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Review

Seasonal climate forecasting

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ABSTRACT: The fascination of seasonal climate forecasting, of which El Niño forecasting is the prime example, comes from its multi-faceted character. Not only does it pose interesting new challenges for the climate scientific community but also it is naturally linked to a great variety of socio-economic applications. Seasonal climate forecasts are indeed becoming a most important element in some policy/decision making systems, especially within the context of climate change adaptation. Thus, seriously considering the management of risks posed by the variability of climate on the seasonal to interannual time scale is key to achieving the longer terms goals of climate change adaptation strategy. This review paper explores the main components needed to construct a seasonal forecasting system, from the physical basis of climate seasonal predictions, to the tools used for producing them, to the importance of assessing their skill, to their use in risk management decision-making. Future challenges are also examined. Copyright © 2010 Royal Meteorological Society

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1. Introduction and a bit of history

When considering prediction of the climate on the seasonal timescale (i.e. typically up to a year ahead) an important distinction has to be made between dynamical predictions, those which use complex dynamical numerical models of the main Earth system components, and statistical predictions, those which use regional historical relationships between physical variables such as temperature and precipitation with statistical models of varying degrees of sophistication. While dynamical seasonal prediction is a relatively recent endeavour, statistical models have been used since the late 1800s. It is only with the advent of the former, however, that seasonal forecasting has grown dramatically.

Key to this burgeoning has been the extensive use of complex dynamical models which have allowed unprecedented detailed investigations of the climate system, consequently with an improved understanding of the dynamical evolution of the main components of the Earth system, including their interaction. In turn, such an understanding has translated into the ability to produce usable and useful operational seasonal prediction on the global scale (although subtly distinct, prediction and forecast are used interchangeably). Unlike with weather forecasting, which has been around for many decades beginning with the hand written charts of the 1950s, dynamical seasonal predictions have been operational for just over a decade, but it is thanks to the similarities with weather forecasting (e.g. relevance of tropical atmospheric dynamics, importance of models' initialization) as well as the sharing of much of the technology that progress in operational seasonal prediction since its inception in the mid 1990s has been rapid. At present, in fact, there are more than 10 major centres that produce dynamical seasonal predictions in an operational/routine basis, including the so-called Global Producing Centres (GPCs) of Long Range Forecasts as identified by the World Meteorological Organization (WMO) (http://www.wmo.int/pages/prog/wcp/wcasp/clips/producers_forecasts.html).

As mentioned above, long before dynamical models were available, prediction of the climate a season ahead was attempted. Prompted by the drought-related Indian famines of the late nineteenth century, especially the one due to the Indian monsoon failure of 1877 and 1878, research carried out at the India Meteorological Department (IMD) unveiled the relationship between the atmospheric pressure over the countries surrounding the Indian Ocean (Davis, 2001). More specifically, Henry Blanford, the first director of the IMD, found that a pattern of abnormally high pressures had extended to western Siberia, northern China and southern Australia during 1877 – we now know that the 1876–1877 El Niño was one of the strongest in the last 200 years (Allan *et al*., 1996). Subsequent research by John Eliot and, especially, by Sir Gilbert Walker, second and third director respectively,

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led to the identification of the Southern Oscillation (SO), the great 'see-saw' in atmospheric pressure differences between the South Pacific and the Indonesian region (Walker, 1924).

Although a satisfactory dynamical explanation for the existence of the SO would only be postulated well after Walker's death (Bjerknes, 1966, 1969), the SO started to be extensively used in statistical seasonal forecast models. Not only that, Walker's work still provides the observational foundation for most modern seasonal prediction approaches. The early statistical models, however, could only rely on short records (typically 10 years) and while they initially proved successful (in the 1910s), empirical relationships started to fail during subsequent decades. This failure, added to the increasing focus in the 1930s on weather forecasting mainly for aviation purposes, meant that longer range climate prediction started to be supplanted in favour of the shorter range weather forecast. With the advent of early computers even more resources were devoted to weather forecasting, which was seen as a necessary hurdle towards longer range predictions, thus widening the gap between weather and seasonal predictions (Nicholls, 2005).

Research on seasonal prediction picked up again in the 1970s when a few scientists began to recognize the relationship between the SO and El Niño, an inter-annual warming of sea surface temperatures along the equatorial Pacific South American coast. It became apparent that these two aspects are part of the same phenomenon, which manifests itself through the strong coupling between the atmosphere and the ocean in the tropical Pacific (to elucidate the coupled nature of this phenomenon the acronym ENSO, El Niño Southern Oscillation, was coined). With that progress came evidence of the general potential for sea surface temperature anomalies, primarily but not uniquely tropical, to influence remote climates on seasonal time scales. Thus, although the 1972–1973 event created a stirring of interest, it was the 1982–1983 event, with its strong worldwide teleconnections, that propelled El Niño into global prominence (Harrison *et al*., 2008b, sect. 2.2). By the time the large-amplitude 1982–1983 event occurred, far greater numbers of scientists were recognizing that a breakthrough was being made in regard to understanding and predicting the climate system, and from then on a new 'industry' was born: an industry that covers the physical understanding, the consequences for predictability and prediction, and the onward use, including the politics, of the predictions, all of which are inherent in the slow changes in the planetary surfaces underlying the atmosphere (Harrison *et al*., 2008a).

As the largest climate signal after the seasonal cycle (excluding externally forced signals such as those due to volcanic eruptions) affecting worldwide climate, ENSO is certainly the dominant driver for seasonal prediction. It is, therefore, critical to understand the physical mechanisms responsible for it and to be able to predict them. However, seasonal prediction is not entirely equivalent to predicting ENSO. Other climate signals, such as the North Atlantic Oscillation (NAO, e.g. Lamb and Peppler, 1987; Hurrell *et al*., 2003), the Pacific-North American (PNA) pattern (Frankignoul and Sennechael, 2007), the Indian Ocean Dipole (IOD, Luo *et al*., 2008) also provide regional predictive potential on the seasonal time scale. For instance, the NAO, a seesaw in pressure between the Icelandic Low and Azores High first introduced by Walker (1924), is now the focal point for much research on climate at mid-high Northern Hemisphere latitudes, especially in western Europe variations from seasonal to decadal time scales (Hurrell, 1995; Katz, 2002). While important sources of regional predictability, modes such as PNA, IOD and NAO are not independent of equatorial Pacific dynamics however (Yu and Zwiers, 2007; Schott *et al*., 2008; Jansen *et al*., 2009). ENSO, therefore, remains the principal global interannual signal seasonal forecasting models seek to capture.

The core of a global seasonal forecasting system is a dynamical model. The more sophisticated models typically contain atmospheric, oceanic, land surface and sea ice modules at a relatively high level of complexity. Once forecasts have been produced by models, the process is far from finished. Numerical models are in fact capable of supplying an extremely large amount of information and, therefore, for seasonal forecasts to be useful in a specific socio-economic sector, it needs to be clear what aspects of the predictions are the most relevant for the problem at hand. Also, since models are often affected by sizeable errors most variables need to be calibrated before they can be used. In addition, model variables are often available only on spatial scales too large to be of direct practical use and, hence, downscaling techniques need to be applied. Furthermore, evaluation of forecasts is essential to acquire confidence, and several assessment (or verification) techniques have been developed for this purpose.

Having identified the relevant aspects of the prediction, one needs to present it in an effective way. Getting the message across to recipients is what really matters: there is little benefit, apart from leaving scientists a feeling of accomplishment, to achieving the 'perfect' forecast if it is not used. However, even when the useful variables have been identified and the message effectively communicated the road ahead is still rough. How does a well-communicated seasonal forecast get considered in the mix of information by the decision taker? For instance, how can the fact be conveyed that there is a high probability that a temperature anomaly of 2 °C may occur for the next season over a certain region and such anomaly may affect the way energy has to be distributed/stored? Indeed, the probabilistic nature of seasonal forecasts can lead to misinterpretations. Communication of forecasts and their uptake by decision takers are, therefore, essential components of seasonal forecasting systems.

Bearing in mind the vastness of the subject and all its ramifications, this paper is an attempt to give an account of all major aspects and issues revolving around seasonal forecasting in a relatively short space. In Section 2 the physical basis of seasonal forecasting is explored. The main ingredients of a seasonal forecasting system are presented in Section 3. Physical and statistical approaches as well as subjective interpretations are key ingredients to a successful post-processing of a forecast as we will see in Section 4. Communication issues and their relevance to societal sectors will be expanded in Section 5. Finally, Section 6 will provide an outlook of possible future developments of seasonal forecasting. Should the reader wish to learn more about the subject, they can access in excess of 600 references (several are cited here too) between the following two publications: Goddard *et al.* (2001) and Troccoli *et al.* (2008).

2. The scientific basis of seasonal forecasts

The chaotic nature of the climate system is such that we will always be limited in our ability to predict the weather beyond a theoretical threshold. This threshold is currently thought to be about 2 weeks but it is critically dependent on numerical model features, including resolution, used to test the predictability assumptions. Given this predictability limit, how can we attempt predictions at much longer ranges? The answer to this question is twofold.

Firstly, there are parts of the geophysical system, such as the oceans and the land, which evolve more slowly than the atmosphere and it is this slower motion that allows us to extend the time horizon of predictions to well beyond the theoretical limit for weather predictions. The ocean, for instance, has a large heat capacity and slow adjustment times relative to the atmosphere. In addition, ocean variability can give rise to enhanced atmospheric predictability in the case of processes that depend on both media interacting. The coupling between the atmosphere and ocean is known to be relatively strong in the equatorial region, *viz.* ENSO.

