climate to ENSO, uses both the present phase and the recent trend in ENSO indices (such as the Southern Oscillation Index (SOI), a measure of the pressure changes across the tropical Pacific basin) to indicate likelihood of above or below median precipitation (Stone and Auliciems, 1992). However, inter-El Niño differences in atmospheric circulation exist, and these differences may be inherently unpredictable in some cases (Kumar and Hoerling 1997). Thus, the probabilistic nature of such ENSO–teleconnection relationships should be emphasized (Mason and Goddard, 2001).

Some improvements in skill have been claimed when, in addition to SSTs, atmospheric predictors are included (Hastenrath *et al.*, 1995; Makarau and Jury, 1997; Francis and Renwick, 1998; Jury, 1998; Jury *et al.*, 1999a; Philippon and Fontaine, 1999). The addition of atmospheric predictors forms an important component of analogue techniques (Livezey and Barnston, 1988; Wagner, 1989). In most cases, however, these predictors are aspects of the atmospheric ENSO signal, and so, do not imply that the atmosphere has sufficient memory of its own to provide predictability at seasonal time scales. Included with this class of statistical models are those for the Indian Monsoon, where precursors indicate either some aspect of ENSO (Shukla and Paolino, 1983; Shukla and Mooley, 1987; Krishna Kumar *et al.*, 1995), despite a relatively weak ENSO-signal (Yang *et al.*, 1998), or provide a measure of the pre-monsoon thermal conditions over the Asian land mass (Hastenrath, 1987; Vernekar *et al.*, 1995; Sankar Rao *et al.*, 1996; Webster *et al.*, 1998), in both cases, implying that predictability is derived from boundary forcing.

All linear statistical prediction schemes suffer from similar instabilities in precursor–predictand relationships (Hastenrath, 1995; Francis and Renwick, 1998). Over India, for example, interdecadal variability in associations between ENSO and atmospheric precursors of the monsoon, which are likely related to interdecadal variability in ENSO variance, have led to interdecadal variability in monsoon predictability (Parthasarathy *et al.*, 1991; Hastenrath and Greischar, 1993; Annamalai, 1995; Krishna Kumar *et al.*, 1999a,b; Sahai *et al.*, 2000). This lack of robustness in predictor–predictand relationships may reflect an absence of explicit references to physical processes in the construction of statistical models for seasonal climate prediction. Given the enormous pool of potential predictors, and limited temporal degrees of freedom of most geophysical data, statistical models require rigorous testing in operational settings to ensure significance. Even cross-validated estimates of skill can be biased (Barnston and van den Dool, 1993; Hastenrath, 1995), and so, careful retro-active skill testing should be encouraged (Wilks, 1995) using a variety of skill score measures (Zhang and Casey, 2000).

Seasonal climate forecasts predominantly focus on mean temperatures or total rainfall; little progress has been made in forecasting more detailed variability, such as rainfall onset (Ahago, 1992; Briggs and Wilks, 1996). Notable exceptions include attempts to forecast frequencies and tracks of tropical cyclones. The main focus has been on North Atlantic hurricanes (Gray *et al*., 1992, 1994; Hess *et al*., 1995; Lehmiller *et al*., 1997; Mielke and Berry, 2000), but some attention has been given to the northwest Pacific (Chan *et al*., 1998), the southwest Indian Ocean (Jury *et al*., 1999b), and the southwest Pacific (Basher and Zheng, 1995). Looking beyond forecasts of seasonal conditions, very few efforts have been made to forecast climate at interannual time scales (White, 2000). In most cases, such long-lead forecasts depend on the extrapolation of trends and cycles (Dyer and Tyson, 1977; Tyson and Dyer, 1978, 1980; Currie, 1993).

Numerical models. Two types of numerical models are currently used for climate prediction: AGCMs and coupled ocean–atmosphere general circulation models (CGCMs). Both are based on the full physical equations of motion. The atmospheric equations in these models can be solved either on model grid points or spectrally, where the highest spectral wave number resolved determines the effective grid resolution of the model. These models are not entirely free of statistical assumptions, however. Because of the relatively coarse resolution used in GCMs, physical processes occurring on scales smaller than the model's grid can resolve are parameterized empirically. Mathematical relationships, based on observed data, describe the larger-scale aggregate behaviour of fundamentally small-scale processes, such as convection and radiative transfer.

A 'two-tiered' climate prediction approach is used with AGCMs (Hunt, 1997; Bengtsson *et al*., 1993), in which the boundary conditions are predicted first, and are then used to force the overlying atmosphere. The atmosphere is a slave to the prescribed boundary conditions in the two-tiered approach. The prescribed SST boundary conditions can be obtained from statistical or dynamical predictions, as described in Subsection 3.1.1, or more simply from persisting the most recent observed SST anomalies on top of the climatological annual cycle. At short lead times (i.e. predicting one season into the future) persistence of SST anomalies constitutes a viable estimate of the boundary forcing (Graham *et al*., 2000) owing to the typically slow evolution of SSTs. At longer lead times, or during the development of an El Niño/La Niña event, evolving SST anomalies are required.

In CGCMs, both the atmosphere and the boundary conditions are allowed to evolve freely and influence each other. This free, coupled evolution is one advantage of the CGCM (or one-tiered approach). A primary drawback of the current generation of CGCMs is that the SST field tends to 'drift' away from realistic values as the integration proceeds, thus forcing unrealistic patterns in the atmospheric anomalies. Drift may occur rapidly, because of an imbalance in initial conditions, or slowly, because of internal parameterization in one of the component models or from the coupling itself (i.e. flux errors) (Delecluse *et al*., 1998). Consequently, CGCMs are most often employed to predict only the SST field (Subsection 3.1.1). Model output statistics (MOS) corrections are sometimes applied to these predicted SST fields to bring the amplitude and/or spatial pattern into better agreement with the observed character of the variability before they are used to force the atmospheric anomalies. Owing to these coupled model weaknesses, AGCMs are still more commonly used than CGCMs (Hunt, 1997; Mason *et al*., 1999); however, CGCMs are beginning to emerge in the arena of operational climate forecasting (Stockdale *et al*., 1998b).

Because numerical models are capable of outputting a full range of atmospheric variables (winds, humidity, cloudiness, heat fluxes etc.), they are useful to climate research for process or diagnostics studies, as well as prediction. Until recently, most emphasis had been placed on the prediction, analysis, and diagnosis of anomalous geopotential heights (700 hPa—important level for moisture transport; 500 hPa—important steering level for mid-latitude storms; 200 hPa—important diagnostic of upper level divergence and thus convective activity in the tropics). Through the early 1990s, researchers were still inquiring whether or not GCMs were even suitable for seasonal climate prediction (Palmer and Anderson, 1994; Kumar and Hoerling, 1995; Stern and Miyakoda, 1995; Kumar *et al*., 1996). Clearly, if a model is incapable of simulating the large-scale atmospheric circulation, it will not be able to simulate regional-scale variability, such as rainfall. It is now accepted that GCMs can replicate much of the

large-scale flow, including anomalous patterns in geopotential fields, although the correlation between a GCM's geopotential height fields and that from observations is generally higher in times of strong SST forcing (Kumar and Hoerling, 1998). Today, the typical variables examined for prediction purposes are those variables that concern society most: near-surface air temperature and precipitation.

The GCM seasonal predictions consist of an ensemble of integrations, i.e. a set of forecasts that verify at the same time (Sivillo *et al.*, 1997). The ensemble members can differ in their boundary conditions, initial atmospheric conditions, and/or model physics (see Subsection 3.5 on multi-model ensembles). An ensemble approach allows for separation between the repeatable portion of the anomalous climate signal owing to boundary layer forcing and the portion that is owing to internal variability or chaos in the atmosphere. Ensemble-based predictions lead naturally to probabilistic climate forecasts (as discussed in Subsection 3.3).

