How predictable is the climate and how can we use it in managing cropping risks?

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Abstract
Our increasing understanding of the underlaying mechanisms responsible for climate variability and change means that some of these impacts are now predictable, although the extend of predictability remains hotly debated amongst scientists. Decision influenced by climate knowledge need to be made at a range of time scales, hence climate research efforts are directed towards investigating phenomena such as the Madden-Julian Oscillation (MJO; 30-60 days), El Niño - Southern Oscillation (ENSO) related variability (2 - 10 years), decadal / multi-decadal climate variability and climate change. The challenge is to further increase our understanding of causes and consequences of climate variability and change to achieve two key outcomes: a) policies suitable for multi-goal objectives resulting in rapid and substantial societal benefits and b) risk management strategies that reduce vulnerability for individuals and businesses.

Farm risk management needs to be seen within the wider societal context: Decisions made at a point in the landscape have implications downstream. Hence, environmental and societal risks (e.g. run-off, drainage, erosion, salinity, nutrient / pesticide movements, health impacts, employment etc) need to be considered and quantified. This requires the ability to effectively consider multi-goal objectives through the evaluation of alternative action outcomes. In this context, quantitative agricultural systems analysis via systems simulation models is an essential tool to provide objective information on which to base such decisions. In order to address issues of climate variability and change, these agricultural systems models require environmental input data – and specifically climate data – that reflects the current state of play in climate science. Statistical climate forecasts as well as forecasts based on coupled ocean/atmosphere models (*GCM*s) will play an increasingly important role in agricultural risk management.

Media Summary
Probabilistic forecasts of climate variability ranging from inter-seasonal to climate change can assist in multi-goal decision-making, leading to better agricultural policies and on-farm risk management.

Key Words
Climate variability, predictability, forecast, agricultural decision making, multi-goal objectives

Background / Introduction
Climate can be one of the biggest risk factors impacting on agricultural systems performance and management. Extreme climate events such as severe droughts, floods, or temperature shocks often strongly impede sustainable agricultural development, particularly in the tropics and sub-tropics. Factors such as climate variability and change contribute to the vulnerability of individuals, businesses, communities and regions. The climate impact on agricultural production also affects food security and exacerbates environmental degradation (Selvaraju et al., 2004).

Recent climate research efforts have demonstrated that targeted and appropriately conceptualised climate knowledge (including seasonal climate forecasting and scenario analyses) can increase overall preparedness of farmers, agribusiness managers and policy makers, hence leading to better social, economic and environmental outcomes (Hammer et al., 2000; Glanz, 2003). To better manage against this background of climate variability and change requires (a) an understanding of the climate system (termed here ‘climate knowledge’) and (b) the ability to change the way we currently manage agricultural systems (Hammer et al., 2000; Selvaraju et al., 2004).

Here, our aim is to explore some of the 'limits of predictability' as a means to prioritise future, applied climate research and to discuss how our limited and uncertain climate knowledge might facilitate improved risk management. To assist readers in understanding the unfamiliar nomenclature of climate science, we have provided a short glossary of terms in the appendix. Any terms defined in this glossary are indicated using hyperlinks throughout the text.

How predictable is our climate?

Although improving climate prediction is at the core of most climate research efforts, from an agricultural perspective, future climate is just one of many unknown risk factors. While skilful forecasting helps to reduce uncertainty, it is rarely the only information that determines a course of action. This simple fact is often overlooked when issues of relevance or adoption are discussed.

It is beyond the scope of this paper to comprehensively review the extensive literature on the predictability of climate. Instead, we will briefly explore predictability at different timescales and suggest areas of priority for climate research that we consider pertinent to improve crop risk management.

Although climate variability is the consequence of an intrinsically non-linear, deterministically chaotic system, we can understand and predict (to a limited extent) aspects of this system and its behaviour. However, there are limits to what can be predicted and better understanding of these limits will not only help us to focus on what might be achievable, it will also help us to determine how best to use the valuable, but uncertain knowledge that we can gain about our future climate.

