Chapter 2
"Flowering Walnuts in the Wood" and Other Bases for Seasonal Climate Forecasting

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Abstract Although it is impossible to forecast the weather more than a few days in advance, the science of seasonal climate forecasting is premised upon an ability to predict the general weather conditions over a prolonged period of time, without trying to predict the precise weather at any specific time during that period. The forecasting is possible only because sometimes, and primarily within tropical latitudes, the atmosphere is sensitive to unusual conditions at the earth's surface, and especially at the sea surface. El Niño, and its counterpart La Niña, are the primary examples of such forcing conditions: during El Niño events, much of the equatorial Pacific Ocean is unusually hot (cold during La Niña), and the consequent changes to the heat and moisture supplied to the atmosphere can disrupt weather conditions in many parts of the globe. However, all seasonal climate forecasts involve a great deal of uncertainty, and a key aspect of forecasting at such time scales is to estimate the uncertainty in the prediction reliably. There are two sources of uncertainty in seasonal climate forecasting: the atmosphere is nowhere completely forced by conditions at the surface, but is free to vary according to its own internal dynamics; and the models used to predict the climate system are imperfect. These two sources of uncertainty are addressed by producing a set of model predictions: different initial weather conditions are used to represent the uncertainty from the internal dynamics, and different models to account for the uncertainties arising from imperfect model physics.

Keywords Seasonal climate forecasting, El Niño, La Niña, uncertainty

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2.1 Introduction

The poem *Wind on the Hill* by A. A. Milne ends with the claim “But where the wind comes from/Nobody knows”, pointing to the perceived impossibility of forecasting the weather. While most people will acknowledge that there have been some advances in weather forecasting over the last half century or so, it is eminently reasonable to ask why scientists can presume to forecast how the atmosphere is likely to behave over the next few months, as they apparently claim to do when issuing seasonal climate forecasts, when it is evident that there is still great inaccuracy in forecasting what is going to happen over the next few days, or even hours. Surely it is much more difficult to forecast the near future than the more distant future. This paradox hinges upon a distinction between “weather” and “climate”, and the fact that there are fundamentally different reasons why each may be predictable. “Weather” can be understood as the state of the atmosphere as it is experienced at any given time, whereas “climate” is some kind of summary (often expressed as a simple average, although involving much more than that) of weather over a longer period of time. Weather forecasting involves making claims about the state of the atmosphere at specific times in the future, whereas seasonal climate forecasting involves making claims only about the general state of the atmosphere over the next few months without having to worry about the precise weather at any time during those months.

An analogy can be drawn by considering the problem of forecasting the outcome of a sporting event, such as a soccer match: forecasting the position of the ball more than a few seconds in advance is virtually impossible, but forecasting the final outcome of the match is much more viable. When forecasting the final score, a statement is made only about the general run of play, and no attempt is made to claim knowledge of where the ball will be at any specific time during the match – it is much harder to forecast exactly when goals are going to be scored than what the final score will be. Similarly, with seasonal climate forecasting, it is only the general weather conditions throughout the season that are being forecast, and no attempt is made to forecast the exact weather on any given day within the season. Thus seasonal climate forecasting works on the basis that, although it is impossible to forecast the weather on each of the next 90 days, say, it may be possible to predict which kind of weather patterns may occur unusually frequently or infrequently, or may persist for unusually long periods of time, or be unusually intense. Just as it is possible for the weaker team to dominate the game for a short period, the length of the season for the climate forecast needs to be sufficiently long to ensure that a short spell of otherwise uncharacteristic weather for the season does not negate the forecast. At the same time, if the target season (the period for which the seasonal climate prediction is made) is too long, the end of the season may be too far in the future for the prediction to be reliable, and/or times of the year with fundamentally different climate characteristics, and hence that may require distinct predictions, may be combined. In most cases, a 3-month period is optimal for a seasonal forecast.