Secondly, the extension of the prediction lead time from a few days (as in weather forecasts) to months (as in seasonal forecasts) is not automatic. Looking at the evolution of a hurricane as predicted for a certain day several months in the future, although doable, has limited scientific validity. This is because, as it may be expected, a prediction of a hurricane at that lead time is of a lower quality than a prediction for a hurricane a few days ahead, say. In other words, what is considered a meaningful feature, according to some metric, varies considerably depending on lead time. So, when we refer to seasonal forecasting we should not expect the same type of information as given by weather forecasts. Something has to give in. This something is temporal and spatial resolution. More simply, the trick is in the averaging. By taking a larger area and a longer averaging period, the signal from the forecasts starts to emerge. In the case of hurricanes this implies that instead of providing the track and intensity of an individual track, seasonal forecasts may provide the level of hurricane activity in relation to past distribution (e.g. Vitart, 2006). In summary, in order to be able to extract potentially useful information, the longer the lead time the larger the averaging time and the larger the spatial area needs to be. The schematic in Figure 1 shows how this can be done in practice for the time averaging case.

Having established these two fundamental aspects of seasonal forecasts, the key physical mechanisms that are conducive to predictability on the seasonal timescale can be explored. For a more detailed account of the relevant physical aspects see Chang and Battisti (1998), Goddard *et al.* (2001), Anderson (2008), Hoskins and Schopf (2008) or the wealth of information available at http://www.pmel.noaa.gov/tao/elnino/ and links therein.

The SO (Section 1) has a period of between 2 and 7 years. The climate system exhibits oscillations of varied periods, the most notable of which is the seasonal cycle but oscillations need a forcing mechanism to sustain them. It was not until the 1960s that a major breakthrough in the understanding of the SO occurred when Bjerknes (1966, 1969) made two important discoveries: (1) he noted the existence of a thermally-driven east-west circulation across the Pacific (which he named after Walker) of which the SO is part of, and (2) he found that changes in the surface winds (i.e. the lower branch of the Walker circulation) were fundamentally coupled to changes in ocean surface temperature. Figure 2 demonstrates neatly the relationship between the atmospheric pressure and the ocean surface temperature: when the SO is positive – i.e. the pressure anomaly in the eastern equatorial Pacific (the EPAC box) is larger than that over Indonesia (the INDO box) – the temperature in the central Pacific (the NIÑO3.4 box) is lower than normal and *vice versa*. (A more modern index, the EQSOI

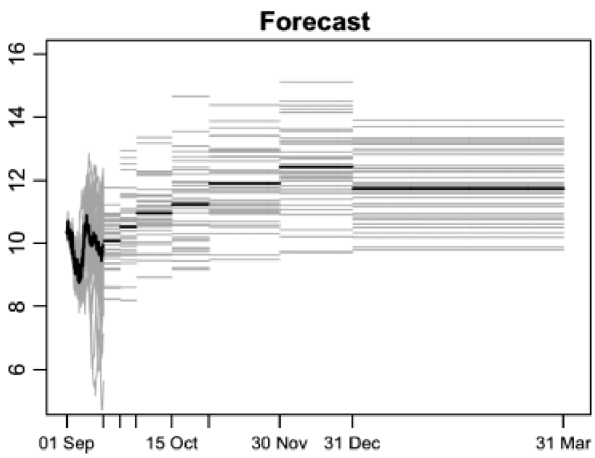

Figure 1. Example of time averaging for a generic forecast (hence dimensionless) started on a September 1. The time averaging has been applied here to an ensemble of forecasts (i.e. different representations of the same event) but the approach is valid even with one model realization only. The grey lines represent individual ensemble members and the black line is their mean. No time averaging is carried out for the first 2 weeks (the direct model output is plotted). This first period is followed by increasing time-window averages: two weekly averages, two bi-weekly averages, two monthly averages and a 3 month average. From Troccoli (2009).

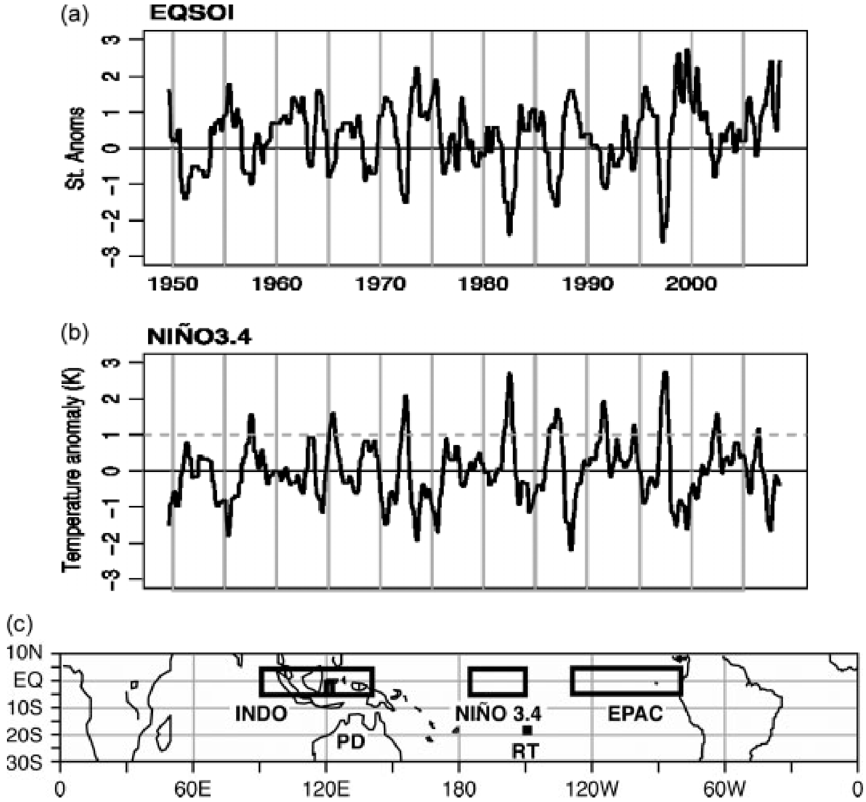

Figure 2. Plot of the pressure index EQSOI (a) and the SST index NIÑO3.4 (b) as a function of time from 1950 to 2008. The dominant time scales in these two indices are very similar. (c) The locations of the two regions used to construct EQSOI (EPAC and INDO) and that for NIÑO3.4. The dashed horizontal grey line at 1 K in panel (b) indicates a possible threshold for El Niño classification (see discussion in Section 5). Data taken from the Climate Prediction Center (CPC) part of NOAA http://www.cpc.ncep.noaa.gov/data/indices/.

(Equatorial Southern Oscillation Index), often replaces the original SOI. The former is a better indicator of large-scale swings in mass between the western and eastern sides of the equatorial Pacific.) To recognize the importance of the coupling between atmospheric and oceanic components the name ENSO (El Niño Southern Oscillation) was adopted. Crucially, this coupling gives rise to a positive feedback: a relaxation in the equatorial easterlies (or trade winds) – due to a decrease in pressure in the central-east equatorial Pacific and an increase in the western part – leads to an increase in sea surface temperature (SST) in the central-east Pacific with a consequent further weakening of the trade winds. This positive feedback, also known as Bjerknes hypothesis, must however be accompanied by a mechanism that reverts the sign of ENSO.

The fact that the SO and SSTs are tightly coupled could be a hint that the ocean subsurface, through its thermodynamics and dynamics, may be a key player in the sustainability of the SO. Theoretical advances and improvements in the observing system of the surface of the ocean – culminated with the deployment of the Tropical Atmosphere Ocean (TAO) array, a network of moored buoys across the tropical Pacific Ocean that measure ocean variables to a depth of 500 m – led to significant developments in the understanding of ENSO (Hayes *et al*., 1991; McPhaden *et al*., 1998). The schematic of how ENSO evolves is shown in Figure 3. The weakening of the trade winds and the consequent increase in temperature in the central equatorial Pacific (the positive phase of ENSO, El Niño) results in the eastern shift of the zone where moisture-laden air converges that gives rise to strong convection (Figure 3(a)). Such a shift is accompanied by the deepening of the equatorial thermocline, a part of the subsurface ocean where the temperature rapidly varies from the warm upper ocean to the colder abyssal ocean.

The depth of the thermocline in the tropics is a very good indicator of how the ocean dynamics evolve. Indeed, by studying its variation it has been possible to determine that the ocean is an essential partner in the coupling with the atmosphere. The two main actors influencing the ocean dynamics of ENSO are the equatorial oceanic Kelvin and Rossby waves. These waves are trapped to within a few degrees of the equator. Kelvin waves travel eastward and can cross the Pacific in about 3 months, Rossby waves westward and can cross the Pacific in about 9 months. The features of these waves and their transit times are what dictate the ENSO evolution. El Niño eventually dissipates and conditions return to 'normal', whereby easterlies drive the warm ocean surface temperature, and together with it the zone of deep convection, to the west. In the negative cold phase of ENSO, La Niña, easterlies intensify even further and SSTs in the central/east Pacific become lower than normal (Figure 3(b)).

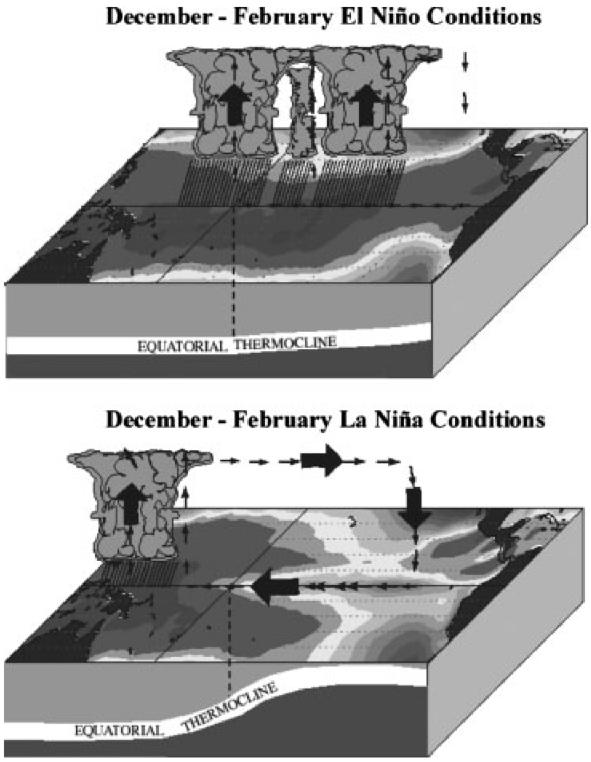

Figure 3. Schematic of (a) El Niño and (b) La Niña. Figures courtesy of CPC, NOAA.

