8

CLIMATE FORECASTS FOR EARLY WARNING

Up to six months in advance

Simon J. Mason
Contributors: Madeleine C. Thomson and Ángel G. Muñoz

> Summer shall come, and with her all delights,
> But dead-cold winter must inhabit here still.
>
> The Two Noble Kinsmen *by John Fletcher / William Shakespeare*

8.1 Introduction

Numerical weather prediction only became practically possible in the 1960s with the availability of sufficiently powerful computers. Prior to then, scientifically-based weather forecasting was based on statistical relationships informed by understanding of the physical processes of weather. Earlier still, weather lore,[1] some of which has some scientific basis,[2] has been used for centuries to make weather forecasts. However, the earliest record of a meteorological prediction is a seasonal climate forecast rather than a weather forecast. In the *Epic of Gilgamesh*, the god Ea warns Utnapishtim (more commonly known through the story of Noah, or Nûh ibn Lamech ibn Methuselah) of persistent torrential rain and a resulting flood. Utnapishtim successfully takes evasive action by constructing a boat (or ark) for himself and for the animals.

Warnings are only useful if they elicit an effective response, if they are clearly articulated and disseminated by mandated authorities, and are accepted as valid and actionable by the intended beneficiary community; budgets must be agreed, commodities moved to the area at risk, public communication campaigns developed, etc. (And, apparently, Utnapishtim was able to tick all those boxes.) All of these actions take time, and weather forecasts provide sufficient warning only to take limited action. If decision-makers could be provided with additional lead-time, they would be better able to organize an effective response.

In Chapter 7, we showed that in most cases it is not possible to make useful weather forecasts much beyond a week (unless we have the prophetic gift of an Utnapishtim). Despite this limitation, forecasts are routinely available at longer ranges. How can that be? Surely the further into the future one tries to predict, the less accurate the forecast will be. A simple response is that it is not true; sometimes it is easier to predict the further into the future one looks, just as a doctor can more accurately predict the status of a patient's cold two months hence (it will have passed) than its status in three days' time. What will differ across the various timescales of predictions are their accuracy and specificity (Chapter 3, Figure 3.1 and Box 8.1).

BOX 8.1 HOW DOES A SEASONAL CLIMATE FORECAST DIFFER FROM A WEATHER FORECAST?

A seasonal climate forecast is an indication of some aspect of the expected weather conditions aggregated over a period of between one and about six months, and typically starting a few weeks to a few months in the future. A typical seasonal climate forecast differs from a typical weather forecast in important ways (Table 8.1), although exceptions can be found. For example, while most seasonal forecasts are probabilistic, a few use intervals (e.g., predictions of tropical storm frequencies[3]).

TABLE 8.1 Differences between weather and seasonal climate forecasts

Characteristic	*Weather forecast*	*Seasonal forecast*
Specificity	Specific timing and intensity	General frequency and intensity
Parameters	Rainfall, max and min temperature, humidity, wind speed and direction, cloudiness	Rainfall, average temperature
Format	Deterministic; prediction intervals for rainfall	Probabilistic
Precision	Nearest °C; prediction intervals for rainfall and wind speed	3 categories (below, normal, above; Box 8.3)
Spatial resolution	Individual locations	Area-averages
Temporal resolution	Hourly to daily	3–4 months

TABLE 8.1 (Continued)

Characteristic	*Weather forecast*	*Seasonal forecast*
Skill (Box 7.4)	High	Moderate at best, often non-existent
Areas of greatest skill	Extratropics	Tropics
Source of skill	Initial conditions	Boundary conditions

The lack of skill in most seasonal forecasts is reflected in the forecast probabilities, which rarely differ from climatological probabilities by much. However, there are also some problems with the reliability of many seasonal forecasts[4] (§ 8.4), and so the probabilities may not provide a good indication of the uncertainty.

In this chapter, we explore the potential value of seasonal climate forecasts to the health community. We begin by considering why the general weather conditions over a season might be predictable, before examining how seasonal forecasts are made, and why they are presented in a different way to weather forecasts. We then examine where and when seasonal forecasts work best, and emphasize that it is possible to make useful seasonal forecasts for health outcomes only in some parts of the world and for certain times of the year (and possibly only for some years). We also review some of the main sources of seasonal forecasts.

8.2 How do forecasters predict the next few months?

When preparations for the 2014 World Cup soccer tournament were underway, concern was raised about the possibility of a dengue epidemic impacting the games, which were being held in cities across Brazil. A dengue early warning system was created that was driven by seasonal forecasts and predictions were made for each participating city.[5] How did this forecast differ from a prediction based on weather forecasts, and how was such a forecast even possible?

Consider a 'Spot the Ball' puzzle. Such puzzles are common in newspapers such as the *New York Times*.[i] They involve a photograph of a soccer (or other sports) match, but the ball has been removed. The problem is to estimate exactly where the ball should be. That question is analogous to estimating what the weather conditions are like at this moment, given the available observations. Now try estimating where the ball will be in ten seconds' time, or two minutes' time. We may be able to estimate where the ball will be in a few seconds' time if we know where it is now, but in two minutes' time the ball could be virtually anywhere, regardless of which is the better team. Although we cannot predict where the ball will be more than a few seconds into the future, it may well be possible to predict who will win the match, or who will win the tournament. For that, we need to know which is the better team. Analogously, estimating the current weather conditions (where the ball is now) is very difficult, and the weather is predictable only a short way into the future (where the ball will be in a few seconds' time). Nevertheless, it may be possible to predict the general weather conditions over the next few months without knowing what the weather will be like at any given time (similar to predicting the final outcome of the soccer match, but not when the goals will be scored).

Forecasts far beyond one week are sometimes possible if forecasters do not try to predict the weather at any specific time, but instead try to predict the general weather conditions over a prolonged period. For example, a forecast of generic weather conditions over the next few months might consider the question of whether there will be many storms – as opposed to, when will specific storms occur? In general, the further into the future the forecast is projected, the longer the period over which the predicted weather conditions are aggregated: typically about one-to-two weeks in the case of sub-seasonal forecasts (Box 7.2); one to four months in the case of seasonal forecasts (Box 8.1); or ten to 30 years in the case of longer-range projections and scenarios (Chapter 9). These aggregated weather conditions describe the climate (Box 4.1), and the reasons why scientists can predict the climate are not the same as the reasons why they can predict the weather. Similarly, the reasons why scientists can predict the climate over the next few months are not the same as why they can predict the climate decades into the future. Timescales of weather and climate variability, their causes and sources of uncertainty are described in Chapter 5, Table 5.1.

8.2.1 Why is the seasonal climate (sometimes) predictable?

As discussed in § 5.3.5, differences in climate from year-to-year can be substantial. An unusually wet season will occur if there is an excess number of rainfall-producing weather events, and/or they are more intense or persistent. Much of these year-to-year differences are completely random, and it is only possible to forecast the individual events at weather timescales. In some cases, however, there may be a reason why the weather behaves unusually. Perhaps the most clear-cut case is after a large volcanic eruption: large amounts of dust many kilometres up can block out the sun and so parts of the globe may cool down noticeably for possibly two years or even longer after the severest eruptions (§ 5.4.2.1). Such large volcanic eruptions are rare and unpredictable, and so their effects can only be predicted after the eruption has occurred. If seasonal forecasts are to be made more regularly than only after volcanic eruptions, other influences on the weather must be sought.

The key to predicting seasonal climate conditions was noted in Chapters 4 and 5: the air is heated by Earth's surface rather than directly by the sun, and so prolonged unusual conditions at the surface will have a (possibly predictable) effect on the climate. Earth's surface consists of sea and other water bodies, land and snow/ice, each of which provides some level of seasonal predictability.[6] Collectively, these surface conditions are called the *boundary forcings*. The mechanisms involved are discussed in the following subsections.