2.2 Why the Seasonal Climate Can Be Forecast

2.2.1 Historical Examples of Seasonal Forecasting

Even if a distinction between weather and climate forecasting is granted, the question remains of how it is possible to forecast the climate when the weather cannot be forecast accurately – climate, after all, is defined by weather. Although a firm scientific basis for forecasting the climate for the next few months has emerged only over the last few decades, it is a discipline that has been practiced for millennia. In fact, the world's earliest surviving work of literature, the *Epic of Gilgamesh*, contains an example of a seasonal climate forecast: Utnapishtim is warned by the god Ea of forthcoming prolonged excessive rainfall, and is told to prepare for flooding. This tale has strong parallels with the story of Noah in the *Book of Genesis*, and there are numerous other examples of warnings of either excessive rainfall or periods of agricultural drought in the Hebrew Scriptures. In all these examples, warnings are provided by divine revelation, but a much more widespread basis for similar predictions has been inference: specifically, various observations of nature have been interpreted as harbingers of coming weather and climate conditions for centuries (Marriott 1981; Inwards 1994). In Vergil's *Georgics I*, for example, a quotation from which forms the title of this chapter, it is observed that heavy blossoming of walnut trees (or sometimes translated as almond trees) typically is followed by weather conditions conducive to bumper harvests.

Examples similar to those of Vergil's, in which weather conditions over the coming season are predicted on the basis of some unusual observation, most frequently in the plant kingdom,[1] can be found from virtually all cultures, some of which still survive in popular folklore. In at least a few of these cases, the observations of nature have been shown to have a sound inferential basis (e.g., Orlove et al. 2000, 2002), and cannot simply be written off as the inevitable few cases of Type I statistical errors to be expected given a large number of spurious forecasting methods. These few examples work because in some places, and at some times of the year, weather patterns can persist for long periods of time, or recur with unusual frequency. That some aspects of nature, such as plants, may be sensitive, or that some observation of the atmosphere itself may be made, in the early stages of these prolonged weather anomalies[2] is perfectly reasonable.

Some modern scientific methods of seasonal climate forecasting work on a similar basis to forecasts based on observations of nature: specifically, various statistical methods of forecasting the climate involve identifying occasions in the past in

[1] Observations of animal behaviour are used more frequently for weather than for climate forecasting.

[2] "Anomaly" is a technical term used in seasonal climate forecasting to define the difference between the observed weather conditions over a period of time (the "seasonal climate"), and the average weather conditions for that time of year as measured over a period of a few years (typically about 30 years – the "climatology").

which climate anomalies at one time of the year have been frequently followed by climate anomalies at a later time of the year. These "analogue" procedures assume that climate anomalies may persist or evolve in predictable ways (e.g., van den Dool 1994; van den Dool et al. 2003). Analogue procedures are familiar to most of us: we often ask questions such as whether the recent hot spell, for example, is likely to continue for the next few weeks, or whether the coming winter is going to be unusually cold given the wet summer that we may have just endured. Unfortunately, many of the methods based on observations of nature cannot be tested scientifically because of inadequate historical records of the relevant observations either because they have not been recorded systematically, or because the observations are inherently subjective and thus difficult, if not impossible, to measure consistently. How does one measure how "heavy" Vergil's walnut tree blossoming is in any given season, for example? Even given sufficient data, any forecasting system has to be supported by sound causal explanations linking the climate to be predicted with the antecedents because of the possibility of identifying relationships that are purely accidental. Thus, despite a long history of practice, seasonal forecasting became a scientific discipline only in the last few decades, after important advances in understanding of the variability of the atmosphere as described below.

2.2.2 Climate Patterns Around the Globe May Be Related

Given that the atmosphere itself, if left to vary freely, can change markedly in a matter of days, for prolonged weather anomalies to be predictable the atmosphere would have to be constrained or forced somehow (Harrison 2005). Further, if such forcing does occur, it is likely that climate anomalies would occur at a number of locations at the same time. Evidence in support of large-scale forcing of the atmosphere was found before the forcing mechanism itself was identified. In the early 20th century, Gilbert Walker, building upon work initiated in the late-1800s (see Allan et al. (1996) for a review of the early history of seasonal climate forecasting), indicated that unusual climate conditions in one part of the globe are frequently associated with unusual conditions in distant locations, either synchronously or at some lag. Climate anomalies in one part of the globe that are associated with anomalies in another part because of related disruptions in the atmosphere are known as "teleconnections". The most important teleconnection pattern identified by Walker involves opposite changes in atmospheric pressure between the western and eastern Pacific Ocean (Glantz et al. 1991). This pattern is known as the Southern Oscillation, and is monitored by comparing the atmospheric pressure at Darwin, in northern Australia, with that at Tahiti, in French Polynesia. Seasonally averaged sea-level pressure values for these two locations are compared in Fig. 2.1 (results are shown only for the January–March season), where a tendency is evident for increased (decreased) pressure to occur in Darwin when decreased (increased) pressure occurs in Tahiti. These pressure changes are important because they