Although the main physical mechanisms are reasonably well understood and have also been synthesized by idealized theoretical models such as the 'delayed oscillator', the 'recharge oscillator' and others (Suarez and Schopf, 1988; Jin, 1997; Wang, 2001; Burgers *et al.*, 2005), several questions still remain open. For instance, what exactly determines the onset of El Niño? Precursors of El Niños are a positive subsurface heat anomaly in the West Pacific and large westerly wind events which trigger Kelvin waves that transport some of this heat eastward: however, not all such waves actually surface in the East Pacific. Also, what determines the recurrence time of El Niño and how does ENSO interact with the annual cycle?

Expanding on the last question, it is apparent that ENSO is locked to the annual cycle. Take El Niños for instance. They tend to initiate during boreal spring in conjunction with the growing phase of the annual cycle in the central/eastern equatorial Pacific (see Figure 4). They then normally reach their peak about a year later at around Christmas time – hence the name El Niño, 'the Christ child', given to this phenomenon by the Peruvian fishermen who noticed the arrival of an anomalously warm current at around this time of the year. The decaying phase of El Niños usually occurs in the spring of the second year but since the range is wider than that of the growing phase, its termination time is more uncertain. Analogous considerations apply to La Niñas. The strongest El Niño events have larger absolute central/eastern equatorial SST anomalies than the strongest La Niña events (cf. the two panels of Figure 4). However, it is also clear that not all El Niño and La Niña events are of equal duration, nor do they all evolve in the same way.

Despite the recurrence of an El Niño every 2–7 years, ENSO is not an oscillatory phenomenon as such: an El Niño is not necessarily followed by a La Niña. The reason for the non-periodicity is not yet understood but several theories have been put forward, all revolving around the hypothesis that ENSO can be approximated by oscillatory systems. These theories can be divided into two main categories: (1) ENSO is a self-sustained oscillator, and, (2) ENSO is a damped oscillator. In (1), the oscillator possesses a natural frequency which is perturbed by chaotic processes (weather) to be irregular, whereas in (2), the oscillator requires some external forcing to keep the system going. The role of non-linearity and noise is markedly different in each case. Despite the attempts to provide unified theories for ENSO, the cause of the irregularity is still an open research topic.

One of the critical factors in these theories is the understanding of how ENSO events are initiated. Once an ENSO event has started, models, and therefore theories, do a reasonably good job at forecasting the subsequent evolution of the event, with lead times up to several months. An atmospheric phenomenon called the Madden-Julian Oscillation (MJO), an intra-seasonal oscillation of about 40–60 days, likely plays a major role in the initiation process and is currently the leading candidate under investigation (e.g. McPhaden *et al.*, 2006b). There is little doubt that weather can influence the evolution of ENSO events: the strengthening of the link between the weather and the seasonal climate communities is likely to be a fruitful path for research and future progress at both time scales. Cassou (2008) provided a clear example of such interaction, demonstrating a clear link between the MJO and the regimes in the North Atlantic European region.

As mentioned in Section 1, ENSO is not alone in forcing interannual seasonal variability. Both the tropical Indian and the Atlantic ocean basins host processes providing predictable climate signals for the surrounding continental masses (Wu *et al.*, 2007; Schott *et al.*, 2008), while the evidence for pertinent roles for extra-tropical oceans is also growing. None appears to exert the global-scale influences of the Pacific-centred ENSO, but nevertheless their effects are undoubtedly critical in some regions, and further understanding will lead almost certainly to improved predictions for these areas. Not all seasonal variability is attributable to atmosphere–ocean interactions, and evidence is mounting that other sources of predictability exist. These sources include amounts of soil moisture across the continental masses (e.g. Koster *et al.*, 2004), the distributions of continental snow and polar ice, atmospheric aerosol distributions (e.g. Engelstaedter and Washington, 2007), and even stratosphere–troposphere interactions (e.g. Baldwin *et al.*, 2003).

It is also intriguing that some El Niño events were preceded by some of the most explosive volcanic events such as Pinatubo in 1991, El Chichon in 1982 (the El

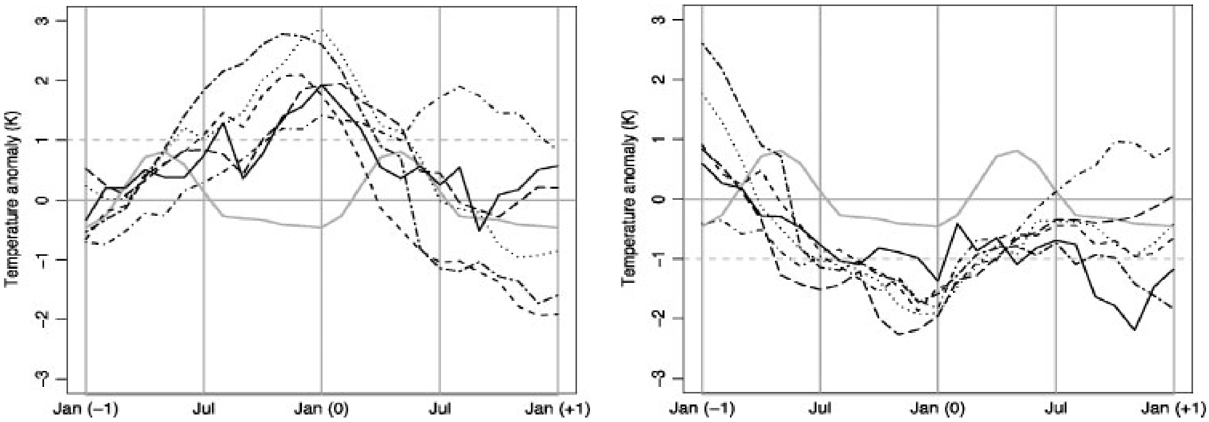

Figure 4. NIÑO3.4 for the six strongest El Niños ——— 1957–1958 - - - - 1972–1973 · · · · 1982–1983 -·-·-·- 1986–1987 — — — 1992–1992 -·-·-·- 1997–1998 (a) and La Niñas ——— 1954–1955 - - - - 1970–1971 · · · · 1973–1974 -·-·-·- 1975–1976 — — — 1988–1989 -·-·-·- 1998–1999 (b) since 1950. All of the plots start in January of the year in which El Niño or La Niña conditions were first observed, Jan (−1), and run through to January 2 years later, Jan (+1). The grey line shows the NIÑO3.4 annual cycle for comparison with the magnitude of the ENSO and to illustrate ENSO's phase locking to the annual cycle. Note also how the spread in the growing phase is tighter than in the decaying phase. The dashed horizontal grey line at + and −1 K respectively indicate a possible threshold for ENSO classification (cf. Figure 2(b) and see discussion in Section 5).

Niño 1982–1983 was the second largest event recorded), Agung in 1963, Santa Maria in 1902, and possibly Tambora in 1815. These eruptions are essentially unpredictable on the seasonal time scale but it is possible that there may be a one-way (volcanic eruptions affecting ENSO evolution) or even a two-way (oceanic mass adjustments related to ENSO triggering volcanic eruptions) coupling between volcanic eruptions and ENSO. Adams *et al.* (2003) suggested that there is an enhanced chance of El Niño happening in the winter following a volcanic eruption. Emily-Geay *et al.* (2008), however, conclude that most of the time volcanic eruptions are found to be too small to significantly affect ENSO statistics unless eruptions are at least as large as that of Mt. Pinatubo in 1991 which caused a reduction in outgoing long wave radiation of about 3.7 Wm^{-2}. Regardless of the direct volcanic impact on ENSO, given that radiative forcing following a volcanic eruption can remain strong for several years (as in the case of Pinatubo, Shindell *et al.*, 2003), it appears to be important to include volcanic aerosol distribution into operational seasonal forecasting models soon after the event (this is not done at present).

Lastly, in light of the findings reported by the Intergovernmental Panel on Climate Change (IPCC, Meehl *et al.*, 2007), it is natural to investigate the interaction between ENSO and climate change. Although ENSO variability has been enhanced by as much as 50% over the past 50 years (Yang and Zhang, 2008), a global mean surface temperature increase of about 1.2 K over the period 2000–2080, as in one of climate change scenarios, does not appear to yield significant changes in the ENSO period, amplitude and spatial patterns (e.g. Zelle *et al.*, 2005). However, expected improvements of climate change scenario runs in the near future will require corroboration of these results.

3. Ingredients of a seasonal forecasting system

The journey that starts from the production of a seasonal forecast and ends with its employment can take several alternative routes but, broadly speaking, the key ingredients of a seasonal forecasting system are:

1. A set of observations of (part of) the climate system;
2. A model that elaborates the observations to yield one (or more) forecast field(s)/value(s);
3. A set of tools to assess the quality of the forecast;
4. A set of tools to post-process the forecast in order to make it usable for specific applications;
5. A strategy to communicate the forecast;
6. A strategy to incorporate the forecast into a decision-making framework, and,
7. A set of tools to assess the impact of the forecast on the decision taken.

The term 'system' may assume different connotations. At its minimum it refers to a set of tools (e.g. a dynamical model) that provide a forecast (e.g. a global temperature field). In a broader sense it refers to the entire process comprising the forecast preparation, its delivery and uptake. Here the second meaning is considered more appropriate for the simple reason that an unused forecast is of limited consequence.

While the undertaking of all seven steps would ensure a proper uptake of a forecast, one can anticipate that not many organizations have the resources to tackle all of them. Although there are no set rules and the landscape is continually evolving, typically there are organizations that deal with steps 1–2 only, others with steps 3–4 and still others with steps 5–7. The discussion here will therefore follow a similar sub-divisions (steps 1–2 in this section, 3–4 in Section 4 and 5–7 in Section 5) but it should be borne in mind that a successful forecast is normally achieved when all seven steps are inter-linked.