Two factors that impose limits on predictability of future climate states need to be distinguished: (a) uncertainty in initial conditions, including uncertainties about boundary conditions (as in the case of climate change) and (b) errors associated with, and gaps in, observational measurements and limitations of climate models, including the parameterisation of physical processes (Smith, 2000; Hasselmann, 2002). Hence, we can say *a priori* that for real, physical systems such as the earth's climate, no perfect model exists (and never will). Consequently, we will always be restricted to probabilistic forecasting, since no accountable forecast system will be able to provide a credible, single outcome prediction or a deterministic forecast.

Further, given (a) the low signal to noise ratio associated with measurements that characterise the climate state, (b) the possibility of stochastic forcing, (c) the existence of stochastic resonance and (d) the possible existence of bifurcation points, which are typical for non-linear, deterministically chaotic systems (Cane, 2000; Ganopolski and Rahmstorf, 2002; Hasselmann, 2002; Stewart, 2003), we need to question whether accountable probability forecast is even a viable goal. Smith (2000) argues that it might not, but concedes in some instances we will be able to decrease uncertainties and refine our probabilistic forecasts. Hence, the best climate science will be able to provide to improve agricultural risk management are sound forecast trajectories. This immediately raises several key issues: (a) how are such trajectories best derived, (b) how should the information and knowledge gained be communicated and (c) how can we ensure that this knowledge will make a positive contribution to agricultural risk management?

Climate variability relevant to agricultural management occurs at a range of frequencies or time scales, ranging from intra-seasonal, inter-seasonal, decadal, multi-decadal to climate change (Donald et al., 2004; Meinke and Stone, 2004; Potgieter et al., 2004b). Spectral variability in time series of open systems is a consequence of (a) specific forcing mechanisms and (b) long-term irregular behaviour caused by the fractal dimension and associated strange attractors of that system resulting in 'deterministic chaos' (Ghil et al., 2002). This means that identifying a specific frequency of variability is important, particularly from an agricultural management perspective, but it does not imply either an underlying driving mechanism nor that such periodicity will ever be predictable (Meinke et al., 2004). However, it is an important first step in analysing variability (Power et al., 2004). Here we focus on the high and low frequency end of the time scales relevant to risk management and specifically consider the Madden-Julian Oscillation (MJO; Madden and Julien, 1972; high frequency phenomenon) and climate change (low frequency phenomenon).

Identifying climate variability and climate change

In order to identify spectral peaks in recorded monthly climate records, we have chosen an advanced, non-parametric statistical method for spectral estimation of noisy time series that may contain broadband variability (multi-taper method, MTM). By averaging over small ensembles of spectra obtained by the multitapers, MTM is less heuristic than traditional non-parametric techniques and therefore yields better and more stable estimates with lower variance than single-taper methods (Mann and Park, 1999; Ghil et al., 2002). MTM's non-parametric nature avoids inaccurate assumptions about the underlying data structure. The method is suitable for auto-correlated, non-stationary data and phenomena, such as ENSO and climate change, which may contain a mix of time-domains. It is suited to data that are likely to contain strong interactions between processes operating at different frequencies (Ghil et al., 2002; Hasselmann, 2002; Fraedrich and Schönwiese, 2002) and identifies spectral peaks with a higher resolution and greater confidence than other methods.

Our analyses (Fig. 1) show typical 'red noise' patterns (i.e. random variability at lower frequencies) in monthly data of minimum and maximum temperatures for a location in Australia (Emerald 23°S, 148°E) and another in Uruguay (La Estanzuela 34°S, 57°W). At Emerald there are at least two frequencies that clearly dominate and can be associated with corresponding phenomena at that frequency, while at La Estanzuela only one frequency dominates, regardless of the arbitrarily chosen level of significance (Nicholls, 2001). At Emerald the first significant frequency is a spectral peak at around 0.015 (0.021) cycles month^{-1} for minimum (maximum) temperatures broadly corresponding to the ENSO frequency (Allan, 2000), while the second, low frequency response is a linear trend in both minimum and maximum temperatures. Data from La Estanzuela shows only one significant peak at the lowest frequency for minimum temperatures (Fig. 1). These low frequency peaks can be regarded as a 'signature' of climate change (Mann and Park, 1999). The trends observed for Emerald are consistent with the Australia-wide analysis of temperature trends conducted by the Australian Bureau of Meteorology (Power et al., 1998).