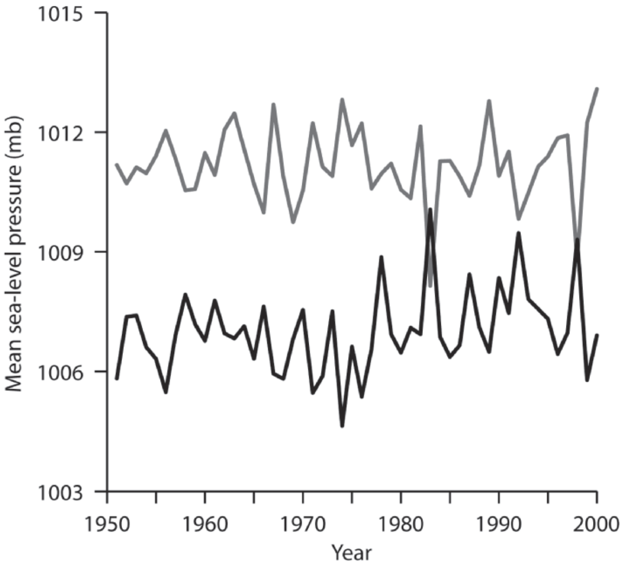

Fig. 2.1 January–March averaged sea-level pressure (hPa) at Darwin (grey line) and Tahiti (black line) from 1951 to 2000

involve major disruptions to the trade winds across the southern Pacific, involve large-scale shifts in the location of areas of heavy rainfall, and, in turn, can affect climate conditions in other parts of the globe.

2.2.3 Causes of Seasonal Climate Variability

Only since about the mid-1960s have mechanisms been identified for explaining why certain weather patterns can be so persistent or frequent, and can occur over distant parts of the globe at the same time. Specifically, it was identified that the behaviour of the atmosphere is closely related to the state of the equatorial Pacific Ocean. About every 3–10 years large-scale warming of the equatorial Pacific Ocean occurs, typically lasting about 9–12 months, and most frequently starting in the spring season of the northern hemisphere (Zebiak 1999). These warming episodes became known as El Niño (after an annually occurring much smaller scale warming off the coast of Peru), and are most commonly measured by averaging sea-surface temperatures over core regions of the warming, the most important of which is known as the Niño3.4 region (5° N–5° S, 170° W–120° W).

The occurrence of El Niño is closely related to the Southern Oscillation as illustrated in Fig. 2.2. January–March seasonally averaged sea-surface temperatures for

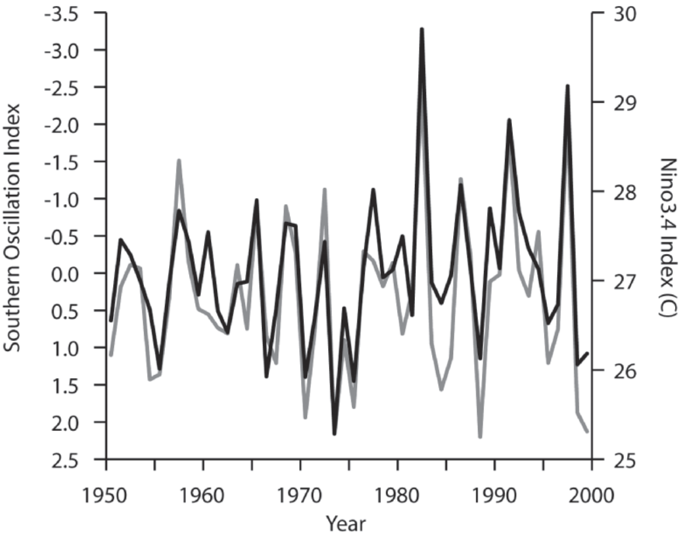

Fig. 2.2 January–March sea-surface temperatures (°C) averaged over the Niño3.4 region (5° N–5° S, 170° W–120° W) (grey line), and of the Southern Oscillation Index (black line) for 1951–2000