The detail in space and time that many users of forecast information claim is necessary has driven research into better resolving seasonal predictions for temperature and precipitation. Methods for increasing spatial and temporal resolution (downscaling) of the global predictions and the research needed to apply those methods in a prediction setting are discussed in Subsection 3.7.2.

Dynamical versus statistical tools. Recently, researchers have begun to question the degree to which the added expense and complexity of GCMs compared with statistical models is justified, but detailed comparisons of statistical and dynamical model skill are still rare. Statistical predictions of the Indian monsoon rainfall do provide an example of a region in which statistical models continue to out-perform dynamical model predictions (Hastenrath, 1995). The dynamical predictions suffer from a consistently large ensemble spread (Webster *et al.*, 1998), which is compatible with the theory that chaotic weather systems in the Southern Hemisphere may trigger breaks in the Asian monsoon, providing short-term predictability, but limited seasonal predictability (Rodwell, 1997). Nevertheless, the statistical models have identified robust atmospheric precursors, and demonstrate useful skill over independent retro-active testing periods (Parthasarathy *et al.*, 1991, 1993; Prasad and Singh, 1992; Singh *et al.*, 1995; Yang *et al.*, 1996; Thapliyal, 1997; Venkatesan *et al.*, 1997; Singh and Chattopadhyay, 1998).

Over southern Africa, the dynamical models appear to be slightly better (Landman *et al.*, 2001), possibly because of instability in important SST–climate associations that are likely to weaken the skill of linear statistical models for the region (Landman and Mason, 1999b). Over North America, the multi-year results from a statistical model are found to outperform some AGCMs (Anderson *et al.*, 1999). However, at certain times, such as when ENSO is changing phase, the statistical response in climate over North America may not be robust and AGCMs may better simulate the appropriate climate shifts (Kumar *et al.*, 2001) owing to the full global patterns of anomalous boundary conditions.

One advantage of numerical climate models over statistical models is that an extensive observational database is not required to generate a prediction. However, in order to make a meaningful forecast, observational data is crucial for both the assessment of the model's historical simulations or retrospective forecasts, and also for the validation of current operational forecasts. Another advantage of numerical models is that they are not limited by non-stationarity of climate, or by extreme or unusual outcomes that may not have occurred in the available historical record. However, numerical models are complex, and can be expensive to run. Most importantly, the regions where numerical models exhibit skill vary with season and variable, and even different GCMs vary in where and when they show skill. The choice of whether to use a numerical or statistical model for seasonal prediction ultimately depends on the focus and resources of the forecast producer(s) and users. There are advantages to using both approaches in parallel.

3.3. Estimating forecast uncertainty

Owing to the chaotic nature of the atmosphere, it is impossible to know exactly how the atmosphere will evolve beyond a few days. Thus, medium and long-range weather forecasts and seasonal climate forecasts are usually presented in probabilistic terms (Murphy, 1990; Tracton and Kalnay, 1993; Déqué *et al.*, 1994; Palmer and Anderson, 1994; Barnett, 1995; Dix and Hunt, 1995; Harrison, 1995; Anderson,

1996; Molteni *et al.*, 1996; Sivillo *et al.*, 1997; Murphy, 1998; Stockdale *et al.*, 1998b; Mason *et al.*, 1999). Forecast uncertainty derives not only from model weaknesses, but also from the inherent unpredictability of the precise state of the atmosphere. Even with a perfect model, atmospheric internal variability would still impose finite uncertainty on the most likely climate outcome. Probabilistic forecasting provides a means of addressing both sources of forecast uncertainty by indicating the probability distribution of expected possible outcomes (Kumar *et al.*, 2000). Statistical and dynamical methods have been developed for estimating the probability distribution function (PDF) for climate outcomes for a coming season.

A climatological PDF of seasonal precipitation, for example, indicates the relative frequency with which accumulated precipitation of differing amounts were observed for that season over a historical period. In the case of forecasts of seasonal precipitation, a PDF indicates the probability with which different accumulated totals are estimated to occur. Simple statistical approaches to estimating the seasonal PDF for a region are based on conditional probabilities, indicating the relative frequency with which a particular climate outcome was observed under certain boundary forcing, such as El Niño or La Niña conditions (Mason and Goddard, 2001). Shown in Figure 2 are observed PDFs conditioned on ENSO phase for several regions with documented ENSO teleconnections (Ropelewski and Halpert, 1987). The gray shaded areas represent the neutral distribution, which is defined as the distribution of rainfall anomalies that occurred when the tropical Pacific SSTs were close to normal. The solid and dashed lines indicate the distributions of rainfall anomalies during El Niño and La Niña conditions, respectively. For most of the regions presented in Figure 2, the distributions during ENSO events are shifted positively or negatively, relative to the neutral distribution. In some cases, such as central eastern Africa (Figure 2(e)), La Niña forcing does not lead to a shift in the PDF relative to neutral ENSO conditions, but El Niño conditions greatly enhances the probabilities for above-average rainfall, even though below-average rainfall occurred during several El Niño events. Over India, the rainfall distribution during El Niño events does not seem that different from the distribution during normal years; however, the driest years in the record were observed to occur during El Niño events. The PDFs shown in Figure 2 illustrate that during years of anomalous boundary condition forcing, such as El Niño and La Niña events, both the mean and the spread of the distribution may change relative to the neutral distribution. Furthermore, the alterations to the distributions are not necessarily linearly affected by the boundary forcing (Hoerling *et al.*, 1997). If it is assumed that these statistics are minimally affected by lower frequency variability, then the observed conditional probabilities, such as those shown in Figure 2, may be used in predictions of the future. The main problem with this approach, besides the assumption of climate stationarity, is that each El Niño and La Niña event is unique in amplitude, spatial structure, and evolution, all of which may lead to uniqueness in the associated climate response.

More sophisticated statistical methods of defining forecast probabilities have been implemented (Ward and Folland, 1991; Casey, 1995; Carter and Elsner, 1997; Lehmiller *et al.*, 1997; Mason, 1998; Mattes and Mason, 1998; Mutai *et al.*, 1998; Mason and Mimmack, 2001), but generally, maintain the assumption of climate stationarity. Regression-based forecasting approaches can provide confidence intervals (Wilks, 1995), but these, while being indications of average model uncertainty, are poorly related to the inherent unpredictability of a particular forecast period.

Dynamical approaches use an ensemble of GCM predictions to sample the seasonal PDF (Murphy, 1990; Tracton and Kalnay, 1993; Brankovic *et al.*, 1994; Déqué *et al.*, 1994; Palmer and Anderson, 1994; Barnett, 1995; Dix and Hunt, 1995; Harrison, 1995; Anderson, 1996; Molteni *et al.*, 1996; Brankovic and Palmer, 1997; Sivillo *et al.*, 1997; Murphy, 1998; Stockdale *et al.*, 1998b; Mason *et al.*, 1999). It is known, however, that GCMs have varying degrees of systematic biases in the pattern, amplitude, and variance of their climate variability (Anderson, 1996; Smith and Livezey, 1999). Furthermore, the effect of climate uncertainties introduced by uncertainties in the evolution of the boundary conditions (Barnett, 1995) are rarely quantified in the predicted PDFs. Recalibration of forecast probabilities is, therefore, required.