8.2.1.1 The oceans

Sea-surface temperatures are the most important source of predictability of seasonal climate[7,8] because:

- Most (70%) of Earth's surface is sea.
- Sea temperatures change much more slowly than air temperatures, and they can therefore have a prolonged effect on the weather.
- The main predictable effect on the air is through changes in humidity rather than changes in temperature, and the oceans are the primary source of moisture.

If the sea is unusually hot or cold, sea temperature anomalies may last weeks or months[9] because it takes so much energy to heat up and cool down water (§ 5.2.3). Air heats up and cools down much more easily than water, and so air temperatures adjust to sea temperatures much more quickly than vice versa. Therefore, sea-surface temperature anomalies can cause large and prolonged changes in evaporation and heating or cooling of the overlying air. Changes in evaporation are important not only because of how much water is available for making rain, but because of the latent heat in the water vapour (§ 4.2.8.1).[10]

The effect of sea-surface temperature anomalies is strongest in the tropics where the sea is hottest because the amount of moisture that the air can hold is more sensitive when the air is hot than when it is cold (§ 4.2.1). Therefore, a 1 ° increase in sea temperature in a hot sea can result in a much larger increase in evaporation than can a similar increase in sea temperature in a colder place. How then do sea-surface temperatures in different areas of the oceans affect climate?

8.2.1.1.1 Tropical Pacific Ocean

Variability in tropical Pacific sea-surface temperatures is dominated by the El Niño – Southern Oscillation (ENSO; Box 5.1). The ENSO is the main reason why seasonal forecasts are possible, because it has a stronger influence on temporal variability in climate at seasonal scales than anything other than the cycle of summer and winter (§ 5.3.3). The development of a numerical model in the 1980s that could predict ENSO events a few months in advance was based on the physics of how wind patterns and ocean currents in the equatorial Pacific Ocean affect each other.[11,12] The success of this model in forecasting the 1988 El Niño was a major stimulus for promoting widespread interest in operational seasonal forecasting, and the motivation for the creation of what is now the International Research Institute for Climate and Society (IRI).[13] Prior to then, forecasts were developed in only a handful of countries (§ 8.2.2).

Over the equatorial Pacific itself, areas of prolonged heavy rain preferentially occur over the warmest part of the ocean, and so these areas may shift thousands of kilometres between El Niño, neutral and La Niña episodes. Because Pacific Ocean sea temperatures near the equator are the highest in the world, the convective rainfall (§ 4.2.2) here is particularly heavy and widespread, such that the rainstorms are large and violent enough to affect weather patterns elsewhere. The ENSO can therefore affect climate in areas well beyond the equatorial Pacific, and so El Niño and La Niña are often used to predict seasonal climate anomalies in areas that do not even border the Pacific Ocean. These remote effects – or *teleconnections* – occur partly because weather patterns around the world respond to the shifts in weather patterns over the equatorial Pacific itself (for example, over southern parts of North America). Remote effects can also occur because some of these changes in weather patterns can disrupt wind patterns over the oceans, which changes the sea temperatures there (for example, over eastern and southern Africa because of changes in the tropical Indian Ocean.

8.2.1.1.2 Tropical Atlantic Ocean

The Atlantic Ocean does experience an El Niño-like phenomenon, called the Atlantic Equatorial Mode.[14] The warming events, Atlantic Niños, can cause drought in the Sahel and increased rainfall along the Gulf of Guinea. However, Atlantic Niños are able to develop only to about half the strength and persistence of those in the Pacific because the Atlantic is so much narrower.

Of greater importance for predicting seasonal climate than Atlantic Niños is the difference in temperature between the North and South Atlantic Ocean. Variations in the difference in sea-surface temperature across the tropical Atlantic have important implications for rainfall over much of West Africa and Northeast Brazil. On a larger-scale the north–south contrast in sea-surface temperatures throughout the Atlantic Ocean and beyond contribute to climate variability at decadal scales over areas such as West and North Africa and India.[15]

8.2.1.1.3 Tropical Indian Ocean

Sea-surface temperature variability in the Indian Ocean is weaker than in the Pacific and Atlantic Oceans, in part because of its size, but primarily because of the influence of the South Asian land-mass in the Northern Indian Ocean. The land-sea contrast and its alternation between summer and winter (§ 5.2.3) dominate the mechanisms of climate in the Indian Ocean, whereas in the Pacific and, to a lesser extent, the Atlantic, there is less interference from the land. An important exception in the Indian Ocean is the so-called Dipole, which describes variability in the difference between western and eastern equatorial Indian Ocean sea-surface temperatures.[16] Although the two sides of the ocean vary independently of each other, the name Indian Ocean Dipole has become standard. The Dipole, and the tropical Indian Ocean more generally, have important effects on climate over parts of Australia and East and Southern Africa, and play an important role in how El Niño affects some areas beyond the Pacific.[17]

8.2.1.1.4 Extratropical oceans

In the tropics, sea-surface temperature anomalies have an impact on the climate primarily because of large changes in evaporation; in the extratropics the impact on changes in air temperature and air pressure may be more important than on evaporation. The changes in air temperature and air pressure can affect storm tracks, intensities and frequencies, because of effects of the temperature and pressure gradients on the jet streams (§ 4.2.8.2).[8] Similar effects occur at the sea-ice boundary: the retreat of sea-ice through warming may therefore have important effects on climate in the mid- and high-latitudes.[18]

8.2.1.2 The land

While changes in tropical sea-surface temperatures are the main reason why forecasters can predict the general weather conditions over the next few months, land and ice/snow conditions should not be completely ignored (§ 5.2.7). For example, after an unusually dry period, the land surface may dry up, and in the summer months it can be heated to unusually high temperatures (a larger proportion of the sun's energy is used to increase the temperature rather than to heat and evaporate soil, plant and surface water). The resultant hot dry air provides a basis for predicting heat waves in places such as Europe[19,20] and South Asia.[21] However, a dry land-surface is usually insufficient in itself to provide a strong basis for seasonal forecasts. Instead it may act to reinforce effects of sea-surface temperature anomalies, as was the case in the US Dust Bowl of the 1930s,[22] for example.

8.2.1.3 Snow and ice

Like land temperature and soil moisture, ice and snow cover have some predictable influences on the weather at seasonal timescales. You may need to wear sunglasses after snow because it acts like a mirror, reflecting the sunlight into your face and back into space. Because this sunlight is reflected rather than absorbed, there is less heating of the surface than if there were no snow or ice, and so the overlying air is not heated much. This cooling can result in more snow or freezing, even more sunlight is then reflected, and further cooling occurs. This albedo effect (§ 4.2.7) is important at multi-year timescales (see Chapter 9), but less so in seasonal forecasting, partly because the year-to-year differences are rather small and only a small proportion of the Earth is covered in ice and snow. However, year-to-year differences can be useful in predicting spring snow-melt in places such as California. Similarly, unusually heavy snowfall over the Himalayas in winter can slow the summer heating of inland South Asia, and thus weaken the summer monsoon (See Box 7.3).