the Niño3.4 region (grey) are shown together with the Southern Oscillation Index (black) for the same period. The y-axis for the Southern Oscillation Index is inverted to emphasise the similarity between the two series. Figure 2.2 shows that when the Pacific Ocean warms the Southern Oscillation Index almost invariably declines – i.e. the difference between the atmospheric pressure in Tahiti and in Darwin decreases, and may even change sign if the warming becomes unusually strong (as in 1983, for example; see Fig. 2.1). Such a strong relationship is highly suggestive of a causal relationship, and indeed the major disruptions in the trade winds over the Pacific Ocean that were mentioned above as being part of the Southern Oscillation are not only required for El Niño events to develop, but the El Niño events themselves cause such prolonged disruptions to the trade winds (Bjerknes 1966, 1969, 1972). The mechanisms involved include the effects of the trade winds on ocean waves and currents, and the effects of the resultant changes in sea temperatures on atmospheric pressure, and hence on the trade winds themselves. A detailed description of these mechanisms is beyond the scope of this chapter, suffice it to say that an interaction between the ocean (El Niño) and the atmosphere (Southern Oscillation) occurs over the equatorial Pacific Ocean. Because the ocean and atmosphere are intricately related in the equatorial Pacific, this coupled system is often referred to as the El Niño – Southern Oscillation (ENSO) phenomenon.

The disruption to the atmosphere that is associated with the Southern Oscillation can be manifest downstream of the equatorial Pacific, and so the impacts of El Niño

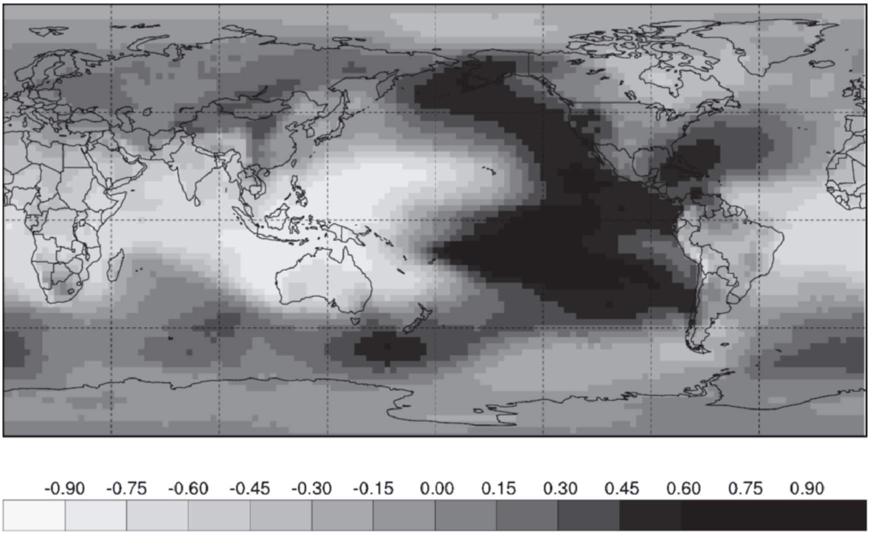

Fig. 2.3 Correlations between January–March 1961–2000 mean sea-level pressure and the Southern Oscillation Index for the same period. Correlations stronger than ±0.30 (covering about 40% of the globe) are statistically significant at a 1% level of significance. The mean sea-level pressure data are from the European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis (Uppala et al. 2005), which is a model’s best estimate of the state of the global atmosphere given scattered observations (*see* Appendix 1)

(and La Niña) can occur in disparate parts of the globe. To illustrate such teleconnections, Fig. 2.3 shows correlations between the January–March mean sea-level pressure and the Southern Oscillation Index for the same period. The polar areas of the Oscillation are clearly evident with strong negative correlations over the western Pacific and eastern Indian oceans, and positive correlations in the central Pacific; but correlations are strong elsewhere too, and sea level pressure over about 40% of the globe is notably affected by swings in the Southern Oscillation at this time of year. Some of the teleconnections in Fig. 2.3 are a result of a reorganization of the general circulation of the atmosphere itself (for example, over southern parts of North America), but others may be fuelled or modified by ocean–atmosphere interactions in other areas (for example, over eastern Africa). The tropical Indian Ocean, for example, typically becomes unusually warm during El Niño events because of changes in the trade winds over the basin, and these changes help to effect an influence of ENSO on Africa. However, ocean–atmosphere interaction can occur independently of ENSO; the tropical Atlantic Ocean, for example, is thought to have an important effect on the overlying atmosphere sufficient to affect rainfall over north-east Brazil and over large parts of West Africa.