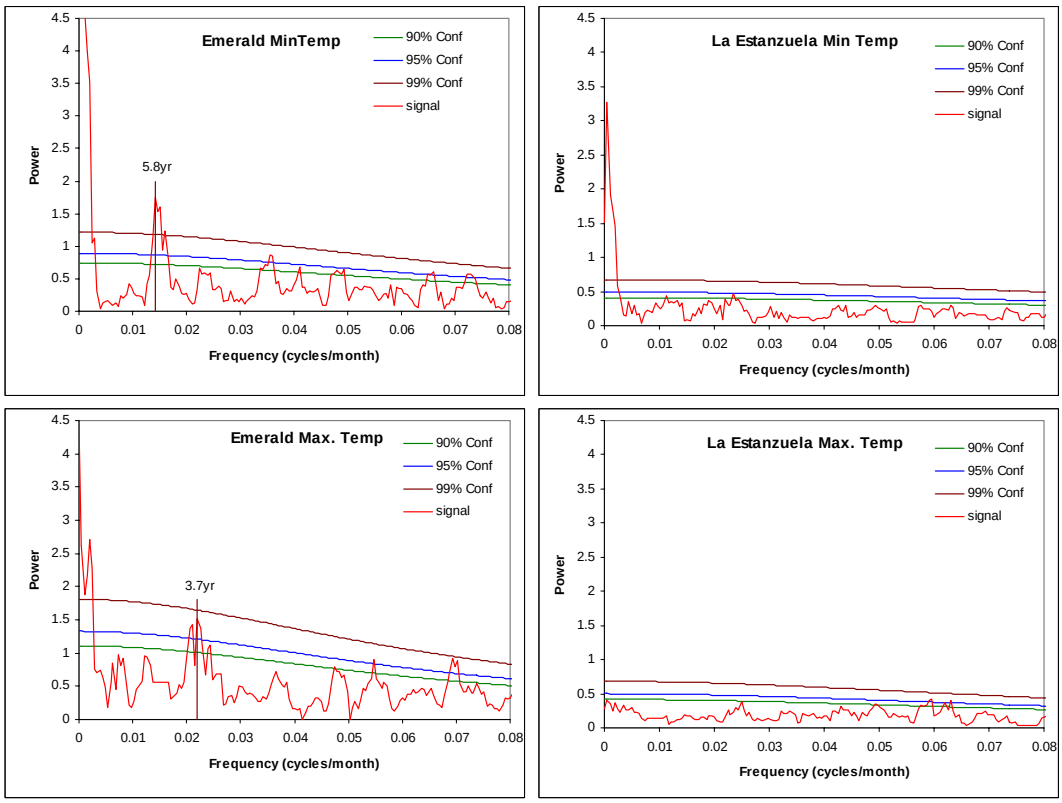

Figure 1. MTM analysis of monthly minimum and maximum temperatures at Emerald, Australia (left) and La Estanzuela, Uruguay (right) for frequencies < one year. Peaks that protrude above the smooth top line are significant at the 99% level. Peaks at the very left side of the diagrams indicate a quasi-linear, non-stationary trend and are indicative of climate change (i.e. a statistical 'signature' of climate change).

It is easier to identify periodicity in temperatures than in rainfall because of the more homogenous nature of temperature data. Rainfall data, particularly at monthly frequencies and higher, has both discrete and continuous properties (i.e. either rain or no rain, with varying rainfall amounts) and can be very seasonal.

The problem could be addressed through applications of Generalised Linear Model techniques (e.g. Tweedie distribution; Lennox, 2003) and requires further investigation. In our case the MTM analysis of rainfall data did not reveal any obvious periodicity beyond red noise at either location, in spite of a strong ENSO signal that is known to impact on rainfall at both locations (Fig. 2).