Two main approaches can be adopted to produce seasonal forecast fields. Statistical modelling, the simpler of the two, is based on the modelling of historical relationships between the climate anomalies to be predicted and the underlying forcing mechanisms – typically observed SST. The other, dynamical modelling, offers a much more complete framework and is based on the solution of numerical representations of fluid dynamics and thermodynamics equations. There is, however, a wide variety of statistical and dynamical models. Indeed, statistical models could in principle be more computationally demanding than some of the simplest dynamical models. Here the focus is on the more complex dynamical models, deemed to provide better long-term strategy as they allow for a much greater flexibility in the description of climate patterns both globally and regionally. It is for this reason that many large research and/or operational centres have invested substantial resources in this strategy and employ such models to produce seasonal predictions routinely, amongst which are the European Centre for Medium-Range Weather Forecasts (ECMWF), Météo-France, UK Met Office, National Centers for Environmental Prediction (NCEP), Australian Bureau of Meteorology, National Aeronautics and Space Administration (NASA), International Research Institute for Climate and Society (IRI), Korea Meteorological Administration (KMA), Japan Meteorological Agency (JMA). Several of these institutes are also part of the APEC Climate Center (APCC). APCC collects seasonal forecasts from 15 institutes in the APEC region (see http://www.apcc21.net). In fairness, since investment to develop dynamical models can be expensive, many Institutes still adopt statistical models for their operational seasonal forecasts. Often, these same institutes can also access the output of dynamical models and are, therefore, able to produce forecasts from the combination of both approaches (e.g. Bellow *et al.*, 2008).

Given their relative simplicity, statistical models are more widely used than dynamical models for seasonal forecasts. Such statistical models are constructed primarily to generate forecasts of seasonal precipitation totals, but air temperature forecasts are also made (Mason and Baddour, 2008). Most statistical models are based on linear regression between the predictor(s) (typically a temperature index linked to ENSO, e.g. NIÑO3.4) and a single predictand index (e.g. rainfall over a specific region, such as the Nordeste region of Brazil). Modifications to the linear model can be made or alternative statistical procedures used when there is good reason to expect a relationship to be non-linear. While most seasonal forecast statistical models are constructed for tropical countries, where ENSO has its largest impact, statistical predictions have been carried out for the extratropics too (e.g. Qian and Saunders, 2003). For a comprehensive overview of available statistical models see Mason and Baddour (2008). It is also interesting to compare the skill of statistical models and dynamical models. One such comparison is provided by Van Oldenborgh *et al.* (2005) who showed that, by using the anomaly correlation of the ensemble mean as their metric, on an annual average the skill of two ECMWF models is higher than the few statistical models considered. On a seasonal level, the ECMWF models are better at forecasting the onset of El Niño or La Niña in boreal spring to summer while the statistical models are comparable at predicting the evolution of an event in boreal fall and winter.

Since it is the slower timescale of variability in the ocean and on the land that affects the predictability, any attempt to predict seasonal climate variability in general or ENSO in particular, should involve properly integrated atmospheric, oceanic, land, and possibly cryospheric, models (see Figure 5). This notwithstanding, there are several levels of complexity even within the dynamical model category. Three main groups can be identified: (1) intermediate coupled models (ICMs) consisting of a simple atmosphere model (possibly statistical) coupled to a simple ocean model (e.g. comprising two layers representing the warmer part above the thermocline and the colder one below); (2) hybrid coupled models (HCMs) consisting of a similar atmospheric model to ICMs but with a full ocean general circulation model that solves the equations of the circulation of the ocean, together with temperature, salinity evolution, in great detail, and, (3) coupled general circulation models (CGCMs), in which the Earth system is subdivided into cells of sizes varying by model (typically 100 km by 100 km in the horizontal), combine general circulation models for the ocean and the atmosphere and often also those for the land surface and sea ice. Sometimes, atmospheric general circulation models (AGCMs) only are used in seasonal forecasting but SSTs have to be predicted first (e.g. using a statistical model) and then used as boundary conditions to the AGCM. Such an approach is normally referred to as a 'two-tiered' approach (Bengtsson *et al.*, 1993).

It was using an ICM that the first successful dynamical forecast of ENSO was made: the model predicted the onset of the 1986–1987 El Niño one year in advance (Zebiak and Cane, 1987). Such a result greatly boosted the interest in El Niño forecasting using dynamical models. Since then more complex models such as CGCMs have been targeted at El Niño simulation and prediction. Many models are capable of simulating several realistic features of ENSO though it is difficult to assess how good they are as even in nature no two El Niños are the same (cf. Figure 4).

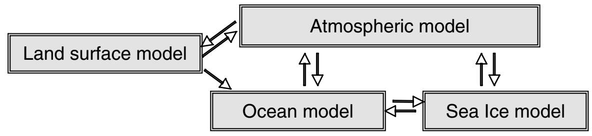

Figure 5. Schematic showing the main model components used by a Coupled General Circulation Model (CGCM) for seasonal climate modelling and forecasts. Double arrows represent a two-way interaction between model components, whereas the single arrow from the land surface to the ocean represents the river runoff.

Any attempt to predict the climate must be supported by evidence that there is a useful level of predictability in the system. Predictability is a relative term that is normally measured by means of numerical models and given the chaotic behaviour of the climate system and model limitations, predictability information is itself imperfect, but what is the cause of the limit in predictability of ENSO? Strategies of ENSO predictions using dynamical models hinge around this question as the paths of model development are rather different depending on the answer. Although related, two main limiting factors can be distinguished: (1) the effects of high-frequency atmospheric 'noise', and, (2) the growth of initial errors in model simulations. According to Chen *et al*. (2004) initial error growth is the more critical aspect, however. This means that model-based prediction of El Niño depends more on initial conditions than on unpredictable atmospheric noise. Encouragingly this would imply that improved initializations should lead to better ENSO. By initializing reasonably well the ocean state as well as the land conditions, it is possible to predict how critical boundary conditions such as the sea-surface temperature and, to a lesser extent, the soil wetness and the snow cover, will evolve in the following months (e.g. Alves *et al*., 2004). It is the simulation of the evolution of these slowly evolving components of the climate system that allows us to predict atmospheric circulation patterns some months ahead. Of particular relevance is, of course, the prediction of ENSO and of the climate conditions in the tropical areas, which might influence regions remote from the tropics through teleconnections.

Thus, the current state of the climate is crucial to seasonal prediction. The most common approach to initialize a CGCM is to initialize the individual main components, namely the ocean, the atmosphere and the land, separately. The separate initializations are done mostly for practical reasons as it is easier and less computationally demanding to deal with one component at a time. The main drawback of this approach is that the separate initial conditions may not be in balance when forecasts are started and, therefore, coupling shocks may impact on the results of the forecast negatively, from early on in the integration. However, coupling shocks may be considerably alleviated if common boundaries (e.g. the SST seen by both the atmospheric and ocean models separately) are treated in a consistent way. By and large, the most important of these initial conditions is deemed to be the state of the ocean, and for predictions up to about a year, the upper few 100 m is the most critical (Anderson, 2008).

The initialization of the models is achieved through an approach called data assimilation, a combination of observations and model data performed with the aim of achieving the 'best' initial state for the model. Ideally all available observations should be used for this purpose. However, practical considerations such as the inter-dependency of different observations, the need for models to be 'in balance' with observations (a technical requirement to ensure the model moves forward smoothly, rather than jumps, from its initial state) and many others put constraints in the way data assimilation is actually implemented. The details of data assimilation will not be discussed here, but it is worth noting that data assimilation is not a specific technique for the climate system only. Rather, it is used in a wide variety of disciplines, e.g. in satellite orbit determination, in any application that requires an optimal way to combine a model with observations. For a more detailed discussion see for example, Tribbia and Troccoli (2008).

The fact that observations of the climate system have thus far been mentioned but not properly discussed in detail should not give the wrong impression: they are possibly the most essential component of a forecasting system. Observations are vital in many ways: they are used to learn about the past, to construct statistical models, to prepare initial conditions for CGCMs, to assess the quality of forecasts in retrospect. Observations can be segregated into two types: (1) *in situ* measurements, which require sensors to be collocated with the quantity to be measured, and, (2) remotely sensed measurements, which rely on inferring physical variables from afar through the inversion of a radiated signal. Radiosonde temperature measurements and satellite temperature retrievals are prototypical examples of *in situ* and remotely sensed data respectively. In the following observations from the three more relevant media for seasonal forecasting, atmosphere, ocean and land surface, are discussed.

Prior to the advent of the routine use of satellites in the 1980s, the majority of atmospheric data were collected through *in situ* measurements. Since then an exponential growth in the volume of remotely sensed data from satellites has been achieved. To give an idea of this growth, about 100 thousand observations of the atmosphere were used for weather forecasting in the early 1990s. Now, this number is about 10 million, i.e. 100 times larger. The spatial data coverage has also become more uniform. Whereas before satellites the southern hemisphere was relatively poorly observed, now the quality of forecasts for the north and south hemispheres is basically the same mainly as a reflection of the more uniform global data coverage.