Where and when the interaction between the atmosphere and the ocean is sufficiently strong, the relatively slow timescale of variability of the ocean can have a prolonged influence on the atmosphere, thus making the climate predictable at seasonal timescales (Barnston et al. 1994; Palmer and Anderson 1994; Shukla 1998).

However, the strength of this interaction permits seasonal climate forecasting only at certain times of the year and in certain parts of the globe (Mason and Goddard 2001). As a rather crude generalization, the atmosphere is most sensitive to changes in sea-surface temperatures in areas where sea temperatures are high, and so the tropical atmosphere tends to be more strongly affected than the atmosphere in higher latitudes. For this reason seasonal predictions of the atmosphere generally are most skilful for the tropics, whereas weather forecasts tend to be more skilful in the extra-tropics where the passage of warm and cold fronts is easier to predict than the vagaries of convection. As mentioned, this tropical – extra-tropical distinction is a crude generalization, and there is considerable spatial and temporal variability in the predictability of seasonal climate, even within the tropics. To illustrate, Fig. 2.4 provides a crude indication of areas within Africa where seasonal rainfall totals are considered predictable. These areas have been identified by isolating areas where

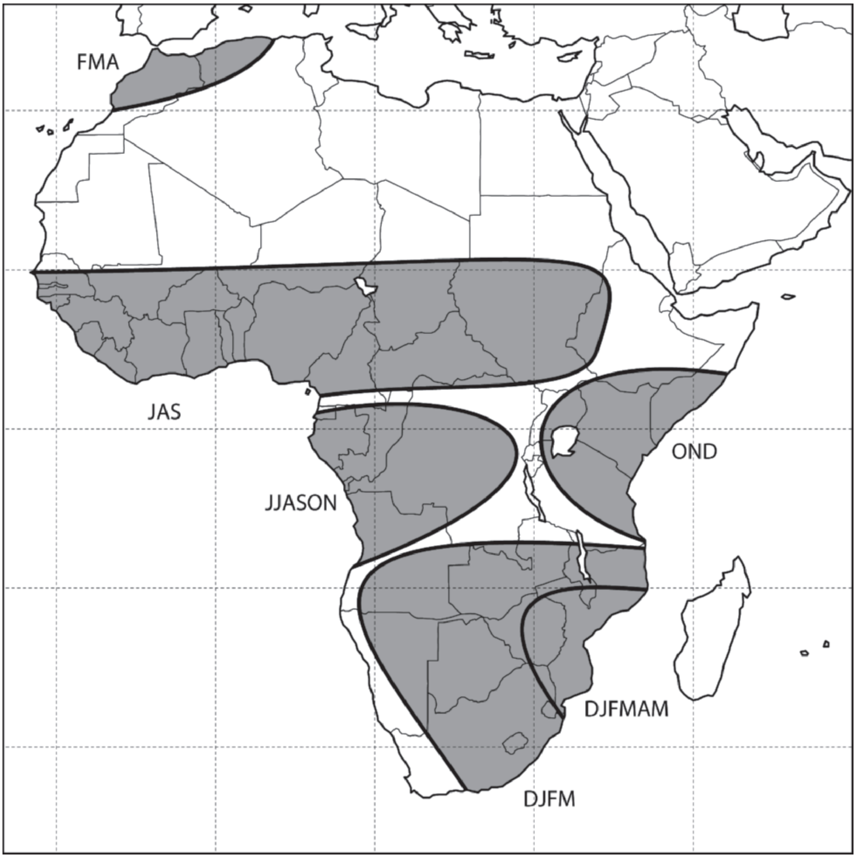

Fig. 2.4 Areas in Africa and seasons for which seasonal climate anomalies are strongly correlated with preceding sea-surface temperature anomalies, and thus which are thought to be predictable

seasonal rainfall is strongly correlated with preceding sea-surface temperatures in at least part of the tropical oceans. The map has been simplified by indicating only those areas in which the strong correlations are spatially coherent. The boundaries of the regions should not be considered precisely marked, and the results are subject to data availability and quality, so other regions and seasons that are not marked may be predictable.