8.2.2 How are seasonal forecasts made?

The principle behind seasonal forecasting is to predict how unusual conditions at Earth's surface (detailed in § 8.2.1) might affect the persistence, frequency and/or intensity of certain weather types (such as rainstorms). The effects of Earth's surface on the seasonal climate are most likely to be detectable if: a) the influence on the overlying air is strong (as is likely in the tropics given large sea-surface temperature anomalies); and b) if this *boundary forcing* persists for a long period. The target period (Box 7.1) must therefore not be too short lest individual weather events, which are unpredictable, mask the effects of the boundary forcing; but the target period must not be too long, lest those surface conditions change unpredictably. Because of these constraints, in practice, seasonal forecasts are rarely made for periods of less than two or three months, and generally for not much longer than four or five months.

The effects of boundary forcing on the climate are modelled using one of two approaches, but in both cases the starting point is with observations of Earth's surface. In contrast, the starting point for weather forecasting is with observations of the initial conditions (§ 7.4). One of the approaches to seasonal forecasting – *empirical modelling* – effectively addresses the question of how similar boundary conditions in the past have affected climate. The other approach – *dynamical modelling* – considers how, in principle, the current boundary forcings might affect the climate.

8.2.2.1 Empirical prediction

Some early, and pre-scientific, methods of seasonal forecasting were based on observations that some climate anomalies seemed to be pre-figured by other climate anomalies or unusual occurrences in nature. Who has not asked questions such as whether we can anticipate an unusually hot summer given the dry winter or abundant spring blossoms we may have just experienced, or whether the coming wet season will be delayed given the cold winds of the last few weeks? Unfortunately, few of these types of observations provide any robust basis for forecasting, and they are often highly subjective.

With our improved understanding of how climate operates, empirical relationships between anomalous surface conditions and subsequent climate, when supported by theoretical considerations, can be used with confidence as a basis for making forecasts. The commonest approach is to use some form of regression or classification procedure to relate observations of sea-surface temperature anomalies, including those associated with El Niño and La Niña (Box 5.1), with climate anomalies over the following few months. A simple example, might consider how climate has been affected by episodes of El Niño conditions in the past. Depending on the sophistication of the statistical model used, sea-surface temperatures in areas beyond the equatorial Pacific may also be considered, as well as observations of other boundary forcings (§ 8.2.1). In fact, the first such model was developed in 1886 to forecast the Indian monsoon, and was based purely on observations of Himalayan snowfall.[6] However, it took almost 100 years before empirical models became more widely adopted. They are used extensively today by many countries to make their national seasonal forecasts, most of which are based on sea-surface temperatures in various parts of the tropical oceans.

8.2.2.2 Dynamical prediction

The second approach to seasonal forecasting is similar to the way in which weather forecasts are made (Chapter 7). Just as weather forecasting relies heavily on numerical models, so dynamical methods of seasonal forecasting use climate models. In many respects, a climate model is virtually identical to a numerical weather prediction model (NWP; see Box 8.2), and so the forecasting procedure follows the same steps as for weather prediction: observation, analysis, initialization, integration and post-processing. The details of each of these steps depend on the complexity of how Earth's surface is represented in the climate model (Box 8.2).

BOX 8.2 CLIMATE MODELS

A climate model is very similar to an NWP model (§ 7.4). However, there are some differences between the two types of models; the most important one for the purposes of seasonal forecasts is that a climate model needs to have a reasonably realistic representation of conditions at Earth's surface. In particular, some representation of the ocean is required, although the most sophisticated models also include ice and land-surface components. Given the importance of sea-surface temperatures in seasonal forecasting (§ 8.2.1) only the representation of the oceans is discussed here.

There are different ways of representing the oceans in a climate model, ranging in complexity from simply specifying the surface conditions, to modelling the ocean in a similar way to modelling the atmosphere. A key distinction is whether or not the surface conditions are predicted independently of making the seasonal climate forecast, or whether the two are predicted together. If the surface conditions are predicted first a two-tiered forecast system is used; if the surface conditions are predicted as part of the climate forecasting step then a one-tiered system is used.

Two-tiered systems

In a two-tiered forecast system the sea-surface temperatures are predicted first, and then these predicted temperatures are prescribed when making the seasonal forecast.[23] The sea temperatures may be predicted as simply as by persisting the current anomalies over the next few months, or gradually damping them towards average.[24] Despite their simplicity, it is difficult to produce forecasts that are a lot more accurate than such procedures for about the first three months. For predicting further than three months, more sophisticated forecasts of sea-surface temperatures are required. These forecasts can be made either by empirical procedures or by running dynamical models of the oceans. One problem with two-tiered forecasting is that the oceans are allowed to affect the atmosphere, but changes in wind and temperature, etc., are not able to affect the oceans adequately (§ 8.2.1.1). Some climate models incorporate very simple models of the oceans, perhaps allowing changes in temperature and evaporation, but not having ocean currents. However, if seasonal forecasts are to consider the development of phenomena such as El Niño and La Niña then a proper ocean model is required.

One-tiered systems

One tiered forecasting systems use 'coupled models',[25] i.e., a model for predicting the atmosphere is run together with a model for the ocean. The ocean models need to be run at higher spatial resolution than the atmosphere because of the importance of small-scale features in the circulation of the oceans. This requirement, together with the importance of initializing the ocean model (§ 8.2.2), means that forecasting with coupled models requires some of the most powerful computers in the world. Only a few of the Global Producing Centres (§ 8.3.1) are able to run such models.

8.2.2.2.1 Observation

With a seasonal forecast, the critical problem is not so much to get the initial atmospheric conditions correct (since those will be lost after the first week or two of the forecast), but instead to get the *boundary conditions* and their effects correct. To a reasonable approximation the boundary conditions are a mathematical representation of the boundary forcings described above. Observations of Earth's surface are therefore required, and most notably of sea-surface temperatures.

With the advent of the satellite era, estimates of sea-surface temperatures over the global oceans have become available. These estimates do not have the same problems as do the satellite estimates of land-surface temperatures (§ 6.3.2.2) except in the presence of persistent cloud. To calibrate and supplement the satellite measurements, arrays of moored buoys have been implemented in the most important areas of the oceans. The Tropical Atmosphere Ocean (TAO) / Triangle Trans Ocean Buoy Network (TRITON) array is in the Pacific Ocean,[26] and was motivated by a failure in 1982 to recognize that the largest El Niño then on record was developing. Similar arrays have been implemented in the tropical Atlantic[27] and Indian[28] Oceans. The moored arrays are supplemented by a set of drifting buoys with other automated instruments.

The various instruments measure more than just sea-surface temperatures; they also take weather observations (winds, atmospheric pressure, etc.; § 6.3.1.1), and measure ocean currents and salinity down to 500 m or more beneath the surface. These additional measurements are important for initializing ocean models

(Box 8.2), and provide essential information if seasonal forecasts beyond about three months are required. Because of their remoteness, maintenance of the moored buoys is difficult and so data gaps can last weeks if they stop transmitting. The buoys are frequently targets of vandalism and theft, especially those near South America, The resulting data gaps can create problems for forecasting and monitoring.

Observations of sea-ice and land-surface conditions (primarily soil moisture and snow cover) have received far less attention for seasonal forecasting than have observations of the oceans. Soil moisture is still poorly measured and is rather estimated from rainfall and soil properties. Snow and ice can be measured by satellite, although it is much easier to measure extent than thickness. Because of the poor availability of data, and the relatively weak influence of soil moisture and snow and ice, such observations are used by only a few centres in operational seasonal forecasting.

8.2.2.2.2 Analysis

The analysis from weather forecasting can be used for seasonal forecasts, but an ocean analysis is also required if an ocean model is being used. The method for generating an ocean analysis is similar to that for the weather analysis, although the procedure is a little more complicated for the ocean, in part because of poorer data availability and because of the greater inertia in the oceans (winds can change much more easily than ocean currents). Because of the greater uncertainty in the state of the ocean compared to the atmosphere, multiple analyses are made; in contrast, a single atmospheric analysis is typically generated. These ocean analyses are then perturbed to produce an ensemble (Box 7.6).