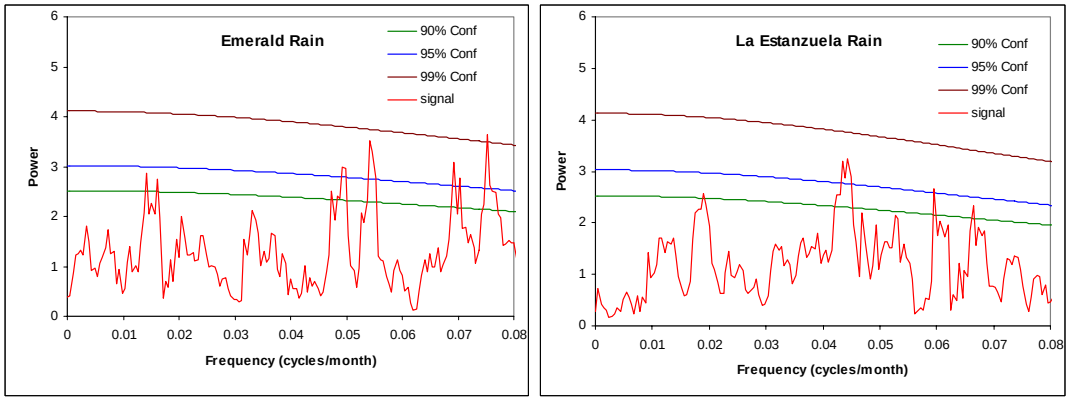

Figure 2. MTM analysis (frequency < 1 year) for monthly rainfall at Emerald, Australia (left) and La Estanzuela, Uruguay (right).

This highlights that although methods such as MTM are useful, they are only first-cut approaches towards a better understanding of temporal variability. In fact, Ghil and Yiou (1996) argue that multiple statistical approaches are needed to shed more light on mechanisms behind the (poorly) observed oscillations (e.g. wavelet analysis, Torrence and Webster, 1999; Arneodo et al., 2002). Not detecting a certain trend in a particular climate variable does not imply that there is no relevant variability occurring at that time scale (e.g. Fig. 2 versus work by Pittock, 1975, on Australian rainfall trends). Conversely, a spurious spike at a particular frequency can be inconsequential for agricultural systems management. At this stage, systems analytical thinking becomes critical: For instance, knowing that there are significant trends in temperatures globally raises many questions for agricultural practice. An obvious one is: what are the implications for frost risk in wheat, as the date of the last frosts limits the opportunities for early-maturing crops that would otherwise mature under milder conditions? Fig. 3 shows that the average frost risk period at Emerald (La Estanzuela) has been reduced from 80 (110) days in 1900 to 17 (67) days in 2000. At Emerald, wheat is now sown earlier than in the 1950s and maturity types have already been adapted accordingly (Howden et al., 2003). This shows that quantifying management and policy relevant impacts of climate change at local levels must be a priority in order to improve agricultural risk management practices.