3.4. *Forecast reliability and recalibration*

Because there is no guarantee that an ensemble distribution of possible outcomes will provide a reliable indication of forecast uncertainty, an important aspect of forecast skill is the reliability or calibration of forecast probabilities (Murphy and Winkler, 1987; Murphy, 1993, 1997; Wilks, 1995). The frequency of particular observed outcomes should match the relative frequency with which they are predicted. However, the fact that a forecast is ultimately matched against a single realization of nature introduces conceptual difficulties in verifying individual probabilistic forecasts. Probably, the only fair assessment of probabilistic forecasts is to judge whether the forecaster is systematically over- or under-confident over a period of time by comparing the frequency of an outcome relative to the confidence of the forecast probabilities (Wilks, 1995, 2000a,b; Murphy, 1997). In a reliable forecast system, the observations should fall between the 25th percentile and 75th percentile bounds of the forecast PDF 50% of the time, for example. Reliability and attributes diagrams (Hsu and Murphy, 1986; Wilks, 1995; Hamill, 1997) provide useful indications of the reliability of forecast probabilities, and can be supported by scores obtained from a decomposition of the half-Brier score (Brier, 1950; Murphy, 1973; Wilks, 1995). The area under a relative operating characteristics (ROC) curve is becoming a common indicator of forecast quality (Swets, 1973; Mason, 1982; Harvey *et al.*, 1992). However, it should be emphasized that the ROC area can be maximized without requiring the forecast probabilities to be perfectly reliable (Mason and Graham, 1999). Thus, the ROC area does not penalize if the forecast probabilities are systematically over- or under-confident, and this does not encompass all aspects of forecast quality.

Reliability of forecast probabilities can be achieved by issuing perpetual forecasts of the climatological probability of an event, and so reliability is a necessary, but not sufficient aspect of forecast skill. Other commonly used verification measures account for the importance of sharpness by penalizing forecasts that do not deviate from the climatological probability (Murphy, 1993, 1997; Wilks, 1995). For example, the Ranked Probability Skill Score (RPSS) (Epstein, 1969; Murphy, 1971; Wilks, 1995) and LEPSPROB (probabilistic version of the linear error in probability space score) (Ward and Folland, 1991; Potts *et al.*, 1996) reach their highest values when the climate variability is correctly predicted with high probabilities.

Proper assessment of the reliability of a prediction tool can reveal biases in the tool's representation of the forecast probabilities. Methods, such as the binned probability ensemble technique (Anderson, 1996; Hamill and Collucci, 1998), can indicate errors in the spread of an ensemble, but such methods do not indicate errors in the central tendency of the predicted PDF that may depend on the magnitude of the predicted climate anomaly (Mason *et al.*, 2001) (Figure 6). Once model biases are identified, the forecast can be recalibrated, such that the predicted PDF is more representative of the true uncertainty in the seasonal climate-state being forecast, and the errors of the forecast tool are minimized.

Forecast probabilities of seasonal climate anomalies, including those from statistical models (Mason and Mimmack, 2001), appear to be less reliable than for short- and medium-term weather forecasts (Wilks, 2000b). The short history for which seasonal forecasts are available is an important reason for the lack of research into their reliability. Most measures of reliability, such as the Murphy (1973) decomposition of the half-Brier score and reliability and attributes diagrams (Hsu and Murphy, 1986; Wilks, 1995; Hamill, 1997), require a long history of forecasts to ensure that the conditional relative frequencies of an event can be estimated with minimal sampling error for each forecast probability bin (Wilks, 1995). However, methods are being developed to indicate reliability from shorter histories of forecasts (Mason *et al.*, 2001).

Some forecast recalibration methods can also be used to obtain a more complete description of the entire PDF (Wilks and Eggleston, 1992; Briggs and Wilks, 1996; Mason and Graham, 1999; Wilks, 2000a). Typically, most seasonal forecasts are expressed in terms of probabilities of positive or negative anomalies of seasonally averaged conditions, or in terms of tercile probabilities (Mason *et al.*, 1999), but statistical methods can be used to estimate additional forecast detail. The lack of a sufficient history of forecasts precludes a more detailed description of the PDF with any confidence. As most user requirements are for more detailed information, methods for increasing the information content of seasonal climate forecasts promise to be important research foci in the future.
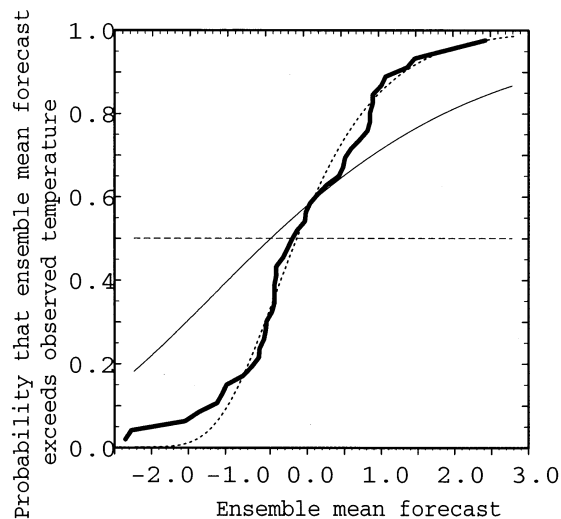
Figure 6. Conditional errors in the simulation of area-averaged September–November 2 m air temperature over eastern Africa (10°N–10°S, 30°–50°E), 1950–1994. The thick solid line shows the cumulative distribution of observed standardized temperatures, while the thin solid line indicates the conditional exceedence probabilities (CEPs), showing how the probability that the ECHAM3.6 ensemble-mean simulation of air temperature exceeded the observed temperature varies as a function of the ensemble-mean temperature. In a model that simulates the central tendency of the seasonal PDF perfectly, the CEP should be independent of the ensemble-mean temperature (dashed horizontal line). In a model with no skill, the CEP will be equal to the climatological probability (dotted line). The CEPs can be defined using generalized linear regression (Mason *et al.*, 2001)