2.3 Approaches to Seasonal Climate Forecasting

2.3.1 Forecast Models

For areas such as those shown in Fig. 2.4 where the seasonal climate variability is predictable, forecasts can be made either by considering the historical interaction between the atmosphere and the ocean using a statistical model to describe these observed relationships (e.g., Namias 1991; Ward and Folland 1991), or by trying to model the actual physical processes involved in the interaction. Alternative, but consistent, examples of statistical modelling have already been mentioned. Specifically, analogue procedures relate climate anomalies in one season to preceding anomalies, but are premised on some form of persistent, or predictably evolving, oceanic forcing. Although analogue models are still used, a more widespread approach is to construct a statistical model to describe the historical relationship between sea-surface temperatures at one time of the year, and subsequent seasonal climate anomalies, and then to use this statistical model and the latest observations of sea-surface temperatures to make a prediction. When describing the historical relationship, a lag between the observed sea temperatures and the seasonal climate anomalies is incorporated to provide scope for prediction. The time period between the sea temperature measurement and the seasonal climate is known as the lead-time. It is assumed that the sea temperatures either remain similar to their measured values through the target season, or evolve in a predictable manner. As the lead-time increases, the uncertainty as to the actual sea temperatures that will occur during the target period increases, and so the ability to make an accurate prediction diminishes.

The second approach to seasonal climate forecasting involves running a model, known as a dynamical model, very similar to those used to make weather forecasts. Apart from the obvious difference in the length of time for which the forecast is made, when producing seasonal climate forecasts it is also necessary to model the dynamics of at least the influence of the ocean on the atmosphere, and ideally the interactions between the two should be considered. In weather forecasting although the influence of the ocean on the atmosphere can be important (Walker and Lindesay 1989; Barsugli et al. 1999) the feedback can generally be ignored because any changes in the ocean over a few days would typically be small.

There are a number of fundamentally different ways of modelling these interactions between the atmosphere and the ocean. These approaches range in complexity:

in the simplest case, only the atmosphere is forecast using dynamical models while the ocean is kept unchanged; in the most complex case the dynamics of the atmosphere and the ocean evolve together. In the simpler case in which it is only the atmosphere that is modelled, accurate seasonal climate forecasts require accurate forecasts of the ocean to be made prior to running the atmospheric model (Bengtsson et al. 1993). A “two-tiered” forecast is thus required: forecasts of the ocean are made first, followed by forecasts of the atmosphere with the ocean conditions prescribed (Barnston et al. 2005). Forecasts of the ocean have involved methods from as simple as assuming that the most recently observed conditions will remain unchanged, or perhaps evolve slowly back towards their long-term average conditions (Mason et al. 1999; Graham et al. 2000, 2005), through more sophisticated statistical forecasts, methods based on dynamical models of the ocean (Stockdale et al. 1998), or some combination of the above (Barnston et al. 2003). These two-tiered approaches allow the ocean to influence the atmospheric variability, but do not permit the atmosphere to feedback to the ocean (Goddard et al. 2001).

The most complex method of seasonal climate forecasting is to model the dynamics of the atmosphere and the ocean together. The standard approach is to “couple” separate models for the atmosphere and ocean that are run synchronously and interactively (Stockdale et al. 1998; Palmer et al. 2004; Graham et al. 2005; Guérémy et al. 2005; Saha et al. 2006). Such “fully-coupled” models generate forecasts of the atmosphere and of the ocean iteratively, and so sometimes are referred to as “one-tiered” forecasting systems. These fully coupled systems are considered the state-of-the-art in seasonal climate forecasting since they represent the most comprehensive attempt to model all the components of the climate system thought to be relevant for understanding atmospheric variability at seasonal timescales. However, because of their computational advantages and, in some cases, higher levels of forecast skill, two-tiered systems and the simpler empirical models are still widely used in operational forecasting.

2.4 Uncertainty in Seasonal Climate Forecasting

2.4.1 Estimating the Uncertainty in the Forecast

Whether it is a statistical or a dynamical approach that is used to forecast the climate, the weather variability over the season constitutes an inherent source of uncertainty, and it is important that the seasonal forecast provides some form of indication of the degree of uncertainty in the prediction. It is because of the large uncertainty that seasonal forecasts are expressed probabilistically rather than as precise estimates of seasonal total rainfall, for example, or of averaged temperatures. The probabilistic forecasts are commonly presented in the form of a set of probabilities that the seasonal total rainfall, for example, will be within specific ranges. The definition of these ranges as the terciles of an historical set of rainfall totals for the same season is widespread, although other ranges that are more meaningful to users of the seasonal forecasts are being used increasingly (e.g., Thomson et al. 2006).