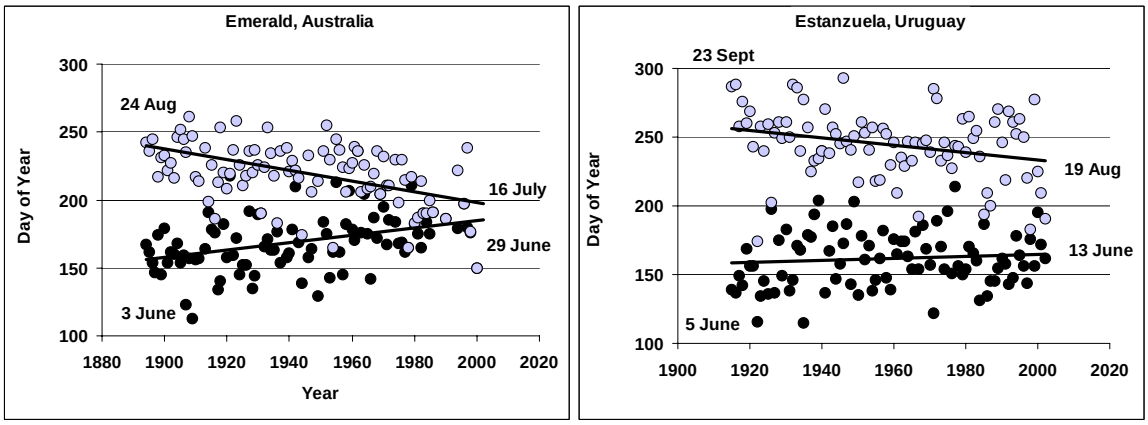

Figure 3. Changes in the dates of first and last frost at Emerald (Australia) and La Estanzuela (Uruguay) during the last century, expressed as a screen temperature of 2°C or lower.

Bridging the weather/climate divide - the Madden-Julian Oscillation

We can identify the key oceanographic and/or atmospheric processes that are responsible for much of the observed variability at most frequencies. At the low frequency end, climate change, as a consequence of increases in atmospheric concentration of greenhouse gasses, is detectable, while at the 2-10 year timescale, ENSO – the most researched of all climate phenomena – is globally dominant. At high, intra-

seasonal frequencies, the Madden-Julian Oscillation (MJO) explains a significant proportion of the measured variability in the Indo-Pacific domain and has significant, untapped potential to improve tactical risk management in agricultural systems (Waliser et al., 2003; Donald et al., 2004).

The MJO is a large-scale, intraseasonal, tropical atmospheric anomaly that originates at more or less regular intervals (30 to 60 days) in the Indian Ocean and propagates eastward at speeds of 5-10 ms^{-1}. It sits at the interface between the prognostic approaches of synoptic weather forecasting (up to 10 days with rapidly declining skill after 5 days) and seasonal climate forecasting. In its active phase, the MJO is associated with convection and rainfall, particularly over India, the Maritime Continent and Northern Australia. The position of the active phase can be determined through measurements of outgoing long-wave radiation. Based on such measurements, 8 possible MJO phases have be determined from the analyses of various modes of coherent synoptic to intraseasonal zonally-propagating tropical variability indices, involving Fourier filtering of a global dataset for the specific zonal wavenumbers and frequencies of each of the phenomena (Wheeler and Weickmann, 2001). Recently, we have shown for Australia that the MJO's impacts extend well into subtropical and even temperate regions via yet to be quantified teleconnections, as evident in large-scale, causally linked synoptic patterns (Donald et al., 2003). For example, in January/February 2004 the passage of the MJO brought substantial, drought-breaking rain and low temperature anomalies to most of NE Australia (Queensland and parts of Northern NSW; Fig. 4).

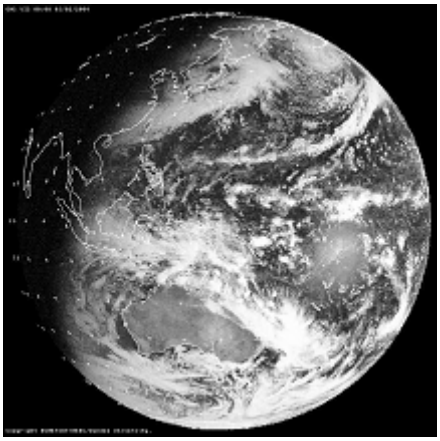

Figure 4. Satellite image, taken on 2 February 2004, of MJO-associated convection in the tropics and induced higher latitude instability over Eastern Australia (corresponding to 'MJO Phase 4' in Fig. 5, centre). This event brought substantial, drought-breaking rain to many parts of Eastern Australia.