Although the ocean is less well observed than the atmosphere there have been important developments in the 1990s. By far the most relevant for ENSO forecasting was the deployment of the TAO-TRITON array (Tropical Atmosphere Ocean/Triangle Trans Ocean Buoy Network), which consists of approximately 70 moorings in the Tropical Pacific Ocean. Each buoy takes detailed measurements of surface winds, humidity, surface and subsurface temperature and salinity, and continuously relays the information via satellites. In 2000, a new observation system, Argo, was also introduced. This system has largely modified the way in which the ocean subsurface is observed. Before Argo, observations were mostly taken at the same location (as for the TAO-TRITON array) or along tracks concentrated along shipping routes or within limited regions during research campaigns. With Argo, which consists of free-drifting profiling floats that measure the temperature and salinity of the upper 2000 m of the ocean, most of the ocean can in principle be covered. About 3000 Argo floats have been deployed so far and their measurements are available in near real time. Figure 6 shows the evolution of the global number of *in situ* oceanic observations since the 1950s. Particularly striking is the rapid increase in the number of observations in recent years, i.e. after the advent of the Argo floats. In addition to these *in situ* measurements, starting in the late 1980s a wealth of satellite oceanographic observations such as sea surface height (SSH), SST, the sea surface salinity (SSS) and ocean colour have become available. Yet remote measurements can only be used to observe the (near) surface of the oceans and given their vastness – they occupy about 71% of the Earth's surface with an average depth of about 3800 m – they therefore remain largely unobserved.

Land surface variables (mainly soil moisture, snow cover and skin temperature) are also not easy to measure because of the heterogeneity and/or remote location of a region. Soil moisture, the main variable for seasonal forecasting, is a key hydrological state variable that integrates much of the land surface hydrological and biophysical processes. However, *in situ* soil moisture measurements are generally expensive and no large-area soil moisture networks exist to measure it at high temporal frequency in multiple soil depths (Ni-Meister, 2008). Satellite remote sensing that provides global quarter-degree resolution near surface soil moisture content has been derived using C-band passive microwave observations (Owe *et al*., 2001). As in the case of the ocean, remote sensing can only measure the top few centimetres of soil.

Not only is the temporal and spatial resolution of observations important, the length of the record is equally critical. In fact, seasonal forecasts need to be executed over a relatively long period (normally more than 15 years) in order for them to be bias corrected, calibrated and assessed. A practical way to extend observational records is to combine available observations with a model. Reanalyses, which might be described as historical global maps created using the most up-to-date technology (e.g. model, data assimilation method) in a consistent way, namely using the same technology throughout the period analysed (e.g. from 1950 to present), are often used for this purpose.

Moreover, recognizing that small changes in the initial conditions or even small changes to the formulation of that model, changes that might otherwise be considered insignificant, can affect any prediction to a major extent, ensemble forecasts have been developed whereby a number of forecasts (currently typically 10–50) are produced at the same time based on variants of these changes. Naturally running a prediction system, say, 50 times rather than just once places an immediate demand on computing power in competition with the demands from resolution and incorporation of more processes. The main argument for using ensembles in predictions is that by taking the average across all predictions within an ensemble the 'unpredictable' smaller scale components would be filtered out leaving a stronger 'predictable' signal, and, hence, greater prediction accuracy. Another related advantage is that ensembles allow for a more immediate estimation of uncertainty – the spread of the ensemble can be taken as being proportional to the uncertainty of the prediction. However uncertainty estimation heavily relies on the manner in which the ensemble is generated – to be a robust estimate, perturbations need to be in some way commensurate with the perceived error of the parameter being perturbed.

This is where dynamical models stop: they have done their part. The end is not in sight though and a lot has to happen in the sphere of post-processing (or *a posteriori* procedures) before one can go out to publicize their forecasts.

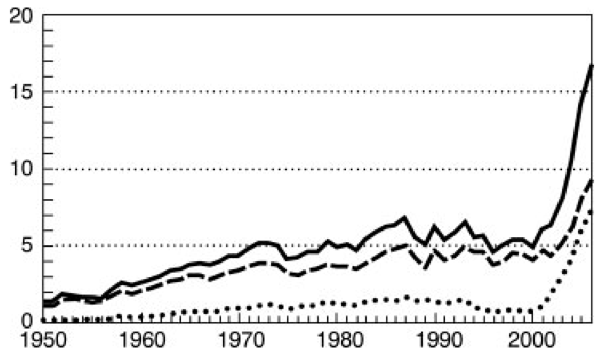

Figure 6. Global number of *in situ* oceanic observations on typical model levels as a function of time (dotted line: salinity, dashed line: temperature, solid line: sum of the two). Temperature observations have historically been more abundant than salinity ones. The noticeable downturn in observations in the 1990s was due to the reduction in XBT (eXpendable BathyThermographs) profiles. Since 2000, however, with the advent of the Argo floats (see text), salinity – as well as temperature – observations have considerably increased (From Tribbia and Troccoli, 2008).

4. Making sense of seasonal predictions

Once observations and models are combined, CGCMs are run for many months ahead (up to about 1 year) to produce a 'forecast'. It is somewhat optimistic, however, to call the millions of numbers churned out by CGCMs a forecast. Considerable massaging has to be usually applied to these numbers in order to obtain a reasonable forecast. Such manipulation, an essential component of a seasonal forecasting system (items 3 and 4 in the 7-ingredient recipe, Section 3), includes bias correction and calibration.

As the name suggests, 'bias correction' indicates that there are some errors in the model output that need to be adjusted. Indeed, substantial differences between the observed and dynamical model climates (the biases) invariably are evident, and normally have to be corrected in order to provide usable forecasts. An example of the speed with which such biases can manifest in coupled forecasts is shown in Figure 7, depicting the systematic 2 m temperature biases at month zero (top) and month 1 (bottom) lead times in an ensemble of ENSO predictions using the ECMWF coupled model. As can be ascertained from Figure 7, not all regions of the globe are affected by biases. Nor is it consequential that regions with larger biases will have a poorer forecast performance: indeed the predicted variability may be reasonable in spite of biases. Although it is clear that the simulated mean climate must be reasonable in order to realistically capture the many important signatures of intra-seasonal variability (Gleckler *et al*., 2007), the interaction between bias and variability is not a simple one. A recent study by DelSole and Shukla (2009) concludes that models that poorly simulate the observed climatology tend to have poor skill in seasonal forecasts, while models that more closely replicate the observed climatology tend to have better skill. Of course it would be desirable to have bias-free models, but whether biases arise mostly from errors in the atmospheric, ocean or land surface component (e.g. Toniazzo *et al*., 2008) is immaterial in the context of trying to achieve a usable forecast.

It is safe to assume that model biases will stay around for many years to come and, therefore, what is needed it is a strategy for firstly detecting such errors and secondly for correcting them *a posteriori*. Maps such as those in Figure 7 are useful to detect the simplest form of error: the mean bias (i.e. the central tendency of the model climatology differs from that for the observations). More generally, biases can manifest as mean, variance, or shape biases or, nastily, even all at once. Figure 8 shows the frequencies of average precipitation rates over a 3 month period for a specified region and exemplifies how biases can manifest. In Figure 8(a) the simulated rates are consistently too high compared to those observed (mean bias) as well as having a larger variance than the observed (variance bias); Figure 8(b) illustrates that variance biases can occur even when the mean bias is minimal; and in Figure 8(c) all three types of bias are present: the model's mean and variance are too high, while the skewness is too low (Mason, 2008). Distributions such as those presented in Figure 8 are computed for fixed regions: but what if these biases are only the result of a spatial displacement? In other words, the model may be successful at forecasting the pattern of rainfall variability but this pattern may be displaced by say 15° to the west. Specialized statistical tools such as principal components need to be used in order to detect any such displacement (an example is given in figure 8.3 of Mason, 2008).

Bias identification is not always practical: model biases are dependent on the variable, region, season and phase of ENSO. For instance, coupled models tend to perform more poorly when the forecast start during boreal spring, hence the so-called 'spring predictability barrier', and more so in the decaying phase of an El Niño than in its growing phase (e.g. Jin *et al*., 2008). This may be linked to a greater SST variability, as seen earlier in the NIÑO3.4 of Figure 4. However, such behaviour is not evident in all ENSO-prediction models, and so may not be an inherent feature of the ENSO phenomenon (Chen *et al*., 1995).

Having detected the face of the bias, the remedy follows relatively easily. The simplest and most common approach assumes that only the mean is biased. A mean removal is then applied, i.e. $g(z) = z - \overline{z}$, where $\overline{z}$ is the sample mean. This procedure is applied to both model data and observations and the resulting fields are referred to as anomalies. Analogously, a correction to both the mean and variance would be applied as follows: $g(z) = (z - \overline{z})/s$, where s its standard deviation. By doing so, data are said to be standardized. Standardization is a widely used procedure that successfully removes mean and variance biases, but can be problematic when used on data with a zero bound and/or when there are biases in the shape of the model's distribution (see Mason, 2008 for more details). To correct for spatial biases, one of the two statistical techniques, maximum covariance analysis or canonical correlation analysis (both extensions of multiple linear regression), are often used (Mason, 2008).

Bias correction, as well as forecast skill assessment, has to be based on past performance. Many runs of the coupled model need to be performed in order to build a sufficient sample, which provides the statistical moments (mean, variance) upon which the *a posteriori* correction is based. A set of re-forecasts (or equivalently back integrations or even hindcasts), run over a past period, constitute the sample. The length of the period is dictated by a mix of practical and statistical considerations. From a statistical viewpoint the sample should contain as many inter-annual modes of variability (e.g. ENSO) cycles as possible. Moreover, due to the pronounced seasonality in model errors as well as in model performance, statistics have to be generated separately for each month of the year and normally several ensemble members are run for each start date (CGCMs are currently typically run on the first of each month). Bearing in mind that coupled models are computationally expensive to run (main constraint) and that the climate is non-stationary (a weaker constraint) a typical choice for the re-forecast period is 15–25 years. A quick calculation demonstrates that re-forecasts, the backbone of model calibration and assessment, constitute a considerable component of the computational cost of a dynamical forecast (number of re-forecasts runs: (15–25) years × 12 months × 10 members = 1800–3000 runs). Careful consideration therefore needs to be given to this aspect when devising a forecasting system.