8.2.2.2.3 Initialization

Regardless of the complexity of the climate model's representation of Earth's surface (Box 8.2), an ensemble approach (Box 7.6) is essential when forecasting seasonal climate using dynamical models. For weather forecasting, the generation of perturbations in the initial conditions is a critical step because predicting the evolution of the current weather is the basis for skilful weather forecasts. For seasonal forecasting, however, there is little pretence that the current weather conditions provide much useful information for predicting weeks and months into the future, and so simpler ensemble generation methods such as lagged averaging (Box 7.6) are widely used. In fact, until only a few years ago, the majority of forecasting centres did not attempt to initialize their models with recent observations of the weather at all.[24] However, initializing a climate model using recent weather observations does become more important if a dynamical ocean model is being used (Box 8.2), or if a seamless prediction system is being operated.[29] In a seamless prediction system, weather, sub-seasonal and seasonal forecasts may all be made in one process.

8.2.2.2.4 Integration

Seasonal forecasts are much more uncertain than weather forecasts, and if representing uncertainty is important in weather forecasting, it is even more so at seasonal timescales. In weather forecasting, the main sources of uncertainty are the initial conditions and the model errors. For seasonal forecasting, the model errors remain as a source of uncertainty, while the initial conditions are effectively forgotten after about two weeks, but an additional source of uncertainty is that Earth's surface has only a limited effect on how the weather varies. As for weather forecasting, these sources of uncertainty can be addressed, at least in part, by appropriate use of ensembles (§ 7.4.4).

The uncertainty from the boundary forcing is addressed by using a large ensemble, but also by considering the forecast over a period of a few months rather than a shorter period of weeks. Thus, if the surface conditions are conducive to the formation of strong and frequent cyclones, for example, strong and frequent cyclones may be detectable because of the large sample size, even if the effect of the surface is weak. However, because of imperfections in climate models, the response to the boundary forcings may not be simulated adequately, and so a large sample of predictions from one model may not be helpful, and may even be misleading (spurious effects of the surface on climate could be simulated). A multi-model ensemble is therefore recommended. Multi-modelling is less important for weather forecasting, but has a clear advantage over a large single-model ensemble at seasonal and longer timescales.[30]

Because seasonal forecasting requires the models to be run much further into the future than for weather forecasting, climate models are typically run at a coarser resolution than for an NWP model. Running at high resolution can be prohibitively expensive. In numerical weather prediction, regional models are used widely to provide more detailed, and hopefully more accurate, forecasts at national or regional scale. Such downscaling models have not been widely used for seasonal forecasts, partly because of computational expense, and partly because of a lack of clearly demonstrated additional benefit over simpler, empirically-based downscaling methods[31] (see further discussion in the Post-processing section below).

8.2.2.2.5 Post-processing

As implied in the previous discussion on model integration, one problem when running a climate model for many weeks is that there are differences between the climate of the model and the climate in the real world because of imperfections in the model. The predictions tend to drift fairly quickly towards the model's climate and away from more realistic conditions. This problem of drift has been particularly severe for climate models that are coupled to dynamical ocean models, although major improvements have been made in the last few years.[32]

The simplest way to correct for problems of model drift is to express the forecast with reference to the model's own (lead-time dependent) climate. For example, the forecast may be presented as an anomaly compared to the model's climatological average (as is widely performed for forecasts of ENSO), or probabilistic forecasts may be derived with reference to the model's climatological terciles (Box 8.3). These procedures are widely adopted for global seasonal forecasts, but do not guarantee good reliability[29] (see Box 7.4 for a technical definition of reliability). As a result, the forecast probabilities from many forecasting centres cannot be taken at face value, and have to be interpreted carefully using detailed diagnostics of model skill (see further discussion in § 8.4). This task of interpretation is difficult even for experts.

BOX 8.3 TERCILE FORECASTS

Because of the large uncertainties inherent in making seasonal forecasts, they are generally presented as probabilistic rather than as deterministic forecasts (Box 7.5). The most common predictands (Box 7.1) are three- or four-month rainfall accumulations, and average temperatures. The forecast indicates the probabilities that the accumulation or average for the predicted period will fall within pre-defined ranges. These pre-defined ranges, or categories, are derived by considering historical values from a recent 30-year climatological period (§ 4.3).

The most common practice is to define three categories. If, the rainfall is more than the 10th wettest within a 30-year climatology, that rainfall would be classified as 'above-normal', whereas if it is less than the 10th driest it would be classified as 'below-normal'. If the rainfall is neither more than the tenth wettest, nor less than the tenth driest then it is classified as 'normal'. An example is shown in Table 8.2, using the same rainfall data from Case Study 5.1, i.e., December–February rainfall over Botswana. (For simplicity, December 1980–February 1981 is listed as 1981.) The tenth wettest year was 1994, with 300 mm. This threshold approximates the 'upper tercile'; one-third (i.e., ten) of the years had 300 mm or more. (There are various ways of calculating the terciles, and a more exact value is somewhere between that for 1981 and 1994.) Similarly, the tenth driest year was 2003 with 200 mm. This threshold approximates the lower tercile; one-third of the years had 200 mm or less. Following this standard, there are equal numbers of years in each category.

Typically, the range of the 'normal' category is narrow, and so 'above-normal' and 'below-normal' may not be particularly extreme (see an additional example in Figure 4.5, where the 'normal' category is bounded by the two vertical dotted lines). In most cases, it is reasonable to interpret 'normal' as 'close-to-average', although if the data are strongly positively skewed (as may be the case for rainfall in arid areas) it is possible for rainfall to be 'above-normal' and still be below-average.

TABLE 8.2 Country-averaged December–February rainfall accumulations for Botswana

Ordered by year			*Ordered by rainfall*		
Year	*Rainfall*	*Category*	*Year*	*Rainfall*	*Category*
1981	326	A	1992	153	B
1982	162	B	2002	158	B
1983	163	B	1982	162	B
1984	174	B	1983	163	B
1985	222	N	2007	169	B
1986	214	N	1987	170	B
1987	170	B	1995	171	B
1988	330	A	1984	174	B
1989	354	A	1998	197	B
1990	219	N	2003	200	B
1991	268	N	2001	208	N
1992	153	B	2005	213	N
1993	223	N	1986	214	N
1994	300	A	1990	219	N
1995	171	B	1985	222	N
1996	342	A	2004	223	N
1997	320	A	1993	223	N
1998	197	B	1999	240	N
1999	240	N	2010	267	N
2000	439	A	1991	268	N
2001	208	N	1994	300	A
2002	158	B	1997	320	A
2003	200	B	2008	321	A
2004	223	N	2009	325	A
2005	213	N	1981	326	A
2006	416	A	1988	330	A
2007	169	B	1996	342	A
2008	321	A	1989	354	A
2009	325	A	2006	416	A
2010	267	N	2000	439	A

Data source: *Climate Prediction Center Merged Analysis of Precipitation [CMAP]*

An alternative way of addressing the problem of drift, and of model systematic errors more generally, is to apply some form of model output statistics (MOS) correction, similar to that applied in the post-processing step of numerical weather prediction (§ 7.4.5). Applying an MOS correction is effectively a hybrid approach combining empirical and dynamical prediction, and it can act as a *downscaling* method (i.e., a method of generating a more detailed forecast) in the same way as for weather forecasting. The main difficulty is sample size: seasonal forecasts are typically updated about once per month instead of four times per day for weather forecasts. Forecasters can pretend to turn back the clock and make 'forecasts' for periods that are now in the past (*hindcasts*). However, even generating a reasonable number of hindcasts is difficult because of computational expense, but more so because of the unavailability of important observational data prior to both the installation of oceanic arrays (see the section on Observation) and the satellite era. Without these important observations the models cannot be initialized well. However, sample sizes of past forecasts are steadily growing, and post-processing schemes are becoming increasingly popular options for regional and national forecasting.[33] If calibrated properly, the seasonal forecast probabilities are more reliable than model outputs that are adjusted only for errors in climatology. Unfortunately, this gain in reliability makes the forecasts look weak much of the time[34] (although appropriately so).