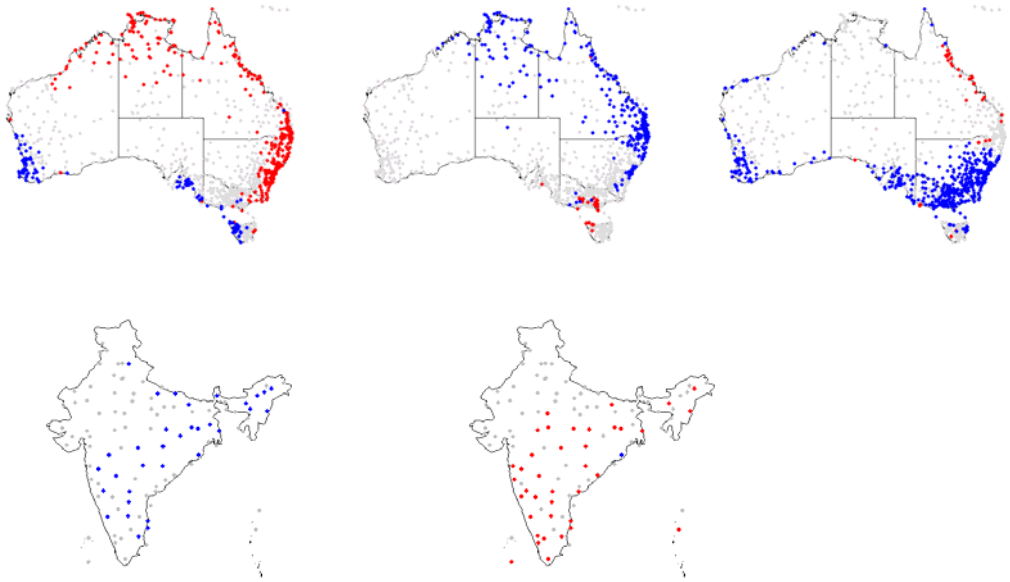

Figure 5. MJO impact evident in long-term rainfall records from recording stations (Australia: Jeffrey et al., 2001; India: data obtained from NOAA, National Climatic Data Center under the WMO World Weather Watch Program). Blue (red) indicates significant increases (decreases) while grey indicates no significant difference in rainfall distributions, depending on the location of the active phase of the MJO. *Top row, Australia*: phase 1 (left; either a decaying event in the E Pacific or the origin of a new event in the western tropical Indian Ocean, 40-60°E), phase 4 (centre; MJO active phase over the Maritime Continent, 100-120°E) or phase 5 (right; 120-140°E), respectively. *Bottom row*: Similar analysis for Indian rainfall station for MJO phase 1 (left) and phase 7 (right, 160-180°E).

Our statistical analysis suggests that the MJO influences, via teleconnections, rainfall patterns right across Australia and India (Fig. 5). The exact nature of these teleconnections, their geographic extent and their synoptic manifestations are currently being investigated. For Australia, Fig. 5 suggests that during a decaying or a newly developing MJO event (phase 1), subsiding air over NE Australia might reduce the chances of rain in that region. When the active MJO centre reaches the Maritime Continent (phase 4), it can interact with monsoonal systems and provide favourable conditions for the development of broad, frontal rain, followed by synoptic conditions that favour higher latitude, low pressure fronts following in the wake of the MJO, resulting in increased chances for rain across Australia's southern states. Similar analyses are now being conducted for other parts of the world where the MJO has significant impact (Vecchi and Bond, 2004). Better forecasting the frequency and timing of MJO events and associated weather impacts would allow better planning of key tactical decisions such as sowing opportunity prediction, disease management, harvest scheduling, irrigation scheduling, product quality management, marketing and the use of weather derivatives.

Statistical approaches and numeric modelling

Strong interactions between climate drivers across timescales via atmospheric and oceanographic teleconnections – a key feature of climate's non-linearity – prevent us from using weak-interaction methods to develop a generally accepted 'closure theory of climate', making it impossible to create from first principles a set of closed equations for the evolution of climate states (Hasselmann, 2002). Consequently, climate scientists have tackled the issue using two fundamentally different approaches: either by statistical methods (as we have done here for the analyses of climate change and MJO impacts) or through the development and use of numerical climate models (i.e. ocean and/or atmospheric models or coupled Global Circulation Models, GCMs). Any internet search will yield a plethora of forecasts based on both approaches.