Another way to side-step model errors is to employ more than one model, under the so-called multi-model approach (Krishnamurti *et al*., 1999; Palmer *et al*., 2004). Use of multi-models is an empirical and pragmatic way to account for errors in individual models: the multi-model hinges on the fact that models have been developed somewhat independently and thus they would satisfy the necessary requirement of independence. However, no theoretical framework yet exists to explain this seemingly successful approach, but ultimately it has to be judged by its performance. Some attempts to try to empirically explain its performance have been made though. Weigel *et al*. (2008) provided one of the most satisfactory explanations to date. Given that a multi-model contains information from all individual models, including the less skillful ones but possibly with different weights, they addressed the question of why, and under what conditions, a multi-model can outperform the best participating single model. By using a synthetic forecast generator, which allows the generation of perfectly calibrated individual models of any size and skill and adjusting the degree of the resulting ensemble under-dispersion (or overconfidence) they concluded that multi-model performance depends on the skill and overconfidence of the participating single models. Since multi-model combination reduces overconfidence, i.e. ensemble spread is widened while average ensemble-mean error is reduced, it can indeed locally outperform the 'best-model', but only if the individual models are overconfident.

Whether for single or multi models, forecast assessment, also known as verification or validation, is fundamental to gaining confidence on the quality of a forecast model: clearly it is desirable to learn as much as possible about past performance before diving into the unexplored territories of the future. A wide range of measures (or scores) to assess performance is available, going from the more standard 'deterministic' correlation and root-mean-square (RMS) difference to the 'probabilistic' Brier score and reliability measure. Forecast assessment is by no means specific to seasonal forecasts and hence many references are available: Jolliffe and Stephenson (2003), Mason and Stephenson (2008) and the Special Issue of Meteorological Applications (2008) on Forecast Verification provide excellent starting points.

By carrying out seasonal forecast assessments one finds that skill varies markedly depending on the region considered, on the state of the climate when the prediction starts (e.g. the ENSO phase), on the lead time and on ensemble size (see Kharin *et al*., 2001; Jin *et al*., 2008 for an analysis of skill dependencies). A recent analysis by Livezey and Timofeyeva (2008) has shown that, except for winter forecasts during strong ENSO episodes, skill does not vary with lead time over the U.S.A.: instead, they concluded, skill comes exclusively from long-term trends, dominantly associated with climate change for this region.

A map of skill for near surface temperature of a seasonal forecasting system as given by the anomaly correlation for forecasts started in February is displayed in Figure 9. This plot confirms that for the tropics forecast skill is highest but higher latitudes also have some potentially useful skill, for instance where correlations are larger than 0.4 (although a correlation of 0.4 is not very large, 'windows of opportunity' may exist. See also later discussion). Somewhat different considerations apply to another important physical variable, precipitation. Although the analogous map for precipitation also displays a maximum in the equatorial Pacific, though with lower values, elsewhere, correlation values are close to zero (not shown). Moreover, because of the relatively large climate anomalies accompanying an El Niño, several global teleconnections are manifest, for instance, over Southern Africa or North America. Thus, although predictions are generally more skillful in tropical areas than at higher latitudes during an El Niño, predictable features can be found at higher latitudes too (Figure 10).

Maps such as that in Figure 9 provide useful indications about the quality of predictions. As one can imagine, a much more extensive assessment than just correlation maps is normally carried out by seasonal forecasting centres and other research/operational institutions in order to examine in great detail how a forecasting system performs. This is because (1) there are many ways skill can be measured, correlation being just one of them (see e.g. Mason and Stephenson, 2008); (2) skill depends on time and location and (3) several other physical variables need to be assessed aside from the most common two, surface temperature and precipitation (e.g. pressure, wind). As a result of such evaluations a wealth of statistics, using both deterministic and probabilistic metrics, is usually produced which can then be used to calibrate subsequent specific forecasts either objectively or subjectively (see for instance the comprehensive analysis carried out by the EU project ENSEMBLES (http://www.ecmwf.int/research/EU_projects/ENSEMBLES/results/)).

Such assessments are doubtless essential. However, care should be taken in order not to over-interpret statistics. By definition, statistics provide a summary of behaviour of a system and as a consequence they may gloss over important details. Imagine a particular skill measure that behaved like the curve in Figure 11 with periods of both negative and positive values, but with a zero mean (as represented for instance by a white area in Figure 9). It is apparent that, based on this skill measure, there are instances in which this forecasting system performed particularly well. This may be the case, for example, for forecasts produced while an El Niño is under way: models are often sensitive to stronger anomalies such as those provided by an El Niño and hence their response may emerge from the noise during such events and may then provide a useful forecast (Goddard and Dilley, 2005; Livezey and Timofeyeva, 2008). Periods of higher positive skill in such circumstances are normally referred to as windows of opportunity as potentially beneficial forecasts may be attainable during such periods.

Being able to exploit windows of opportunity would therefore equate to achieving a higher skill than that yielded by assessing the system purely from a statistical basis. Critical to the exploitation of these windows is the understanding of how the physical system works. The forecast provided by the model then becomes just one, though an important, piece in the jigsaw of the final forecast. This was the case for instance with the seasonal forecast issued by the UK Met Office in the winter 2005–2006 discussed in the next section.

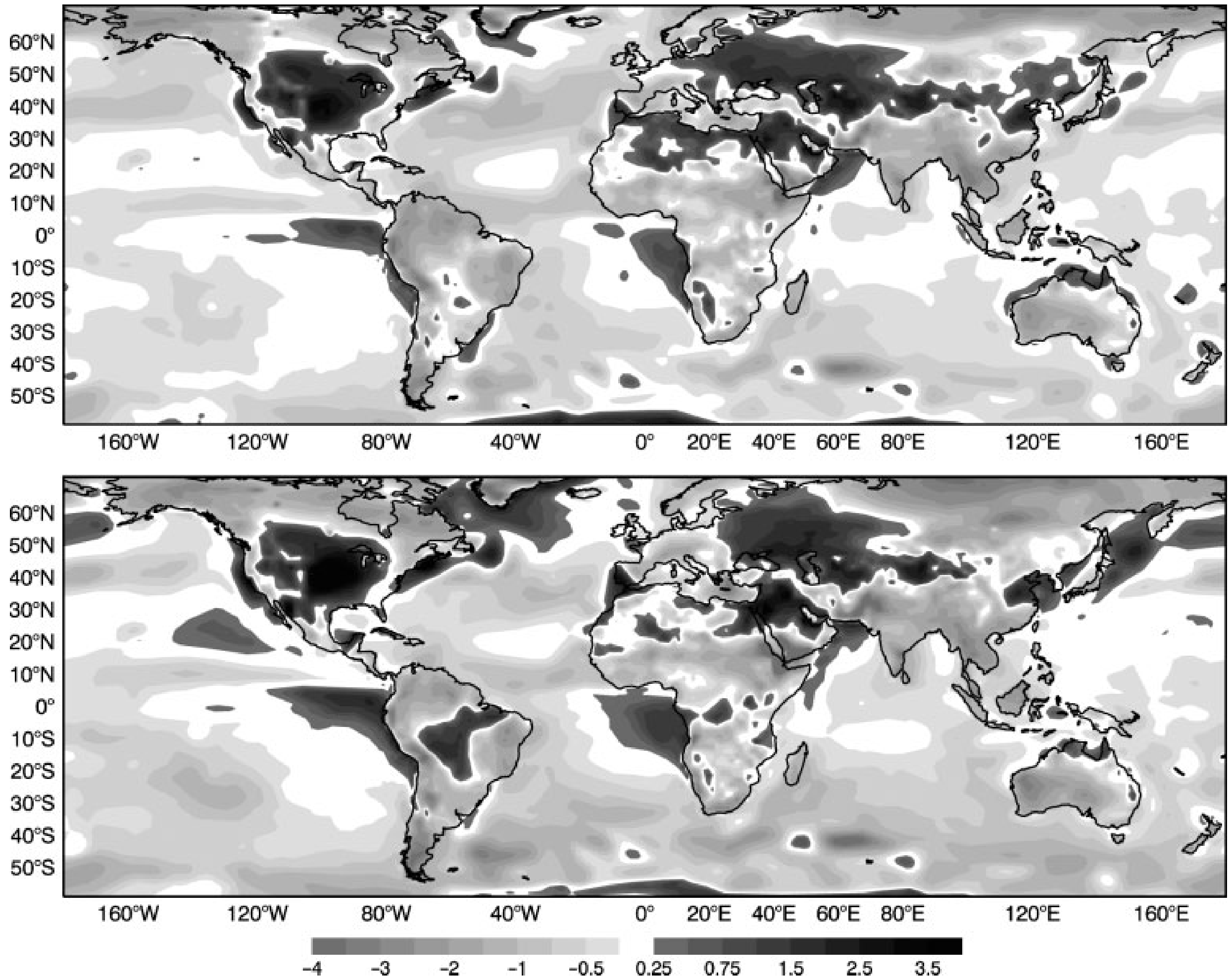

Figure 7. The evolution of the 2 m temperature systematic error (or bias) in °C at month zero (top) and month 1 (bottom) lead times in an ensemble of seasonal forecasts using the ECMWF coupled model (System 3). Note how the bias generally increases with increasing lead time (From Tribbia and Troccoli, 2008).

Since global model predictions represent large spatial averages, and generally are presented as seasonal averages, downscaling may be required to make the forecast relevant for specific locations, and to provide more detailed information about the statistics of weather within the season. Thus, downscaling involves the translation of a forecast to a spatial and/or temporal resolution that is finer than that at which the forecasts are produced. Two downscaling methods are available: statistical and dynamical. In the former category there are methods such as canonical correlation analysis for the spatial downscaling and weather generators (a weather generator is a statistical tool built to produce long-term forecasts of weather at a site based on statistical characteristics of the observed weather at that site) for the temporal downscaling. Dynamical methods involve running a higher resolution regional model using the global model output as boundary conditions. The merits of these methods are not discussed since, as for forecast assessment, seasonal forecasts normally apply generic approaches to downscaling. For further details see Mason (2008) and for more specific examples Chu *et al.* (2008), Zhu *et al.* (2008) and Schoof *et al.* (2009).