3.5. Combining predictions

That the combination of predictions from different models can result in improvements in forecast skill has been long recognized in the weather forecasting field (Thompson, 1976; Clemen and Murphy, 1986; Clemen and Winkler, 1987; Fraedrich and Leslie, 1987). The combination of forecasts has also been a topic of lively debate in economics (Clemen, 1989; Granger, 1989; Winkler, 1989). Objective forecast combination schemes have been applied to seasonal climate forecasts only recently (Fraedrich and Smith, 1989; Casey, 1995; Krishnamurti *et al.*, 1999; Doblas-Reyes *et al.*, 2000; Palmer *et al.*, 2000; Pavan and Doblas-Reyes, 2000). A very straightforward approach to combining predictions from different tools that retains characteristics of the predicted PDF, and retains skill, is through pooling ensembles from different models. The skill of the pooled super-ensemble is not measurably higher or lower than that of the best tool included (Graham *et al.*, 2000) (Figure 7). The advantage gained by creating a super-ensemble in this way is that higher skill can be obtained for larger regions because the best tool will vary with season and region. However, equal weighting of forecasts from models with both good and poor skill leads to a loss of sharpness, or refinement in forecast probabilities, often reducing the information from the predicted PDFs (Zhang and Casey, 2000). Reductions in regional forecast error have been demonstrated by combining weighted model predictions on the basis of previous model performance. The weighted combinations typically outperform simple averages of model predictions as greater weight is given to models with better historical performance. This improved performance results more from the appropriate combination of different models rather than the increase in number of ensemble members (Pavan and Doblas-Reyes, 2000). However, increasing the number of ensemble members through forecast combination usually leads to a decrease in mean squared-errors (Doblas-Reyes *et al.*, 2000). The impacts of increasing ensemble sizes, within and among different prediction tools, on the reliability of forecast probabilities will need to be considered carefully. More comprehensive validation is required to ensure that objectively combined predictions yield improvements in forecast quality and value (Palmer *et al.*, 2000). Forecast combination constitutes an important direction for future research (Epstein, 1988), but needs to draw on experience from other applications.
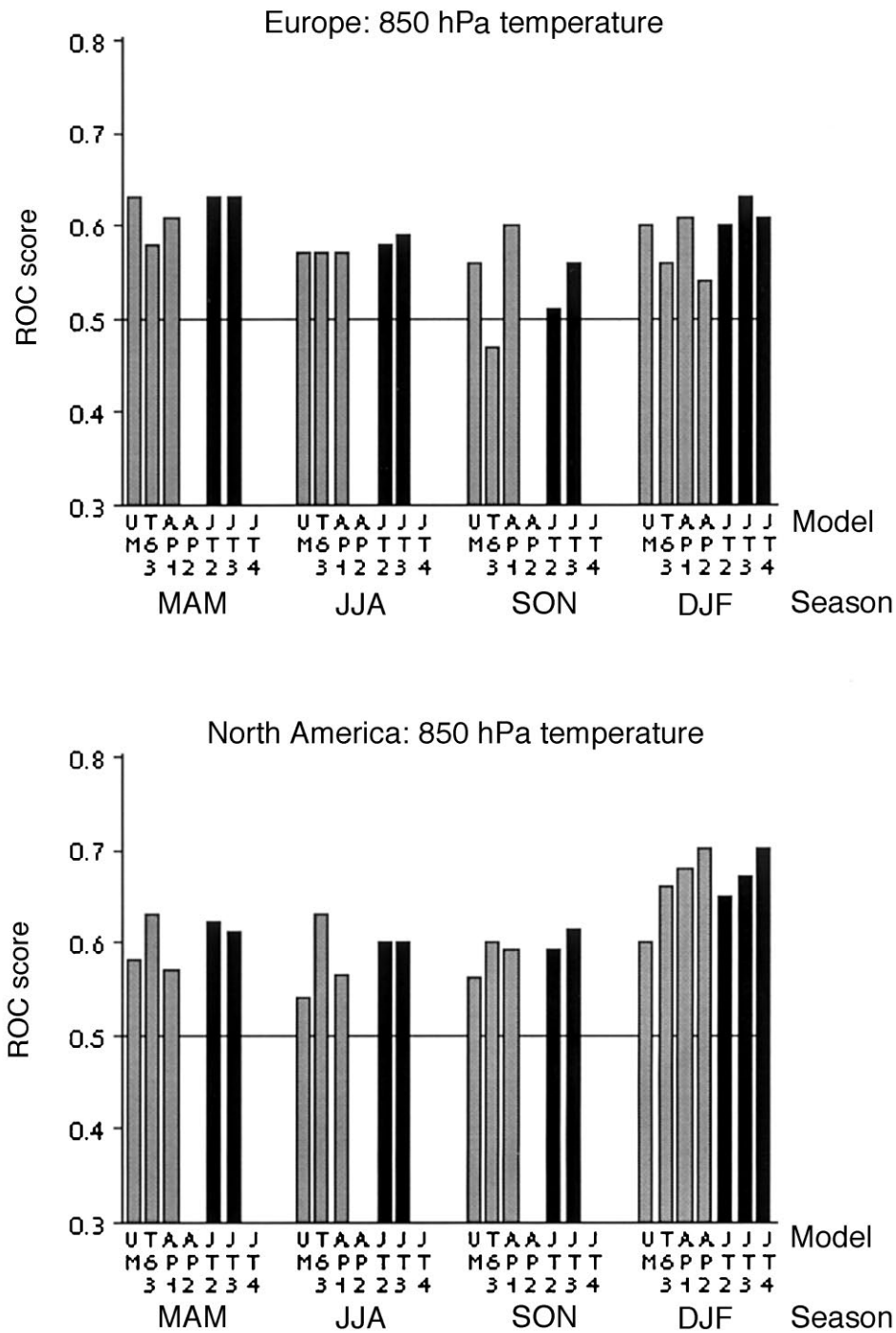
Figure 7. ROC scores (area under ROCs curve) for below-normal 850 hPa temperature. ROC scores for above-normal temperature are identical. Results are from all four participating PROVOST models (grey bars) and the multiple-model configurations: JT2, JT3, JT4 (solid bars). UM = UKMO Unified Model; T63 = ECMWF T63 model; AP1 = Météo France ARPÈGE T42 L31 model; AP2 = the ARPÈGE T63 L31 (run at Electricite de France (EDF)—DJF season only); JT2 = UM + T63 (18 members); JT3 = UM + T63 + AP1 (27 members); JT4 = UM + T63 + AP1 + AP2 (36 members, DJF only; from Graham *et al.*, 2000, reproduced by permission of the Royal Meteorological Society)

Subjective forecast combination has become an important area of development with the advent of the regional forecast fora (e.g. Drought Monitoring Centre, 1998; Buizer *et al.*, 2000), and is used in the construction of the International Research Institute (IRI) 'net assessments' (Mason *et al.*, 1999), and the NCEP seasonal forecasts (Van den Dool *et al.*, 1998). The subjective process of blending forecasts for adjacent areas and of combining different forecasts for the same regions is known as 'consensus forecasting'. Although the subjective process could, in theory, be improved upon by implementing some objective combination techniques, the consensus forecasting approach has some practical value, in that it permits a simple combination of all available forecasts when full or compatible verification data are unavailable. The risk is that forecasts with minimal or no skill can affect the consensus adversely, but the approach is supportable on the basis that a simple averaging of forecasts is often an improvement on any one forecast product.

3.6. Examples from 1997–1998

The exceptional El Niño event of 1997–1998 provided an excellent test bed for climate prediction tools, and many successes were advertised (Shukla, 1998). The evolution of tropical Pacific SST anomalies associated with the 1997–1998 El Niño event were well forecast by both numerical and statistical means (Barnston *et al.*, 1999a), but the timing of the initial onset was not well predicted by any of the tools (Landsea and Knaff, 2000).

At its peak, the 1997–1998 warm event exhibited a magnitude and spatial structure very similar to the 1982–1983 El Niño event (Figure 8); these two El Niños are the strongest warm episodes experienced in the 20th century. Overall, the SSTs throughout the tropics were warmer during 1997–1998 than during 1982–1983. The northern tropical Atlantic warmed in response to El Niño in the tropical Pacific, as often happens (Enfield and Mayer, 1997), and the southern tropical Atlantic, which has little relation to the variability in the Pacific, was also over 1°C warmer than usual. By the end of 1997, the response of the atmospheric circulation over the Indian Ocean region was so strong that the local air–sea system actually developed La Niña-like conditions through coupled instability (Chambers *et al.*, 1999; Webster *et al.*, 1999). On the ocean side, this feature appeared as a cold tongue in the eastern Indian Ocean accompanied by warm anomalies in the central/western Indian Ocean. On the atmosphere side, unusually strong and persistent easterly wind anomalies were observed along the equatorial Indian Ocean, enhancing the anomalous convergence over eastern Africa that typically occurs when the central/western Indian Ocean warms (Goddard and Graham, 1999) and leading to record rainfall over Kenya. The 1997–1998 evolution in the Indian Ocean has led to considerable debate over whether coupled instability is a primary or anomalous mechanism for the warming of the central and western tropical Indian Ocean associated with El Niño events (Saji *et al.*, 1999; Reason *et al.*, 2000). The magnitude of the warming in the Indian Ocean was atypical and was not captured by statistical predictions.