Sample size problems are also an issue when combining predictions from multiple models. In theory one would expect that a better forecast could be obtained if the more skilful models were given greater consideration than the weaker ones. In practice, however, it is difficult to demonstrate that one model is unequivocally better than another given only a small number of forecasts. It is therefore hard to improve upon treating each model equally, although perhaps after selecting a subset of what appear to be the better models.

8.3 What seasonal forecasts are available?

Since the late-1990s, the World Meteorological Organization (WMO) has been facilitating and directing the establishment of a seasonal forecasting infrastructure to support countries around the world to make regular operational forecasts. The vision for this infrastructure is similar to that of the World Weather Watch (§ 6.2), and is now being implemented through the Global Framework for Climate Services.[35] The main components of this infrastructure are described in the following sub-sections.

8.3.1 Global Producing Centres of Long-Range Forecasts

In 2006, the WMO established a process for designating centres that produce global seasonal forecasts and that make these products available to countries for producing their own official forecasts. There are currently 13 of these Global Producing Centres of Long-Range Forecasts (GPCs),[36,ii] most of which provide a range of publicly available forecast products. Their predictions are collected by the Lead-Centre for Multi-Model Ensembling,[iii] which produces multi-model predictions that are accessible by National Meteorological and Hydrological Services, and a few graphical products that are accessible publicly. These forecasts are updated monthly. As part of the designation process, a set of hindcasts has to be produced and verification information must be provided to the Lead-Centre for Standardized Verification System of Long-Range Forecasts.[iv] Most of this verification information is likely to be too technical for most purposes in public health work.

Two additional centres provide global seasonal forecasts, but are not formally designated as GPCs: the Asia-Pacific Economic Cooperation (APEC) Climate Center (APCC), and the International Research Institute for Climate and Society (IRI). The APCC has played an important role in research on multi-model forecasting. It has recently been developing some experimental sub-seasonal forecasting products (Box 7.2) that are available publicly. The IRI has a long history of producing multi-model seasonal forecasts, and is one of only a few centres that calibrates its forecasts in an effort to provide reliable forecast probabilities (Box 7.4). As well as a forecasting centre, the IRI is a World Health Organization Collaborating Center (USA 430) for early warning systems for malaria and other climate sensitive diseases.[v] As such, the IRI engages in developing climate services for particular health issues – such as Zika virus transmission in the Americas (see Case Study 8.1).

CASE STUDY 8.1 UNDERSTANDING AND PREDICTING LATIN AEDES-BORNE DISEASES IN LATIN AMERICA AND THE CARIBBEAN USING CLIMATE INFORMATION

Madeleine C. Thomson and Ángel G. Muñoz, IRI, Columbia University, New York, USA

The Zika virus (ZIKV), which emerged in Brazil in 2015 to devastating effects, is principally transmitted globally, and in Latin America and the Caribbean (LAC), by the container breeder mosquito *Aedes aegypti. Aedes albopictus* (the Tiger mosquito) is identified as a possible significant future vector because of its recent rapid spread.[37] Both species also transmit dengue fever, chikungunya and yellow fever viruses, and other viral diseases making their presence in the region a significant public health concern.

Ae. aegypti is common in urban environments in the tropics and sub-tropics. Its success comes from its preference for ovipositing in both natural and artificial water-filled receptacles, where the eggs can survive when the water contents fluctuate and regularly expose them to drying conditions.[38] Although ZIKV transmission depends on several factors including human behaviour, temperature is a significant driver of the development rates of juvenile *Aedes aegypti* and *Aedes albopictus* and adult feeding/egg-laying cycles along with the length of extrinsic incubation period and viral replication of arboviruses.[39] Both drought and excess rainfall have been implicated in the creation of indoor and outdoor breeding sites for *Aedes* vectors of ZIKV and associated epidemics of dengue and chikungunya. Climate-based early warning systems for dengue, a related virus that is transmitted by the same vectors, have been suggested in different regions of the world.

The ZIKV epidemic that emerged in Brazil in 2015 occurred during a period of exceptionally high temperatures and drought in association with an El

Niño event. However, the extreme climate anomalies observed in most parts of South America during the 2015 epidemic were not caused exclusively by El Niño or climate change, but by a combination of climate signals acting at multiple timescales.[40]

Aedes vectors can respond to both unusually dry and wet conditions (as they may switch from indoor domestic breeding sites to outdoor sites made temporarily available). This change in dominant breeding sites has implications for the development of control measures for wet or dry years. Given the importance of climate's year-to-year variability in determining ZIKV risk potential, an early warning prototype for environmental suitability of *Aedes spp.* disease transmission was developed using a basic reproduction number -R0- model,[41] combined with state-of-the-art seasonal forecasts from the North American Multi-Model Ensemble (NMME).[42] Using this approach, probabilistic predictions of above-normal, normal or below-normal potential risk of transmission for at least the following season (three months) are made. Such information is deemed useful for health practitioners and other decision-makers. The predictive capacity is highest for multiple countries in LAC during the December–February and March–May seasons and it is slightly lower – although still of potential use to decision-makers – for the rest of the year. It is important to emphasize that although it is possible at seasonal timescale to forecast suitable environmental conditions for transmission of *Aedes*-borne diseases, this does not mean that the actual transmission, or even epidemic events, are predictable with this type of forecast system.

8.3.2 Regional Climate Centres and Regional Climate Outlook Forums

Regional Climate Outlook Forums (RCOFs) were initiated in 1997 to promote the production of an authoritative seasonal forecast through regional consensus.[43] They have since been established in most regions of the world,[44,45] and are an important source of seasonal forecasts. The Forums themselves are intended as a means of interaction between forecast producers and users,[46] and may serve as an opportunity for public health specialists to provide feedback on existing forecast products and their broader needs for climate services. In Southern Africa, the Malaria Outlook Forum (MALOF) was initiated by the health community after evidence emerged of the significant predictability of malaria incidence using climate information.[47] Instead of the malaria control managers attending the RCOF, members of the climate community participated in the preparatory malaria meeting, which was held immediately prior to the rainy season. At this meeting the seasonal climate forecast was integrated directly into the planning process for the coming malaria season.[48] The MALOF was run successfully between 2004 and 2007, but was then discontinued when external donor funding dried up.

While also subject to fluctuating donor funds, the RCOFs have become a routine fixture in the annual climate services calendar. They are convened up to three times per year in a given region, but monthly updates to the seasonal forecasts are coordinated by Regional Climate Centres,[vi] and participating National Meteorological and Hydrological Services (NMHSs) are encouraged to update their own national forecasts.