Reliable estimation of the uncertainty in the forecast is a non-trivial problem. When the forecasts are made using statistical models, the errors in past predictions using the same models can be measured, and the distribution of the sizes of these errors, given a sufficiently large number of past forecasts, provides an indication of the distribution of expected errors for the current forecast (Mason and Mimmack 2002). Although a similar approach could in theory be used for the dynamical model predictions, in practice not only is the availability of past forecasts almost always highly limited, thus precluding any reasonable estimate of the distribution of forecast errors, but uncertainty in any single prediction from a dynamical model is much greater than that from a statistical model, and these additional sources of uncertainty need to be understood before using dynamical models for making a seasonal forecast. Specifically, there are two sources of uncertainty when using dynamical models: the representation of the physics of the real atmosphere within the model is greatly simplified, and there are aspects of the physics of the climate system that are poorly understood; the prediction by the dynamical model is highly sensitive to the initial weather conditions that are specified within the model. This latter problem is considered first.

2.4.2 Sources of Uncertainty in Seasonal Forecasts

2.4.2.1 Uncertainty Resulting from Weather Variability

Dynamical models work by predicting how the state of the atmosphere will evolve given the laws of physics that govern the evolution of the atmosphere. They therefore require the current state of the atmosphere to be specified. However, even very small errors in the estimate of this initial state of the atmosphere (known as the "initial conditions") can magnify very quickly such that very different weather conditions can be predicted for only a few days in the future given only a very small change in the initial conditions. It is believed that the real atmosphere behaves in the same way: that a minor disruption to the atmosphere (perhaps by the proverbial flutter of a butterfly's wings) will magnify over a few days so that very different weather conditions are experienced to what would have occurred had the butterfly stayed still. This sensitivity of the atmosphere (both the real one and the model's) explains why the weather is so poorly predicted beyond a few days: the unpredictability of the exact state of the atmosphere any time in the future is an inherently insurmountable problem.

So why is this "chaotic" nature of the dynamical model's atmosphere a problem when predicting seasonal climate; presumably, if the dynamical model is a good one, the predicted weather over the target season should be influenced by the model's sea temperatures in a similar way to the real oceans' influences on the real atmosphere? The problem arises from the fact that since even in the most predictable areas and seasons only about two-thirds of the year-to-year variability in rainfall can be attributed to sea-surface temperature forcing, a single model prediction with a similar degree of forced variability is quite likely to be a poor estimate of how the real atmosphere will evolve. While nothing can be done about the fact that the actual evolution of the observed atmosphere represents only one possible outcome, we can at least get an idea of how characteristic the single model prediction is of other possible predictions given similar sea temperature forcing (in a "two-tiered" system) and/or initial conditions (in a "one-tiered" system). Dynamical models therefore are invariably run a number of times using similar initial conditions, so that a set, or "ensemble" of predictions are generated. The objective of generating an ensemble of predictions is to simulate the distribution of possible outcomes that the real atmosphere can take.

Assuming that this distribution is estimated reliably, one indication of the uncertainty in the seasonal forecast could be provided by the degree to which the seasonal statistics of these various predictions agree. If the average of an ensemble of predictions indicates a seasonal rainfall total that is unusually high, then presumably we can be more confident that the actual seasonal total will be high if all the predictions indicate a similarly high total than if the totals are more scattered even though the average is unchanged. In practice, however, it has been difficult to demonstrate that year-to-year changes in the spread of the ensemble of predictions from a dynamical model represent meaningful variability in the actual uncertainty in the predicted outcome. Part of the problem is methodological: powerful procedures for identifying a relationship between the ensemble distribution and the uncertainty in the prediction are lacking. However, this problem does not negate the generation of the ensemble: it has been widely demonstrated that the mean of an ensemble of predictions is a more accurate forecast, on average, than the predictions of any of the individual ensemble members (Kumar and Hoerling 1995; Kumar et al. 2001). This principle of improving the forecast by considering the mean of an ensemble of predictions can be illustrated simply by comparing 30 years of model forecasts[3] of January–March precipitation for Kalbarri,[4] Australia (27°42′43″ S, 114°09′54″ E, 6.0 m altitude). The correlations between the simulated and the observed rainfall are shown in Fig. 2.5 with the forecasts calculated from the mean of an increasing

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[3] The forecasts are from the ECHAM4.5 atmospheric general circulation model, which was developed by the Max Planck Institute (Roeckner et al. 1996). The model was run in a two-tiered mode, with sea-surface temperatures predicted by persisting observed anomalies for November.