5. Taking decisions on the basis of seasonal predictions

A wide variety of societal sectors are exposed to the variability of climate. For some diseases close direct and indirect links with climate conditions exist (e.g. malaria epidemics; see Thomson *et al.*, 2006; Abawi *et al.*, 2008) and in such cases, climate prediction might give public health systems early warning of the likelihood of epidemics. Likewise, using seasonal predictions as input for load-balance models has the potential to optimize the matching of supply and demand in the energy industry. Similar examples could be mentioned for many other sectors like water resource management, retail industry, finance, insurance, fishery, transport, tourism and policy making (section 2.4 of Harrison *et al.*, 2008b). Given the wide-ranging applicability of seasonal predictions, it becomes apparent, therefore, the strong interest in improving our ability to predict the climate of the next seasons. It is worth noting that the initial driving force behind this research was of socio-economic nature (with food security in India, see Section 1). Now that the scientific component of seasonal forecasting has almost reached its adulthood, it is picking up the

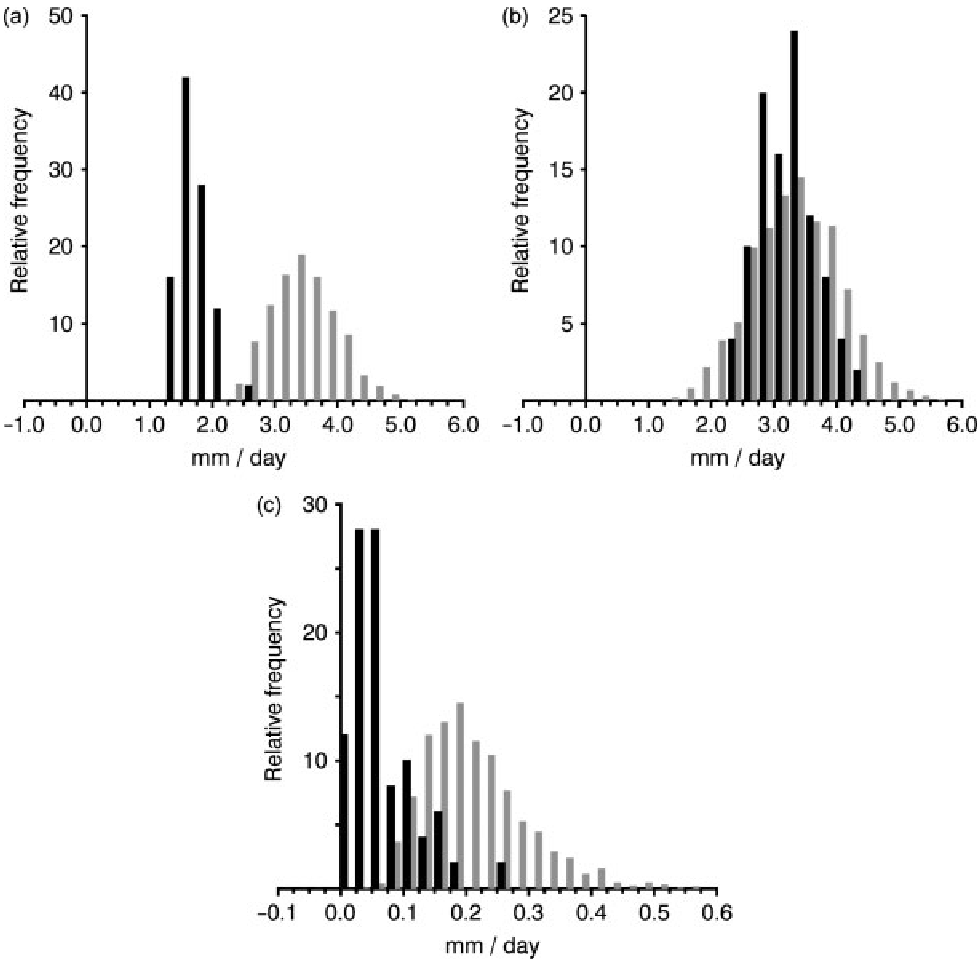

Figure 8. Example of model systematic errors for observed (black) and simulated (grey) daily precipitation intensities: (a) mean and variance biases; (b) variance bias; and (c) mean, variance, and shape biases (From Mason, 2008).

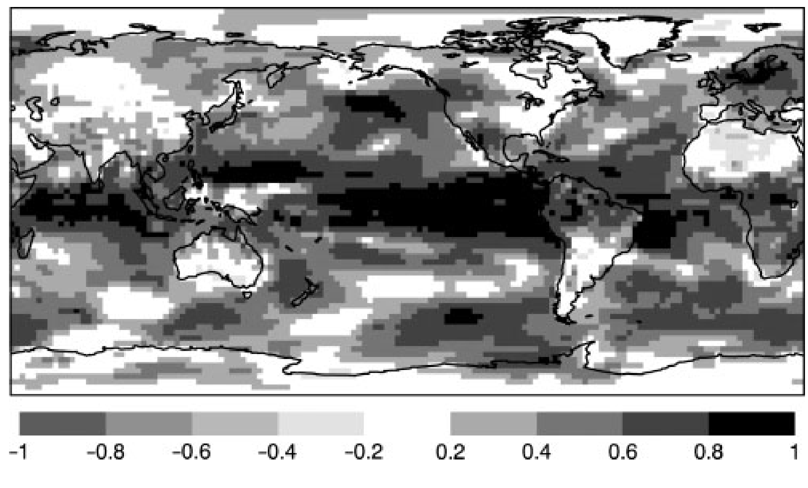

Figure 9. Skill of a seasonal forecasting skill as measured by anomaly correlation for near surface temperature. Results will vary depending on the season being predicted. In general skill is higher in the tropics than at higher latitudes and for this particular season (March-April-May) the temperature signal over northern Europe is real (From Anderson, 2008).

threads with the economic and social aspects which were left a bit behind as attention was mostly devoted to improving our scientific understanding of seasonal predictions.

Major societal climate-related impacts are normally linked to strong ENSO episodes. Indeed the two main recorded El Niño events, 1982–1983 and 1997–1998 had dramatic worldwide consequences, and because no two El Niño events are the same in terms of their evolution and consequent impacts, it is critical to have some indications of whether an El Niño or a La Niña are likely to occur several months hence.

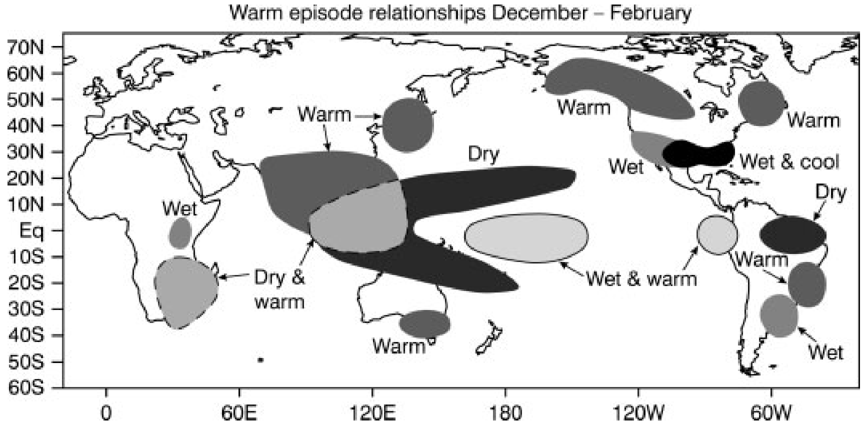

Figure 10. Plot of the frequently observed climate anomalies in temperature and precipitation associated with El Niño. This plot is for Dec–Feb, often the peak phase of El Niño. Other seasons will have other climate anomalies (teleconnections). A given El Niño will not necessarily show all of these climate anomalies.

While weaker El Niño events such as that of 2004–2005 may be of less consequence than larger ones, how can one discriminate between ENSO and non-ENSO events? This is a very important issue as decisions at different levels (political, economical) can be taken solely based on the fact that an El Niño is predicted to happen. Such decisions would then be broadly based on forecasts but, critically, also on the historical impact of El Niño events, even if the actual effect could be rather different from earlier events. Typically, in fact, humans tend to relate current or future situations to past and recent experience. While such mental analogues are valuable because the mind can more easily access a wealth of recent information on the behaviour of the whole system with which the decision-maker is concerned, they could actually distort the decision-making process. Therefore in order to avoid any such distortion, it is paramount to access also objective information such as a relatively long record (e.g. 20+ years) of the event affecting the decision (e.g. the minimum temperature for a specific region).

Caution has to be taken also with objective measures, however. Although attempts have been made to define an easy-to-interpret metric to indicate whether there is an ENSO or not, any such metric would be an oversimplification. Thus, defining an El Niño by selecting a threshold of say 1° for the NIÑO3.4 index as done in Figures 2(b) and 4, though appealing it is likely to be interpreted and acted upon in different ways by different people. Glantz (2003, p. 202) describes for instance the very different ways three governments (Peru, Kenya and Costa Rica) responded to the early forecasts in June 1997 of the impending 1997–1998 El Niño.

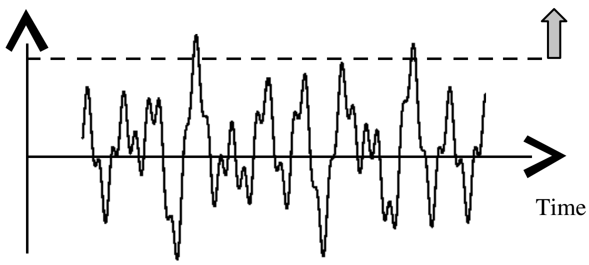

Figure 11. Schematic of temporal evolution of a generic skill measure with zero mean. Values above a chosen threshold (dashed line) may provide potentially useful predictions (the so-called 'Windows of Opportunity'). From Troccoli (2009).