There is broad diversity amongst the RCOFs, but all produce a standard seasonal forecast indicating probabilities of 'below-normal', 'normal' and 'above-normal' accumulated rainfall and/or average temperature (§ 4.3.3 and Box 8.3). The probabilistic tercile-based formats have been justly criticized as being unnecessarily obtuse and of minimal relevance,[44] but are likely to remain the staple output of the RCOFs for the foreseeable future. These forecasts may be of some value for indicating *suitable* climate conditions for supporting pathogens, pests and diseases (§ 7.2), but are unlikely to be good indicators of *hazardous* or *inhospitable* conditions. For example, even perfect seasonal forecasts of rainfall would still be poor indicators of flood risk because of a weak relationship between seasonally accumulated rainfall and flooding.[49] A few of the RCOFs are attempting to address these limitations by developing experimental forecasts of extreme events.[50] However, as discussed in § 8.4 the reliability (Box 7.4) of many of the RCOF forecasts is problematic, and rigorous skill assessments have yet to be published. Some of the RCOFs make archives of past forecasts available so that some assessment of their value in specific applications can be conducted.

8.3.3 National meteorological and hydrological services

In general, climate services in most countries are much less well-developed than weather services. This lack of capacity is being addressed by the Global Framework for Climate Services,[35] but the capacity of many NMHSs to interact with public health specialists is likely to be limited, especially in developing countries. Nevertheless, most countries where there is some predictability of seasonal climate (see § 8.4) have developed a seasonal forecasting capability through their participation in the RCOFs.

The WMO is promoting the production of national climate watches, along similar lines to weather alerts (§ 7.6.1). These watches will act as official national alerts of developing and expected hazardous climate conditions. As with the weather alerts, it is important to work with alerts from mandated government authorities. Standards for climate watches have yet to be set, but some countries have implemented systems already. The watches combine monitoring and forecast information, and are particularly useful for slow-onset hazards like drought.

8.3.4 Additional global products

The Global Seasonal Climate Update[vii] is intended as a quarterly forecast and monitoring product that is coordinated by the WMO. The Update is not yet fully operational, and is initially targeted at Regional Climate Centres and NMHSs to assist in the production of their own information products. However, the intention is for the Update to be of value to public users with global and regional-scale interests.

The idea for the Global Seasonal Climate Update emerged from interest in WMO's El Niño/La Niña Updates. These Updates summarize the current status of the ENSO (see Box 5.1) and review the available predictions. Amongst other sources, the El Niño/La Niña Update draws from the Climate Prediction Center/IRI joint ENSO Diagnostic Discussion. This information is updated monthly, and provides a comprehensive review of ENSO forecasts from around the world.

8.4 Do seasonal forecasts work well?

A key message when considering the possible value of seasonal forecasts is that, unlike weather forecasts, seasonal forecasts only work in some parts of the globe, for some times of the year, and even for some years. Whereas a weather forecast should be available every day, seasonal forecasts may only provide indications of possible anomalous climate conditions occasionally. The reason for this intermittency is simple: in many places and for much of the time the climate is insufficiently affected by unusual conditions at Earth's surface. Consider ENSO, for example, which is the primary reason seasonal forecasts are possible (§ 8.2.1). Despite its importance, ENSO affects less than a third of global land areas in a predictable way,[51] and El Niño and La Niña episodes occur less than half the time. Therefore, just like volcanoes, ENSO (and other influences on the climate) provides a basis for making a seasonal forecast only sometimes. In addition, the frequency and intensity of El Niño and La Niña vary inter-decadally and inter-millennially,[52,53] and the predictability of ENSO, and of climate variability in general, is relatively poor during the quiescent phases. We have been experiencing a relatively active phase of ENSO since the last few decades of the 20th century, but in the mid-20th century, ENSO variability was relatively weak, and some early operational seasonal forecasts performed poorly in this period. It is unclear how long this current active period, and therefore this period of good seasonal predictability, will last.

If seasonal forecasts do not work everywhere, where do they work? An indication is provided in Figure 8.1, which illustrates the skill (Box 7.4) of IRI's seasonal forecasts over the last 20 years. Since the forecasts are in the standard probabilistic format (Box 8.3), measuring the skill in a simple manner is a non-trivial matter (Box 7.4). Figure 8.1 uses a measure that scores the forecasts well if the observed category had a high probability rather than only considering whether the category with the highest probability occurred. Hence, if the observed category had a 60% probability that forecast will score more highly than if the forecast probability was 50%.

The skill of the seasonal temperature forecasts (top) is notably higher than that for rainfall (bottom). (Note that the grey-scales are different for the two maps; the

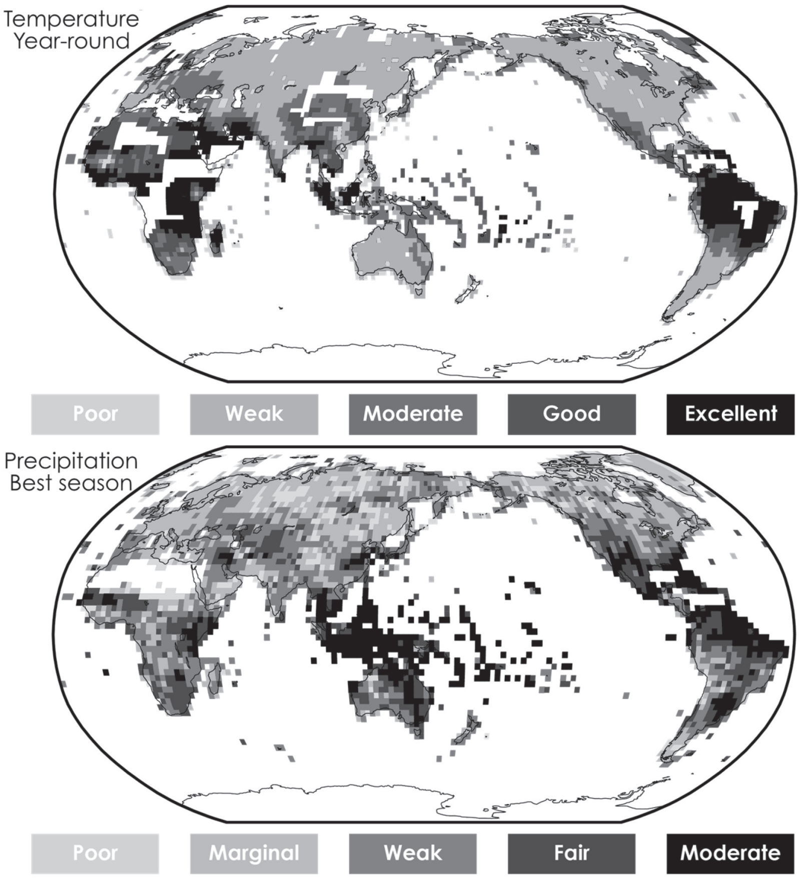

FIGURE 8.1 A measure of value of IRI's seasonal (three-month) average temperature (top) and accumulated rainfall (bottom) forecasts for 1997–2017. The value is estimated by calculating the percentage return on investments on IRI's shortest lead-time probabilistic forecasts if paid out with fair odds.[54] For temperature, the value is calculated using forecasts year-round, and the score is classified as 'excellent' (> 30%), 'good' (20–30%), 'moderate' (10–20%), 'weak' (1–10%) or 'poor' (< 1%). For rainfall, only the value for the highest-scoring season is shown, and the score is classified as 'moderate' (> 10%), 'fair' (5–10%), 'weak' (2.5–5%), 'marginal' (1–2.5%) or 'poor' (< 1%). Climatological forecasts would score 0%.

online colour versions of the maps use consistent colours and so the difference in skill is easier to see.) This difference is actually under-represented by the maps since the skill for the temperature forecasts is calculated using forecasts throughout the year, whereas for rainfall the skill is shown only for the season that is easiest to forecast. One reason why the temperature forecasts are much better than the seasonal forecasts is because of global warming. Above-normal temperatures have occurred far more frequently than below-normal over at least the last 20 years as a result of global warming, and because the seasonal forecasts have been able to predict this ongoing trend, they have been scored well. The usefulness of such information is open to debate, and discussions about how best to communicate variability in temperature from year-to-year rather than the longer-term trends would be beneficial.