Statistical forecasting is valuable and sound, providing there is an *a priori* understanding of the drivers that give rise to the prediction in the first place. In addition to this theoretical understanding, statistical forecasting requires sound observational data (both spatially and temporally), suitable statistical techniques to quantify the relationships between variables ('signal intensity', Maia et al., 2004) and sound judgement to limit the number of predictors to avoid, as much as possible, the occurrence of artificial skill

(Drosdowsky and Allan, 2000). Artificial skill is the apparent hindcast skill in statistical forecasting schemes that does not survive when the forecasting scheme is applied in real time to new or independent data. It arises when statistical models are over-parameterised using a number of cross-correlated predictors or when a multitude of possible, statistical forecasting schemes are employed and 'best' performing schemes are selected on the basis of some test statistics, rather than first principles (Meinke et al., 2003). Countless seasonal forecasting schemes based on multiple regression techniques have been developed. Many of them rely on a rather limited understanding of the underlying dynamics and are hence unlikely to stand up to a rigorous elimination of artificial skill.

However, in regards to ENSO-related variability, statistical forecasting is possible due to our comprehensive understanding of the ENSO lifecycle (e.g. Nicholls and Wong 1991; Stone et al., 1996, to cite just a few). This understanding of the fundamental ENSO drivers, coupled with easily measurable ocean and climate variables that index the overall state of the ENSO system (e.g. anomalies in sea surface temperatures, SST, and the Southern Oscillation Index, SOI) have prompted the development of statistical forecast systems that are now used operationally in many parts of the world. Most of these forecasts have at least been influenced by researchers such as Nicholls (e.g. 1983), McBride and Nicholls (1983), Ropelewski and Jones (1987) and Drosdowsky and Chambers (1998), although the latter, due to its near global nature of the analysis, also contains non-ENSO related SST anomalies as a basis for the forecast.

The need to convert climate forecasts into alternative decision options with the assistance of dynamic agricultural models such as APSIM (Keating et al., 2003) has lead to the wide-spread adoption of forecasts that can provide 'analog years'. Such forecasts allow historical climate records to be partitioned into 'year- or season-types' based on concurrently prevailing ocean and atmospheric conditions (i.e. SOI and/or SST anomalies), resulting in SOI phases (Stone et al., 1996) or ENSO phases (e.g. Hill et al., 2000; Potgieter et al., 2004). Current conditions can then be assigned to a particular category and compared to other categories in order to assess the probabilistic performance of the managed system in question (Maia et al., 2004). This is an easy and convenient way of connecting climate forecasts with biological models that only requires historical weather records. The method has been used extensively throughout the world and has provided valuable information for many decision makers (e.g. Messina et al., 1999; Meinke and Hochman, 2000; Nelson et al., 2002; Podestá et al., 2002).

To our knowledge there are currently no new statistical, ENSO-centric forecast systems on the horizon that clearly outperform existing techniques. Further, dynamic modelling approaches are still struggling to surpass the forecast skill of statistical techniques, providing some indirect, corroborating evidence that at least for the ENSO time scale we might be approaching the limits of predictability, limits which are determined by sparse observational data, the chaotic nature of the climate system and stochastic forcing (Cane, 2000). These limitations are not necessarily insurmountable should new data sources or novel approaches become available in the future. However, there remains more scope to improve our statistical forecasting techniques at frequencies that are distinctly different from ENSO and that rely on fundamentally different climate drivers as we tried to indicate earlier using examples from the high and low frequency end of the climate variability spectrum (e.g. MJO and climate change), respectively.

Typically, statistical methods do not account for dynamic interactions between distinctly different climate phenomena (e.g. such as MJO and ENSO). Hence, it is generally expected that dynamically coupled climate models (GCMs) will eventually provide much improved forecast skill. One of many unresolved issues concerning the application of GCM based forecasts are the methods used to derive probabilistic forecasts. Allen and Stainforth (2002) criticise the probabilistic outputs generated by GCMs through altering initial and boundary conditions without explicitly accounting for the climate's response. They argue that climate forecasts are intrinsically five-dimensional, spanning space, time and probability. This will require more attention to formal uncertainty analyses including much more rigorous sensitivity testing including many more elaborate ensemble runs before reliable probabilistic trajectories of future climate states can be provided.