Naturally, different interpretations may also arise because of the probabilistic nature of seasonal forecasts. For whichever variable, region and lead time, seasonal forecasts always need to carry a label that says how likely the prediction is going to be. As a consequence any one forecast can not be right or wrong: trust needs to be built over time. However, by clearly stating the uncertainty of an individual forecast and properly factoring in this intrinsic uncertainty valuable risk-management decisions can be taken. Practical frameworks for taking uncertainty into account in order to assess the level of risk associated with decision making processes is given for example by decision tree diagrams and influence diagrams (e.g. Goodwin and Wright, 2003). Such diagrams are devised to take into account a variety of factors that shape the final decision, seasonal prediction being just one of them (see Figure 12 for an example of a tree diagram). With any such tool, however, given the variety of potential decision makers, some level of customization is necessary. Examples of how seasonal forecasts and climate information more generally are used in practical contexts are given in Stern and Easterling (1999), Hammer *et al.* (2000), Cash and Buizer (2005), Abawi *et al.* (2008) and Bellow *et al.* (2008).

One of the keys in demonstrating the value of seasonal predictions lies in the manner forecast information, and especially its uncertainty, is communicated to the decision making community. Miscommunications may in fact occur in a number of ways, including through the psychological processes that are sometimes referred to as 'cognitive illusions'. The 'framing effect' offers a straightforward example – the two statements 'there is a 30% chance of a drought this coming season' and 'there is a 70% probability that rainfall will be adequate for cropping this coming season' effectively provide the same information, but the manners in which the

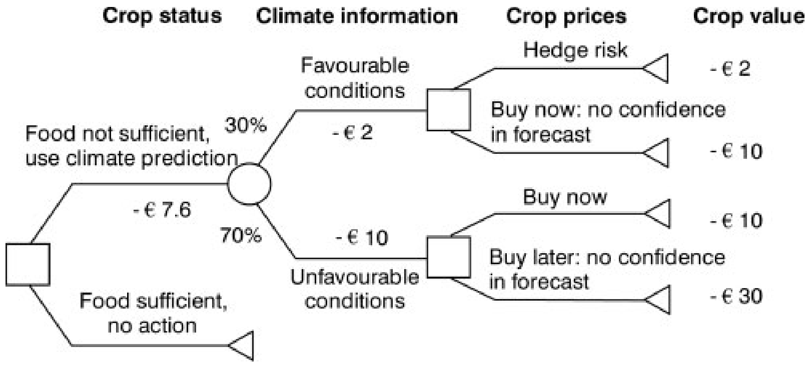

Figure 12. A highly simplified decision tree diagram to incorporate Climate information (of which seasonal forecast is a subset) into the decision making process for a food security application (From Harrison *et al*., 2008b).

statements are stated, or framed, invite possibly diverse decisions, a defensive approach against drought in the first case and a positive response to take advantage of possible beneficial climate conditions in the second (Nicholls, 1999; Harrison and Williams, 2008).

Despite these challenges, prudent use of ENSO forecasts has proven to be highly advantageous. California, for instance, saved US $1 billion in 1997–1998 as a result of actions taken by individuals, businesses and government in response to advance warning of El Niño's impending impacts (Changnon, 1999; McPhaden *et al*., 2006a). More broadly, Goddard and Dilley (2005) demonstrated that, in spite of the greater exposure during ENSO extremes, climate-related socio-economic losses are not greater overall during such events than during neutral periods, indicating that seasonal forecasts, and climate information in general, may have contributed to an overall beneficial socio-economic impact.

As mentioned in the previous section, knowing how to interpret seasonal forecast and other related climate information from a physical viewpoint may enhance its value *via* so-called windows of opportunity. One such case happened recently in the United Kingdom. In August 2005 and in updates during the subsequent autumn, the UK Met Office issued a forecast for the United Kingdom and the rest of Europe for the boreal winter 2005–2006, indicating a colder and drier than average winter for much of Europe (with a 66% probability of occurring). Judging by the overall skill of the UK Met Office (and others) dynamical model outputs this forecast looked hazardous: the skill of temperature predictions of the dynamical model over the region is in fact negative on average. However, the dynamical forecast constituted only part of the forecast preparation process. The final forecast was prepared by considering also information from a statistical model, from observed subsurface ocean conditions and their evolution, as well as from interpretation by operational forecasters (Graham *et al*., 2006). In spite of the impossibility to state after the event whether an individual probabilistic forecast is correct, most of northern Europe (albeit except northern United Kingdom) did experience colder and drier than average conditions (Folland *et al*., 2006). Although there was no impact on economic activities at the time of the Met Office winter forecast press release in September, some markets, like the energy sector, did however react significantly when the first anomalously cold weather hit London in November, so it is possible that the winter forecast primed the markets and made them more sensitive (Troccoli and Huddleston, 2006). Overall wholesale gas prices for the United Kingdom remained well above the long term average for the whole winter 2005–2006. Clearly other significant factors were also at play including the fact that the United Kingdom was turning from a net exporter of gas to a net importer around that time as well as high gas demand in other areas of Europe. All in all, important lessons were learned by the scientific community in the United Kingdom following the 2005–2006 winter forecast, exposed as it was to public reaction to a long-range (seasonal) forecast. One such lesson was that it is crucial to engage with a wide range of stakeholders to ensure they understand the forecast and that they do not base their decisions on, say, newspaper headlines, as happened in some cases.

6. Looking ahead

As argued in this paper, key to producing seasonal predictions is the ability to identify anomalous climate signals such as ENSO extremes. This ability stems from understanding the way in which components of the Earth system provide such predictive skill and from being able to extract the signal from the noise present in the climate system (i.e. its internal variability due to physical mechanisms such as convection). Despite considerable advances in the understanding of the physical system and in model development, some fundamental questions still remain unanswered: what exactly sets off an El Niño? Why does there appear to be a limited predictability in boreal Spring? What modulates ENSO on the decadal time scale? How does ENSO behave in a warmer climate? These issues directly reflect on our ability to model the climate system and as a consequence progress in improving prediction skill has been modest in recent years.

It is also likely that models, reflections of our understanding of the system, do not describe some relevant processes. For one, all coupled climate models exhibit significant bias errors in the simulation of ENSO. In addition, coupled model forecasts are also prone to 'initialization shock', a rapid unphysical adjustment toward the model climatology that can interfere with the ability to correctly evolve real climate signals (McPhaden *et al*., 2006a). Although most of these errors can be corrected *a posteriori* and therefore valuable forecasts can be attained anyway, it is clear that a substantial amount of research is needed. For example, soil moisture anomalies can induce significant signals in precipitation and air temperature, which may persist for weeks to months but their full potential has yet to be exploited. Other variables such as snow cover, subsurface heat reservoirs, vegetation health (leafiness) may also prove to have an important role in understanding the evolution of interannual variability such as ENSO. Even more remote effects such as the interaction of sea ice with the rest of the climate system or stratospheric processes may provide useful insights.

There is also evidence from natural climate archives such as corals and lake sediments that ENSO varied considerably in strength in the geological past. For example, changes in the Earth's radiation balance due to major volcanic eruptions, variations in solar output, and the precession of the Earth about its axis have all affected the ENSO cycle over the past 130 000 years (Mann *et al*., 2005). Paleo-climate may therefore provide important clues about the evolution of ENSO under different external forcings, such as those experienced with the increased greenhouse gas levels of recent decades.

Crucial to the proper uptake of seasonal forecasts is the whole host of procedures, which elaborate the output of a model in order to make it relevant to socio-economic applications. Whilst a lot has been done in terms of forecast calibration, assessment, downscaling and delivery, the fact that there is a wide variety of socio-economic applications which can potentially benefit from seasonal forecasts means that tailored, improved and innovative ways to take the forecasts from the 'factory' to the 'desk' of the decision maker has to be sought. It cannot be stressed enough that the delivery process, both in its technical and communicational forms, are fundamental aspects in the seasonal forecasting system. Fortunately, the technical component, namely the access to the forecast normally via the Internet, is in an advanced phase. Numerous prediction centres, such as ECMWF, IRI, APEC Climate Center, now provide open or subscribed access to their latest prediction information, created using numerous numerical and/or statistical modelling approaches, through this channel. However, technical delivery must be accompanied by an appropriate communicational delivery. Just posting information on the Internet does not ensure that it is properly understood and used. Direct engagement with users of seasonal climate information is paramount, especially given the high level of technical procedures required to produce the seasonal forecast final product. Although steps have been taken to establish links with users since the late 1990s with for instance the Regional Climate Outlook Forums (RCOFs), the level of skill of seasonal forecasts is such that continuous and enhanced interaction between forecasters and decision makers is fundamental as a two-way process, namely to expand the utilization of seasonal forecasts in one direction and to receive feedbacks for an improved forecast product on the opposite direction (Harrison and Williams, 2008). Communication is necessary also to strengthen institutional commitment and to introduce the conditions suitable for the creation of favourable policies, including government policies, where they do not exist (Harrison *et al*., 2008c).

It is important to realize that while numerous types of decisions in socio-economic sectors are aligned with the seasonal timescale (e.g. seeding and harvesting in agriculture) there are also several others that span a wider time scale ranging from a few hours to a few decades (e.g. energy demand and infrastructure planning). Seasonal forecast models have, therefore, the opportunity to provide a basis for validating climate change models, as well as offering a bridge to weather forecasting models in what is often referred to as seamless forecasting system. Such a seamless system across time scales framed in a scientific context needs, however, to act alongside an analogous seamless decision making system for it to accrue its full benefit. Adaptation and modelling together, in both seamless decision making and forecasting contexts seems indeed a logical path forward (Harrison *et al*., 2008c). In order to achieve such a mammoth objective a more harmonized coordination between the weather, seasonal climate and climate change communities as well as with several socio-economic stakeholders needs to be pursued. Steps towards achieving this goal have been made already for instance with the World Climate Research Programme (WCRP) Coordinated Observations and Prediction of the Earth system (COPES) but much more needs to be achieved in terms of exchange of appropriate weather and climate data and forecast products between members of the international scientific community as well as in terms of more proactive engagement with the socio-economic sectors.

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