The skill of the rainfall forecasts is generally poor partly because of the difficulty of predicting accumulated rainfall. At the weather forecasting timescale, it is harder to predict rainfall amount than occurrence (§ 7.5.2); this difficulty translates into the seasonal timescale. A simple principle is that it is easy to forecast (at all timescales) a meteorological parameter that is spatially coherent than one that is localized. Since rainfall intensity tends to be highly localized, whereas rainfall occurrence is more coherent, intensity is harder to predict. For the same reason, it may be possible to make more accurate forecasts of climate impacts, such as crop yields[55] or disease incidence,[47] directly from the drivers of climate variability rather than using the predicted climate per se. Perhaps regrettably, seasonal accumulations, rather than some other measure, continue to be the main predictand for seasonal rainfall forecasts. Some of the RCOFs are beginning to experiment with new seasonal forecast products such as numbers of wet-days and wetspells,[46] but products of this nature are not yet part of standard practice.

One other strong message from Figure 8.1 is that, in general, seasonal forecasts work much better in the tropics than in the extratropics.[56] This pattern is the opposite of that for weather forecasts (Figure 7.1); weather forecasts work better in the extratropics than in the tropics. The better quality of the seasonal forecasts in the tropics is a result of the stronger effect of sea-surface temperatures there (§ 8.2.1).

The IRI's forecasts are carefully calibrated, and so the forecast probabilities are broadly reliable.[34] However, unfortunately, the same cannot be said of some of the RCOF and national forecasts,[57] where there has been an ongoing problem in assigning too much probability to the 'normal' category. That is not to say that these forecasts are unskilful, but only that care needs to be taken in interpreting the probabilities.

The health community has a strong focus on using evidence-based policies and practices. An evidence-based approach should also be taken when incorporating climate information into health decision-making. With increased knowledge about the way forecasts are made, their strengths and their limitations, we believe that the health community will be better placed to work with climate scientists to improve the transparency, relevance and quality of the information provided.

8.5 Conclusions

Seasonal climate forecasts are predictions of the general rather than the specific weather conditions of the coming few months. In contrast to weather forecasts, seasonal forecasts generally work better in the tropics than in the extratropics, but even in the tropics, seasonal forecasts are only useful intermittently, and there are many parts of the world where there is no skill at all. Most available operational seasonal forecasts may be of some value for indicating suitable climate conditions for supporting pathogens, pests and diseases, but further research is required to assess their value as indicators of hazardous or inhospitable weather conditions over the coming few months. Despite their limitations, seasonal forecasts create a gap in forecast skill between the next few days and the next few months. This gap is being explored through research on sub-seasonal forecasting. There is another gap between seasonal forecasts and long-term climate change projections; timescales beyond seasonal are discussed in the subsequent chapter.

Notes

i https://www.nytimes.com/interactive/projects/spot-the-ball/2014/06/17.
ii A map is available online: www.wmo.int/pages/prog/wcp/wcasp/gpc/gpc.php.
iii https://www.wmolc.org/.
iv www.bom.gov.au/wmo/lrfvs/.
v http://apps.who.int/whocc/.
vi www.wmo.int/pages/prog/wcp/wcasp/rcc/rcc.php.
vii https://www.wmo.int/pages/prog/wcp/ccl/opace/opace3/documents/GSCU-Brief.pdf.

References

1 Inwards, R. *Weather Lore: A Collection of Proverbs, Sayings and Rules Concerning the Weather.* 190 (Senate, London, 1994).
2 Mason, S. J. in *Seasonal Forecasts, Climatic Change and Human Health, Advances in Global Change Research (AGLO)* (eds. M. C. Thomson, R. Garcia-Herrera, & M. Beniston), 13–29 (Springer, New York, 2008).
3 Vecchi, G. A. *et al.* Statistical–dynamical predictions of seasonal North Atlantic hurricane activity. *Monthly Weather Review* **139**, 1070–1082 (2011).
4 Weisheimer, A. & Palmer, T. N. On the reliability of seasonal climate forecasts. *Journal of The Royal Society Interface* **11**, 20131162 (2014).
5 Lowe, R. *et al.* Evaluating probabilistic dengue risk forecasts from a prototype early warning system for Brazil. *Elife* **24**, doi:10.7554/eLife.11285 (2016).
6 Slingo, J. & Palmer, T. Uncertainty in weather and climate prediction. *Philosophical Transactions of the Royal Society A* **369**, 4751–4767 (2011).
7 Goddard, L. *et al.* Current approaches to seasonal to interannual climate predictions. *International Journal of Climatology* **21**, 1111–1152 (2001).
8 Palmer, T. N. & Anderson, D. L. The prospects for seasonal forecasting – a review paper. *Quarterly Journal of the Royal Meteorological Society* **120**, 755–793 (1994).
9 Namias, J., Yuan, X. & Cayan, D. R. Persistence of North Pacific sea surface temperature and atmospheric flow patterns. *Journal of Climate* **1**, 682–703 (1988).
10 Kushnir, Y. Interdecadal variations in North Atlantic sea surface temperature and associated atmospheric conditions. *Journal of Climate* **7**, 141–157 (1994).
11 Cane, M. A., Zebiak, S. E. & Dolan, S. C. Experimental forecasts of El Niño. *Nature* **321**, 827–832 (1986).
12 Zebiak, S. E. & Cane, M. A. A Model El-Niño Southern Oscillation. *Monthly Weather Review* **115**, 2262–2278 (1987).
13 Vaughan, L. F., Furlow, J., Higgins, W., Nierenberg, C. & Pulwarty, R. US Investments in international climate research and applications: reflections on contributions to interdisciplinary climate science and services, development, and adaptation. *Earth Perspectives Transdisciplinarity Enabled* **1**, 23, doi:10.1186/2194-6434-1-23 (2014).
14 Wang, C. Atlantic climate variability and its associated atmospheric circulation cells. *Journal of Climate* **15**, 1516–1536 (2002).
15 Ward, M. N. Diagnosis and short-lead time prediction of summer rainfall in tropical North Africa at interannual and multi-decadal timescales. *Journal of Climate* **11**, 3167–3191 (1998).