Although the strong SST forcing of El Niño resulted in climate anomalies in many areas that could have been predicted using simple linear statistics, a few regions, with robust climate associations to El Niño, did not experience the expected anomalies during the 1997–1998 event. Such examples invite investigation into whether differences between the deterministic prediction and the observed outcome are owing to inherent uncertainty represented in the seasonal PDF, or are owing to errors or omissions in the modelled climate. Queensland, Australia is a prime example of such climate surprises observed during the 1997–1998 El Niño event (Goddard *et al.*, 1998). During El Niño, this region typically experiences lower seasonal totals over their rainy season (October–February). Based on the conditional probabilities of observed rainfall during the 20 warmest October, November and December (OND) values of the NINO3 index from 1890–1989, the OND season has seen rainfall in the upper tercile (> 67th percentile) of the climatological PDF during only one El Niño case (Figure 2(d)). The observations for OND 1997 (Figure 9) clearly indicate well-above average rainfall over parts of Queensland, although the apparent extent of the coverage is highly dependant on the resolution of the observations. Statistical deterministic rainfall predictions for this area failed.
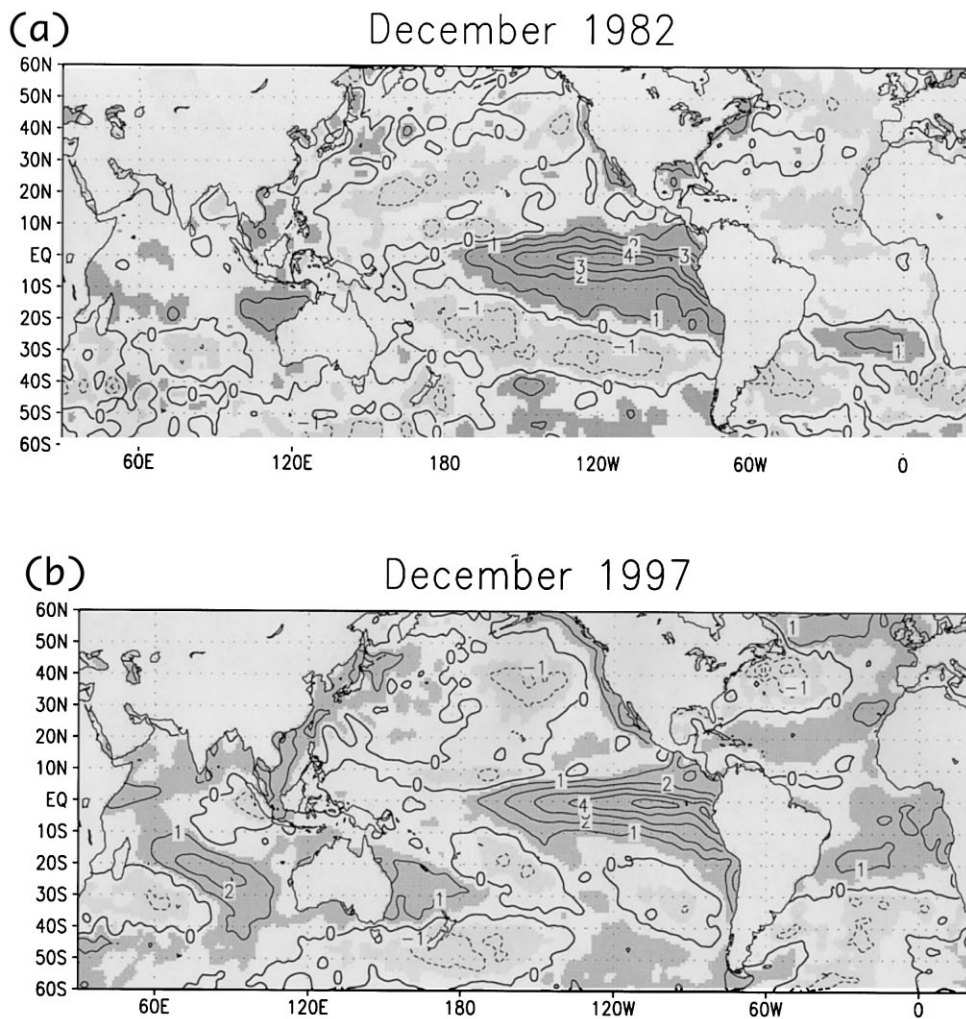
Figure 8. SST anomalies from NOAA's Climate Prediction Center (Reynolds and Smith, 1994) at the peak of the two strongest El Niño events of the 20th century. Units are degrees celsius. Light shading (values less than −0.5°C) and dashed contours (1°C interval) indicate negative anomalies, and darker shading (values greater than 0.5°C) and solid contours (1°C interval) indicate positive anomalies

Dynamical deterministic predictions for Queensland did not perform any better. The question pondered is whether dynamical probabilistic predictions were accurate as it is impossible to assess probabilistic forecasts for an individual season. Several of the models used by the IRI have statistically significant ensemble-averaged skill in simulating rainfall variability in this region for the OND season, but these models were not suggesting above-normal rainfall for OND 1997.

These AGCMs were unanimously indicating high probabilities of below-normal rainfall over Queensland under a selection of SST scenarios. Even when forced with observed SSTs for the period, high probabilities of widespread below-normal rainfall are simulated. In the previous one occasion on record that above-normal rainfall had been experienced during an El Niño event in the region, similar SST anomalies had occurred off the eastern coast of Australia, but again, the models continued to simulate below-normal rainfall. Possibly, with improved models, it may be possible to generate more accurate ensemble forecasts under such conditions, but the possibility that the observed rainfall was simply an unlikely event cannot be ruled out.

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3.7. Future directions

3.7.1. Improved GCM physics and parameterizations. Current predictions are limited by very obvious systematic errors in atmosphere, ocean and land models, and especially, coupled models. These errors result in incorrect model climatologies and 'climate drift', which compromise forecasts at even modest lead-times of a few months. Diagnosing and rectifying errors in such complex models is extremely difficult, as many of the processes interact strongly, and can mask the true source of error. Still, it is possible to identify a number of important common problems with current models. For the atmosphere, parameterizations of convective and marine stratus clouds are extremely important, and are in need of improvement. Likewise, improvements are necessary for boundary layer parameterizations, which control fluxes that govern coupling with the land surface and oceans. For the oceans, a primary concern is correctly parameterizing mixing processes in the surface layers, and more generally above the main thermocline. Arriving at more general mixing schemes that can cope with the wide range of conditions encountered in the equatorial and higher latitude oceans is a key problem of relevance to seasonal prediction.