[4] General circulation models produce forecasts that represent average conditions over relatively large grids (in this case about 2.8° × 2.8°, or about 60,000 km²) rather than for specific locations. Because of model inaccuracies, resulting in part from the coarseness of the spatial resolution of the model, geographical features in the model can be displaced. Normally a "downscaling" procedure would be applied to try and convert the model output to a prediction for a specific location, but for this example the simulations for Kalbarri are taken simply as the model value for the grid containing 27°42′43″ S, 114°09′54″ E.

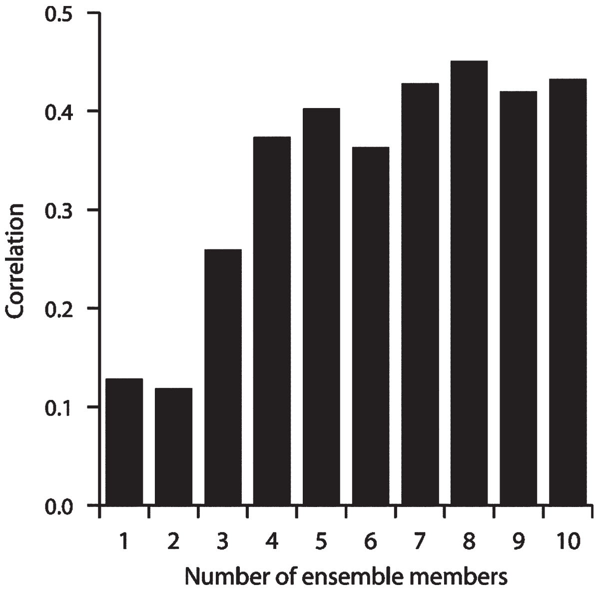

Fig. 2.5 Correlations between observed and ensemble-mean simulations of January–March 1971–2000 precipitation for Kalbarri, Australia, for varying ensemble sizes

number of ensemble members. The improvement in the correlation is quite marked, but the correlation stabilizes given an ensemble size of about seven or eight, which is typical for many areas in the tropics (Kumar et al. 2001).

2.4.2.2 Uncertainty Resulting from Imperfect Prediction Models

Moving on to the other source of uncertainty in dynamical model predictions, just as errors in the forecast can arise from imperfect knowledge of the current state of the weather (the "initial conditions"), so also uncertainties arise from the simplification of the real climate system by the models. This problem is addressed in a similar way to the initial condition problem: generate a large number of predictions by adjusting the physics of the model and/or by using a set of completely different models, and construct a forecast by considering this set of predictions. A number of recent studies have demonstrated that an ensemble of predictions from different models affords a better forecast than a similarly sized ensemble of predictions from any single model (Hagedorn et al. 2005; Doblas-Reyes et al. 2005), provided that there are no major differences in the quality of the individual models. These "multi-model" predictions improve upon the single model because of the improved indication of uncertainty in the forecast resulting from imperfections in the model physics. Because of the differences in the physics of two models (or because of the perturbation of the physics in a single model) the predictions from a set of initial conditions diverge just as if the initial conditions themselves had been perturbed, and so a distribution of predicted outcomes is generated in the same way as for an ensemble from a single model.

Multi-model ensembles are currently considered the preferred approach to operational seasonal climate forecasting. The idea permits the combination of predictions from dynamical and statistical models, although in practice the dynamical and statistical approaches remain largely distinct. Some consideration has been given to optimal ways of combining the predictions from different models by assigning models differing weights depending upon their relative historical performances (e.g., Rajagopalan et al. 2002; Robertson et al. 2004), but since it is difficult to demonstrate robust differences in model performance, equal weighting of models is a hard standard upon which to improve (Mason 2008).

2.5 Summary

Seasonal forecasting is possible because the atmosphere is forced and constrained in some parts of the globe and at certain times of the year by conditions in the oceans, especially in the tropical Pacific. However, because of the vagaries of the atmosphere it is not possible to predict what the weather is going to be like beyond a few days. Because the seasonal forecast is itself sensitive to the details of the weather forecast, a large number of predictions are typically made so that the uncertainties arising from the inherent errors in the weather forecasts are represented. These uncertainties are a result both of the imperfect nature of the models themselves and of imperfect knowledge of the current state of the weather. Given the impossibility of deciding which of the ensemble of predictions is the most likely, probabilistic forecasts are issued instead, and aim to indicate the range of possible climate conditions that may occur.

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