16 Saji, N. H., Goswami, B. N., Vinayachandran, P. N. & Yamagata, T. A dipole mode in the tropical Indian Ocean. *Nature Letter* **401**, 360–363, doi:10.1038/43854 (1999).
17 Goddard, L. & Graham, N. E. The importance of the Indian Ocean for simulating precipitation anomalies over Eastern and Southern Africa. *Journal of Geophysical Research* **104**, 19099–19116 (1999).
18 Cohen, J. *et al.* Recent Arctic amplification and extreme mid-latitude weather. *Nature Geoscience* **7**, 627 (2014).
19 van den Hurk, B. *et al.* Soil moisture effects on seasonal temperature and precipitation forecast scores in Europe. *Climate Dynamics* **38**, 349–362 (2012).
20 Fischer, E. M., Seneviratne, S. I., Vidale, P. L., Lüthi, D. & Schär, C. Soil moisture–atmosphere interactions during the 2003 European summer heat wave. *Journal of Climate* **20**, 5081–5099 (2007).
21 Nissan, H., Burkart, K., Mason, S. J., Coughlan de Perez, E. & van Aalst, M. Defining and predicting heat waves in Bangladesh. *Journal of Applied Meteorology and Climatology* **56**, 2653–2670, doi:10.1175/JAMC-D-17-0035.1 (2017).
22 Schubert, S. D., Suarez, M. J., Pegion, P. J., Koster, R. D. & Bacmeister, J. T. On the cause of the 1930s Dust Bowl. *Science* **303**, 1855–1859 (2004).
23 Barnston, A. G., Kumar, A., Goddard, L. & Hoerling, M. P. Improving seasonal prediction practices through attribution of climate variability. *Bulletin of the American Meteorological Society* **86**, 59–72 (2005).
24 Mason, S. J. *et al.* The IRI seasonal climate prediction system and the 1997/1998 El Niño event. *Bulletin of American Meteorological Society* **80**, 1853–1874 (1999).
25 Stockdale, T. N., Anderson, D. L. T., Alves, J. O. S. & Balmaseda, M. A. Global seasonal rainfall forecasts using a coupled ocean-atmosphere model. *Nature* **392**, 370–373 (1998).
26 McPhaden, M. J. *et al.* The Tropical Ocean – Global Atmosphere Observing System: a decade of progress. *Journal of Geophysical Research* **103**, 14169–14240 (1998).
27 Bourlès, B. *et al.* The PIRATA program: history, accomplishments, and future directions. *Bulletin of the American Meteorological Society* **89**, 1111–1125 (2008).
28 McPhaden, M. J. *et al.* RAMA: the research moored array for African–Asian–Australian monsoon analysis and prediction. *Bulletin of the American Meteorological Society* **90**, 459–480 (2009).
29 Vitart, F. *et al.* The new VAREPS-monthly forecasting system: a first step towards seamless prediction. *Quarterly Journal of the Royal Meteorological Society* **134**, 1789–1799 (2008).
30 Hagedorn, R., Doblas-Reyes, J. F. & Palmer, T. N. The rationale behind the success of multi-model ensembles in seasonal forecasting. Part I: basic concepts. *Tellus A* **57**, 219–233 (2005).
31 Robertson, A. W., Qian, J. H., Tippett, M. K., Moron, V. & Lucero, A. Downscaling of seasonal rainfall over the Philippines: dynamical versus statistical approaches. *Monthly Weather Review* **140**, 1204–1218 (2012).
32 Reichler, T. & Kim, J. How well do coupled models simulate today's climate? *Bulletin of the American Meteorological Society* **89**, 303–311 (2008).
33 Manzanas, R., Lucero, A., Weisheimer, A. & Gutiérrez, J. M. Can bias correction and statistical downscaling methods improve the skill of seasonal precipitation forecasts? *Climate Dynamics* **50**, 1161–1176 (2018).
34 Barnston, A. G. *et al.* Verification of the first 11 years of IRI's seasonal climate forecasts. *Journal of Applied Meteorology and Climatology* **49**, 493–520 (2010).
35 Hewitt, C., Mason, S. & Walland, D. The global framework for climate services. *Nature Climate Change* **2**, 831–832 (2012).
36 Graham, R. J., Yun, W.T., Kim, J., Kumar, A., Jones, D., Bettio, L., Gagnon, N., Kolli, R.K. & Smith, D. Long-range forecasting and the Global Framework for Climate Services. *Climate Research* **47**(1/2), 47–55 (2011).
37 Messina, J. P. *et al.* Mapping global environmental suitability for Zika virus. *eLife* **5**, e15272, doi:10.7554/eLife.15272 (2016).

38 Faull, K. J. & Williams, C. R. Intraspecific variation in desiccation survival time of Aedes aegypti (L.) mosquito eggs of Australian origin. *Journal of Vector Ecology* **40**, 292–300, doi:10.1111/jvec.12167 (2015).
39 Brady, O. J. *et al.* Global temperature constraints on Aedes aegypti and Ae. albopictus persistence and competence for dengue virus transmission. *Parasites & Vectors* **47**, 388, doi:10.1186/1756-3305-7-338 (2014).
40 Muñoz, A. G., Thomson, M. C., Goddard, L. & Aldighieri, S. Analyzing climate variations at multiple timescales can guide Zika virus response measures. *GigaScience* **20165**, 41, doi:10.1186/s13742-016-0146-1 (2016).
41 Caminade, C. *et al.* Global risk model for vector-borne transmission of Zika virus reveals the role of El Niño 2015. *Proceedings of the National Academy of Sciences* **114**, 119–124, doi:10.1073/pnas.1614303114 (2017).
42 Kirtman, B. P. *et al.* The North American multimodel ensemble: phase-1 seasonal-to-interannual prediction; phase-2 toward developing intraseasonal prediction. *Bulletin of the American Meteorological Society* **95**, 585–601 (2014).
43 Buizer, J. L., Foster, J. & Lund, D. Global impacts and regional actions: preparing for the 1997–98 El Nino. *Bulletin of the American Meteorological Society* **81**, 2121–2139 (2000).
44 Patt, A. G., Ogallo, L. J. & Hellmuth, M. Learning from 10 years of climate outlook forums in Africa. *Science* **318**, 49–50 (2007).
45 Ogallo, L., Bessemoulin, P., Ceron, J.-P., Mason, S. & Connor, S. J. Adapting to climate variability and change: the Climate Outlook Forum process. *Bulletin WMO* **57**, 93–102 (2008).
46 Gerlak, A. K. *et al.* Building a framework for process-oriented evaluation of Regional Climate Outlook Forums. *Weather, Climate, and Society* **10**, 3–4 (2018).
47 Thomson, M. C. *et al.* Malaria early warnings based on seasonal climate forecasts from multi-model ensembles. *Nature* **439**, 576–579 (2006).
48 Thomson, M. *et al.* Climate and health in Africa. Special Issue: The International Research Institute for Climate & Society: Shaping the Landscape of Climate Services. Section 1: IRI Approach & Examples of Integrated Research & Demonstration. *Earth Perspectives: Transdisciplinarity Enabled* 1, 17 (2014).
49 Coughlan de Perez, E. *et al.* Should seasonal rainfall forecasts be used for flood preparedness? *Hydrology and Earth System Sciences* **21**, 4517 (2017).
50 Hamilton, E. *et al.* Forecasting the number of extreme daily events on seasonal timescales. *Journal of Geophysical Research: Atmospheres* **117** (2012), doi.org/10.1029/2011JD016541.
51 Mason, S. J. & Goddard, L. Probabilistic precipitation anomalies associated with ENSO. *Bulletin of the American Meteorological Society* **82**, 619–638 (2001).
52 Diaz, H. F. & Markgraf, V. E. *El Niño: Historical and Paleoclimatic Aspects of the Southern Oscillation* (Cambridge University Press, Cambridge, 1992).
53 Enfield, D. B. & Cid S, L. Low-frequency changes in El Nino-southern oscillation. *Journal of Climate* **4**, 1137–1146 (1991).
54 Hagedorn, R. & Smith, L. A. Communicating the value of probabilistic forecasts with weather roulette. *Meteorological Applications* **16**(2), 143–155 (2009).
55 Cane, M., Eshel, G. & Buckland, R. Forecasting Zimbabwean maize yield using eastern equatorial Pacific sea surface temperature. *Nature* **16**, 3059–3071 (1994).
56 Kim, G. *et al.* Global and regional skill of the seasonal predictions by WMO Lead Centre for Long-Range Forecast Multi-Model Ensemble. *International Journal of Climatology* **36**, 1657–1675 (2016).
57 Mason, S. J. & Chidzambwa, S. *Verification of RCOF Forecasts*. Report No. 09-02, 23pp (International Research Institute for Climate and Society, Palisades, New York, 2008).