3.7.2. Data assimilation. In every dynamical forecast system, it is necessary to initialize the ocean and atmosphere components. The methods used for initialization may be at least as important a limitation on current forecasts as model flaws (Chen *et al.*, 1995, 1998; Behringer *et al.*, 1998). The primary problem lies in the ocean because the ocean contains the 'memory' for time scales longer than a few weeks, and the observations are much more limited for the ocean in most regions. The schemes that are currently used at operational centres involve optimum interpolation or three-dimensional variational methods (Derber
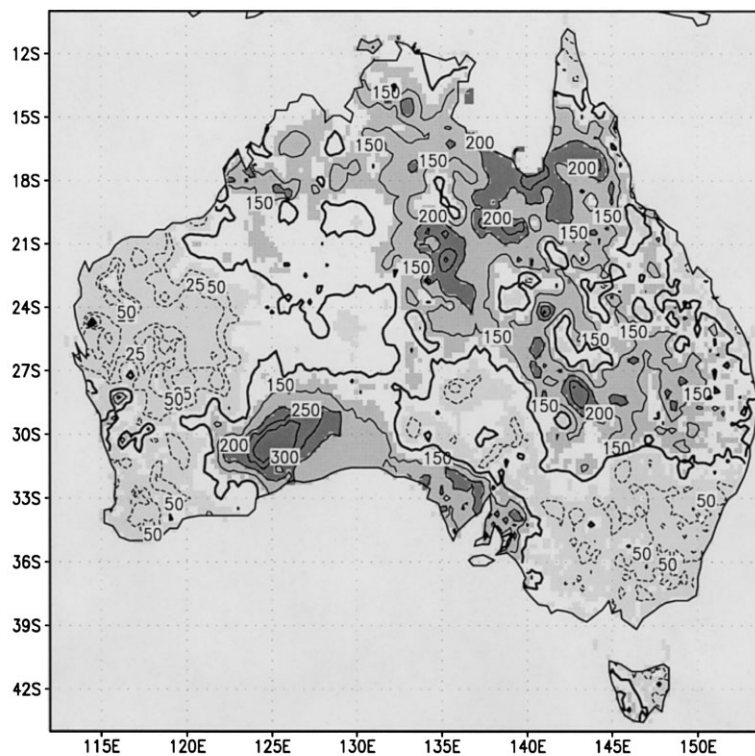
Figure 9. Observed rainfall anomalies over Australia for the OND 1997 season. Units are percentage of average for the OND season, based on 1961–1990 climatology. Very light shading (starting at 75%-average) and dashed contours (25%- and 50%-average) indicate less than average rainfall. Darker shading (starting at 125%-average, with very dark shading for rainfall anomalies greater than 200%-average) and solid contours (150%-, 200%-, and 300%-average) indicate above average rainfall. Data provided by Queensland Department of Natural Resources at 25 km gridded resolution

and Rosati, 1989; Smith *et al.*, 1991; Ji *et al.*, 1995), which are quite simple methods, typical of those used for atmospheric assimilation more than a decade ago. More sophisticated methods have been introduced, involving Kalman filter and adjoint approaches (e.g. Cane *et al.*, 1996; Bennet *et al.*, 1998), but are still experimental. At present, only thermal data is assimilated in ocean models used for prediction. Experiments have been done with altimeter data (Ji *et al.*, 2000; Segschneider *et al.*, 2000), and efforts are underway to include such data in prediction systems in the near future. Much more work is needed, not only in developing methodologies, but also in applying additional data sources that are presently available, such as satellite scatterometry. A major advancement now being proposed is *in situ* monitoring of upper-ocean temperature and salinity via programmable buoys. This or other enhanced real-time monitoring of the upper ocean is of fundamental importance in improving predictions, especially outside the tropical Pacific.

3.7.3. Increased spatial and temporal resolution. As the use of climate predictions increases, the demand for more detailed information also increases. Very localized predictions, often made using statistical tools, can be tailored to any spatial and temporal resolution desired. Dynamical predictions on regional and global scales, however, typically provide seasonally averaged climate at spatial scales on the order of hundreds of kilometres. In fact, the GCMs run operationally by most centres use an effective grid resolution of approximately $2 \times 2°$ (approximately 200 km grid spacing). A few approaches to gaining spatial and temporal resolution exist. One may increase the resolution of the global model, or if a specific region is of concern, one may choose a method of statistical or dynamical downscaling. Spatial downscaling may also have the added benefit of improving temporal information, such as the daily statistics of the weather within the seasonal climate. Rainfall in GCMs is generally considered to represent an average quantity over the grid box (Osborn and Hulme, 1998). As a result, GCMs generally overestimate the daily rainfall frequency and underestimate the rainfall variance relative to point observations.

Denser grid spacing in dynamical models obviously improves the resolution of the terrain, which can influence the large scale atmospheric circulation and also local orographically forced precipitation. In addition, the parameterized model physics, such as cloudiness, precipitation, and surface energy fluxes, may exhibit strong sensitivity to increasing horizontal resolution (Giorgi and Marinucci, 1996). For example, Figure 10 shows the climatology of precipitation over the United States for observations at 0.5° resolution (New *et al.*, 1999) compared with that from an AGCM run at T42 spectral truncation (approximately 2.8 degrees resolution) and at T106 (approximately 1.2 degrees resolution). Not only are orographically related features improved such as the separation in rainfall maxima over the Sierra and northern Rocky Mountains, but also features related to the strength and placement of the large scale flow are improved, such as the local rainfall maximum in the southeast. Certain gains of higher resolution global models are obvious, but they come at a price: the amount of computer time needed to run a model at high resolution, and the amount of storage space needed to archive the results are enormous. Furthermore, increasing the resolution of an AGCM is not trivial. Because the sub-grid scale parameterizations, such as convection, may be not be optimized for the higher resolution version, the results may actually be worse in some places (Boyle, 1993).

Alternatively, if increased resolution is required only over a specific area, one may nest a higher resolution limited area regional model within the global GCM. The regional model is driven by the time-dependant large-scale fields that are produced by the GCM. Inside the regional model domain, the terrain is better resolved and the physical equations are integrated on the higher resolution grid. The GCM drives the regional model by flow through the lateral boundaries (Giorgi, 1990) or by specifying the large scale flow structure throughout the domain which is then refined by the regional model (Juang and Kanamitsu, 1994). The most common problems with nested models are boundary effects resulting from the abrupt change in spatial scale and parameterizations that are not tuned for the region or high spatial resolution of the limited area model. Of course, propagation of errors is also a concern, as the regional model will add detail, and possibly even amplitude to errors in the large-scale circulation coming from the GCM. Indeed, almost all aspects of regional modelling including domain selection, physical
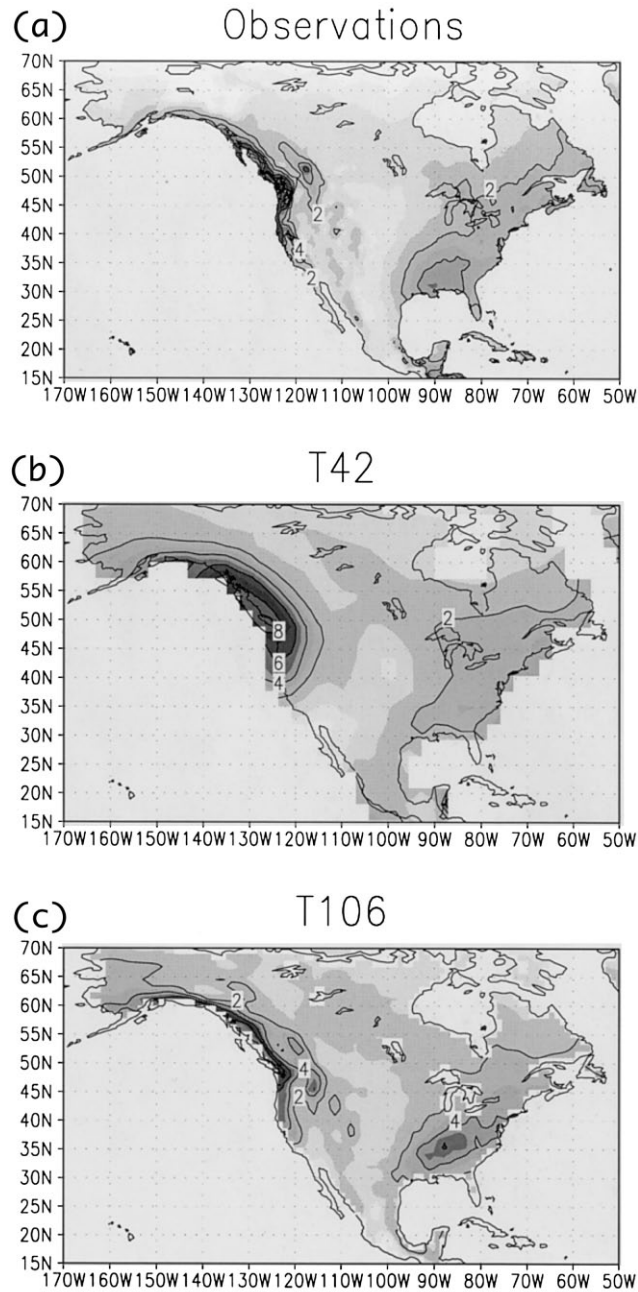
Figure 10. Observed precipitation from University of East Anglia (New *et al.*, 1999) at 0.5 degrees resolution. T42, AGCM simulated precipitation from model run at approximately 2.8 degrees resolution. T106, AGCM simulated precipitation from model run at approximately 1.1 degrees resolution. Units are mm/day. Shading contours at 0.25, 0.5, then every 1.0 over 1.0 mm/day, superimposed are contour lines at 2.0 intervals over starting at 2.0 mm/day

parameterizations, and resolution must be carefully investigated on a case by case basis before the merits of regional modelling can be determined for seasonal climate variability (Giorgi and Mearns, 1999). Assessment of gains from this approach is judged over multi-year, preferably ensemble, integrations of the regional model forced by the global model. When this approach succeeds, great improvements can be achieved not only in the details of the surface climate, but in spatial coverage of simulation skill and its level of statistical significance (Sun and Graham, 2001).

Using a regional model for prediction has yet another level of issues to consider. One must still have a multi-year integration so that anomalous behaviour can be properly recognized relative to the model's time-averaged behaviour. One must also consider how to treat the problem probabilistically. If the predictions are meant to refine potential climate scenarios, how should the ensemble member(s) from the global model be chosen? Should the treatment of the highly detailed prediction ensemble differ from that of the global prediction ensemble, because the downscaling process may produce locally stronger signals leading to locally larger uncertainty over the ensemble. The main scientific argument against dynamical downscaling using nested models is the physical inconsistencies introduced by the one-way flow of information from the global model to the regional model. There also exist global GCMs that have been designed with stretched or telescoping grids, which gradually increase resolution over the area of interest, avoiding the boundary problems and the inconsistent information flow problems possible in nesting experiments (Fox-Rabinovitz *et al.*, 1997). The other issues of assessment and prediction are not avoided. The main practical argument against dynamical downscaling is the expense of computer time needed to run the historical simulations and predictions and the amount of storage space needed to archive the output. Again, the existence of a good observational network is crucial for validating the data from high resolution models. For validation of higher order statistics of seasonal climate especially, such as characteristics of the daily rainfall, the observations must be available at a scale comparable to that of the model.

Several less complex and less costly approaches exist that currently may give comparable or even better results than dynamical downscaling for some cases. The simplest is statistical downscaling, in which local patterns of climate and the associated weather statistics are conditioned on some larger mode of the climate, such as ENSO, or more generally recent observations of global SSTs and/or atmospheric circulation. The larger scale SST or atmosphere patterns are often filtered to a lower dimensional space using EOFs, for example, to focus on the dominant patterns of the variability. The main caveat in using statistical downscaling, as with any purely empirical method, is that the past climate on which the tool is based may not be representative of future variability.

A compromise exists between the empirical approach and the dynamical approach. Hybrid downscaling follows a similar methodology to statistical downscaling, but the downscaled climate is conditioned on the SST or atmospheric circulation prediction from a dynamical model for the same season, as opposed to the previous season's observations. A review comparing various statistical downscaling methods applied to GCM output can be found in Wilby and Wigley (1997). For some applications, and in some regions, hybrid downscaling may show marked improvement over purely statistical downscaling, and may be comparable with dynamical methods (Gershunov *et al.*, 2000), for temporal as well as spatial downscaling. A dense network of observations is assumed in the statistical and hybrid approaches as these tools could not be constructed without them.

To date, most of the successes of downscaling, through whatever method, have focused on improved spatial patterns and climatologies. It is not currently clear what additional predictability exists at time scales higher than the seasonal average. Forecasts of quantities, such as rainy season onset, relative frequencies of extreme rainfall events, dry spells, cold outbreaks and heat waves, or even monthly rather than seasonal averages would be of great value to society. Forecasts for such quantities will be more impacted by the unpredictable noise component of atmospheric variability, and thus, significant levels of predictability will likely exist for very few regions and under particular seasonal or interannual circumstances. A few empirical studies for the western United States suggest some potential predictability of variability of weather characteristics with ENSO events (Cayan *et al.*, 1999; Robertson and Ghil, 1999). Empirical methods can be employed to determine how certain weather characteristics may change conditioned on the seasonal climate forecast. However, for a region where different weather characteristics (e.g. changes in rainfall frequency versus changes in rainfall intensity) can lead to the same seasonal outcome, empirical methods conditioned only on the seasonal forecast and not considering other potential environmental predictors will combine rather than distinguish these possibilities. Further, research on weather within the climate is needed to quantify the extent to which information beyond the seasonal aggregate is potentially predictable through dynamical or hybrid methods.

4. APPLICATION OF CLIMATE PREDICTIONS

4.1. *Rationale, impediments, approaches*

The primary motivation for public support of climate prediction science is the desire to reduce the enormous socio-economic costs of climate fluctuations, especially of the major floods and droughts to which less developed countries are so vulnerable (Glantz *et al.*, 1991; NOAA, 1994; Glantz, 1996; Moura and Sarachik, 1997; Stern and Easterling, 1999; WMO, 1999; Agrawala *et al.*, 2001). However, the presence of a skilful forecast product does not guarantee that benefits will accrue; these can only be realized through the parallel development of application science and the ongoing institutionalization of the lessons learned. This short section rounds out the paper's discussion of climate prediction science with a brief introduction for climate scientists to the issues involved in the application of climate predictions.

An *application* of climate prediction information may be defined as a conscious effort to use that information in decision making, in the expectation of benefits such as reduced risk, reduced costs, or increased production or profits. Decisions can range from simple choices about the priorities for a farmer's workday to million-dollar decisions about seasonal operating strategy for a hydro-electricity reservoir. Intrinsic to the decision process is a system that is sensitive to climate, a model of that system in the mind or computer of the user, and a range of decision options. The wide public interest in El Niño implies that countless day to day decisions are influenced by seasonal climate outlooks, but beyond this, progress in the systematic application of climate forecasts has been rather slow, being mainly limited to specific research-based projects in areas having very strong ENSO signals (Hammer *et al.*, 2000).

Impediments to the application of climate forecasts arise from several causes. First, the climate exhibits only limited predictability and skilful forecasts are available only for some seasons and regions (as discussed in Subsection 3.2)—unlike the case of weather forecasts, where useable forecasts are available for all times of the year and all regions of the world. Climate forecasters do not always make the predictability limitations transparent, or provide adequate useable guidance on the accuracy or reliability of the forecasts. Second, the uncertainty and probabilistic nature of climate forecast information is often difficult for the user to understand and to incorporate into their decision processes (Nicholls, 1999). Probabilistic forecasts are too often wrongly communicated or interpreted as deterministic forecasts, and the simplistic use of such deterministic forecasts may neglect the chance of costly failures. For other users, the risk of such failures may negate the potential long-run value of the probabilistic forecasts. Third, current forecast products generally lack the spatial, temporal and element specificity that users seek for their particular decision making needs—forecast are generally made for 3-month seasons, large regions over 1000 km in width, and mean temperature and rainfall totals only. Fourth, users may not have sufficient understanding of their system or acceptable options for using a skilful forecast. Fifth, the huge diversity of user circumstances, and the lack of familiarity of the producer and the user with the basic knowledge and language of each other's world compound the above difficulties. Because there is a cost to learning and communication, the investment by the user may exceed the potential benefits to them of the forecast information.

In addition, the application of climate prediction information necessarily spans a range of disciplines in the climatic, biophysical/ecological and socio-economic fields, and will usually need to be well grounded in knowledge of the situation of a particular region, country, sector and user group. The goal of developing applications thus involves considerable complexity. At the most quantitative, technically sophisticated extreme, there are simulation models or *decision support systems* that can be driven by observed or model simulated historical data to explore retrospectively and test complex decision options. Farm system models that incorporate details of soils, crops and management options are a particular focus for such applications research (Messina *et al.*, 1999; Hammer, 2000; Jones *et al.*, 2000). In public health, models of disease vectors are being studied (Bouma *et al.*, 1997; Linthicum *et al.*, 1999), while in water resources, reservoir management is a focus (Georgakakos *et al.*, 1997, 1998) A major issue in this research is how to downscale the spatially and temporally coarse output of global climate prediction models to meet the needs of crop models, which focus on specific fields or districts and are driven by daily

weather data (Hansen, 2000). Generally, decision support systems studies have concentrated on the biophysical and economic parts of the spectrum, with little work on social systems modelling.

The application of climate forecasts has been explored largely by top-down approaches, by seeking uses for existing forecast information, and less commonly by a bottom-up approach, by examining a decision situation to identify niches and needs for climate forecasts (Stern and Easterling, 1999). It is also possible to take an '*end-to-end*' approach (NOAA, 1994), which emphasizes that the effective application of climate predictions requires consideration of the full span of factors and their interactions, including social behaviour, institutional constraints, sector system models (e.g. crop-climate models), the design and communication of forecast products, the choice of prediction models, and the adequacy of observational data (Figure 11). The end-to-end approach applies to both the research stage, and to the operational stage. Both cases require transdisciplinary collaboration and close interaction between users, producers, their intermediaries, and the applications scientists.

4.2. The user and societal perspective

If societal benefit is the goal of climate prediction, then it is clear that a strong orientation towards users, the decision-making process, and the social setting is required in applications research. There is a wealth of related information in the fields of development studies, global change, technology transfer, and weather forecast application upon which to draw. Furthermore, experience with users forms a critical basis for guiding the priorities for prediction research, as well as justifying the funding for such research. As an example, user demand for predictions of extreme seasonal rainfall has led to the development of an 85%-ile seasonal rainfall forecast at the IRI (Mason *et al.*, 1999).

Whether or not a formal quantified decision model exists, there will always be some qualitative mental model in the mind of the user, based on custom, direct experience and hearsay. These may incorporate traditional or evolving coping strategies, for example, water harvesting and storage practices, and diversification of crop types. Such mental models filter the incoming information and shape the interpretation, and hence, degree of effectiveness of forecast use, depending on the source, form, mode and language of the communication. Typically, people want a forecast to be set in a context of their past and recent experience, for example, by comparing with the previous year's situation, or with a particular extreme event. Such mental analogues are valuable because they contain a vast richness of information on the behaviour of the whole system with which the user is concerned (e.g. for a farmer this might include patterns of weeds, pests, animal health, harvesting problems, produce quality and prices, damage to farm roads, debt status, credit availability, community confidence, government policy shift etc.) However, from the climate perspective, individual analogues can be misleading, as the climate outcome in any particular year is only one realization (possibly even an unlikely one) from a distribution of possibilities.

Usually, a user will face a cascade of multiple decision possibilities, some being of the 'no regret' type, such as advancing the maintenance of machinery, where the cost of the marginal action and the potential for losses are small, and some involving very high costs, or the potential for intolerable losses, such as bankruptcy or the total loss of the family's animal herd. In principle, a decision situation can be described by utility or cost–loss functions for the distribution of possible decisions and outcomes. In the simple binary case (event occurring or not, event forecast or not), a 2×2 matrix can be used to represent net
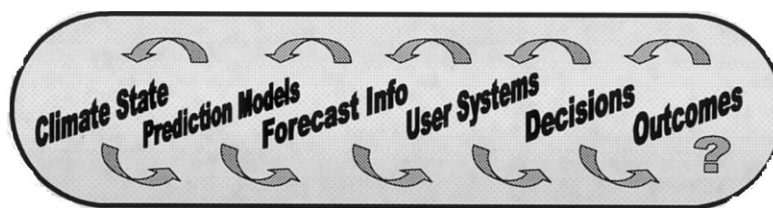

Figure 11. Schematic representation of the *end-to-end* concept, which indicates that desired outcomes require attention to *all* processes throughout the chain—physical, biological, socio-economic. An application involves a complex web of interactions, transformations and multiple feedbacks along the whole chain

economic consequences of a single decision, as well as its component costs and gains (see Katz and Murphy, 1997). This approach can be useful to help users conceptualize and assess the potential consequences of decisions, such as the trade-offs between long-term average gains versus short-term risks, though ordinarily, the user will have more that just two options to consider and accurate cost/loss data will not be available. It should also be recognized that users face a multiplicity of decisions and that, relative to the effects of prices, social or political expectation, imposed regulations etc, a forecast of the season's climate may form only a minor component of most decisions. For these and other reasons, even a technically skilful forecast is not necessarily a useful forecast for the decision maker.

The design and communication of prediction information to users is an active subject of research. Typically, the forecast information is communicated to the end-user or decision-makers by an intermediary, such as a journalist, agricultural extension worker, government officer, or climate consultant, and end-users are likely to have more than just one source of information, including web sites, advisors, the media, acquaintances and community leaders. There are often several steps in the information wholesaling process, in which each intermediary interprets and transforms the information to suit the intended recipient, possibly with the aid of a system model. Dissemination by rural radio and the use of local languages is being explored in parts of Africa (J. Phillips, N. Ward, personal communication). The media is a valuable channel for timely broadcast of basic information, but it may distort the message to make it simpler or more sensational or owing to lack of expertise (Nicholls and Kestin, 1998) Institutions may be externally constrained, structurally unable or unwilling to hear, learn or apply new climate prediction methods (Rayner *et al.*, 2000).

The justification of an application ultimately lies in the benefits it generates. Public expenditures on climate prediction research and operational forecasting are rightly argued for on the grounds of the potential benefits but, as yet, there is relatively little detailed understanding and quantification of these benefits and how they might be distributed in the community. In less developed tropical countries that are particularly vulnerable to climatic stresses, the primary benefits being sought are those of increased resilience of livelihoods and of land use—such things are difficult to measure even over long periods. Some studies in developed countries have reported good benefit/cost ratios at a macroeconomic level though many assumptions are involved (Katz and Murphy, 1997; Solow *et al.*, 1998). There will be winners and losers. For example, any increased agricultural production resulting from widespread use of climate prediction-based farming strategies will act to drive down prices bringing benefits to consumers but not necessarily to farmers (Mjelde *et al.*, 1998; Mjelde *et al.*, 2000). A study of the use of climate information by the main actors in Peru's fisheries (artisanal fishers, factory fishing companies, company labor, and fisheries conservators/regulators) showed that the design of forecast products and dissemination strategy plays an important role in determining the actors' options for action and the participation by actors and others in the resulting benefits and detriments (Pfaff *et al.*, 1999; Broad *et al.*, 2001).

4.3. Demonstration and implementation

Finally, in order to achieve lasting benefits of climate prediction information, it is necessary for applications researchers to go beyond basic research, to undertake progressively pilot and demonstration projects and associated capacity building for the people and institutions expected to carry out the applications in individual countries (NOAA, 1999; Stern and Easterling, 1999). It is also necessary for the climate operations community to provide an operational infrastructure that fosters the generation and exchange of appropriate climate data and forecast products between countries, together with initiatives to enhance the user–producer interface. These implementation activities are an integral part of the end-to-end concept.

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