A further issue that requires urgent attention is the 'connectivity problem' between GCM output, agricultural decision tools and agricultural simulation models. While GCM output is sometimes used to inform the policy process, it needs to be 'converted' in some form before it can be used operationally with risk management models. For meaningful decision analyses, rigorous and transparent methods must be

applied to convert large, grid GCM output into something akin to point scale, daily weather station data. There are no agreed method to achieve this, which explains why GCMs do not yet contribute substantially to operational risk management. The use of higher resolution regional climate models initialised from GCM data is considered an option, but statistical properties of these data usually differ considerably from the observed historical climate records, requiring further manipulation (Bates et al., 1998; Wood et al., 2004). Other approach may include (a) application of a statistical clustering process to GCM forecast output (hindcasts) in order to derive analog years or seasons suitable for input into agricultural simulation models (Timbal and McAvaney, 2001); (b) use of weather classification schemes (Charles et al., 1999; Huth, 2000); and (c) use of regression models for continuous atmospheric circulation indices, geographic location and topographical variables (Wilby et al., 1998) and artificial neural networks (Crane and Hewitson, 1998). Alternatively, GCM output can be used to establish climate trends, with these trends then used to modify historical climate records for use with biological models. This approach is often taken when the impact of climate change on agricultural systems is to be assessed (e.g. Reyenga et al., 1999; Howden et al., 2001). While there are several plausible solutions to solve this connectivity problem, there are no agreed methods to achieve this, in spite of the millions have been invested in GCM development. To address this imbalance, R&D investment is now urgently required to connect GCM with risk management tools. This work is essential to unlock the potential of GCMs so that they can be used operationally in management decisions.

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Appendix

Glossary for some climate science terms used in this article (indicated throughout the document using hyperlinks).

Analog years	A cluster of years when oceanic and atmospheric conditions were the same or similar.
Artificial skill	The apparent hindcast skill that does not survive when the forecasting scheme is applied in real time to new or independent data.
Bifurcation point	Changing control parameters of a linear process will result in this process to change trajectory and to remain off track. In contrast, a non-linear, chaotic system, due to it's strange attractors, tends to return to its starting point. However, smoothly varying the control parameter can result in abrupt systems changes once a threshold is exceeded. A bifurcation point is reached when a qualitative change in an attractor's structure occurs in response to a varied control parameter.
Deterministic forecasts	Non-probabilistic forecasts of either a specific category or particular value for either a discrete or continuous variable. Deterministic forecasts fail to provide any estimates of possible uncertainty, and this leads to less optimal decision making than can be obtained using probabilistic forecasts. Sometimes (confusingly) referred to as categorical forecasts in the earlier literature.
Forcing	'Forcing' describes control parameters that are used either as input into models of climate systems or are known drivers of climatic processes (e.g. greenhouse gasses). For instance, GCMs are often forced with observed sea surface temperatures in order to investigate dynamic atmospheric responses to ocean temperatures. In time series, forcing can generate transient artificial 'predictability' know as 'on-off synchronization'. Hence any observed 'predictability' that cannot be conclusively linked to first principles will always entail at least the possibility of artificial skill.
Forecast trajectories	Trajectories describe the expected future path of systems variables – they are an important means for visualizing model output. A set of likely (possible) trajectories derived from either the same forecast system using different starting conditions or several, different forecast systems are referred to as a 'plume' of forecasts or 'ensemble' forecasts.
Fractal dimensions	The Hurst exponent (H) measures the fractal dimension (1/H) of a data series. A Hurst exponent of 0.5 indicates white noise with a corresponding fractal dimension of 2 (effectively no autocorrelation). Higher values of H indicate an increasing presence of autocorrelation. A time series with autocorrelation will have a fractal dimension between 1.0 and 2.0.
GCM	A Global Circulation Model (GCM) is a computer simulation model of the earth's climate used to predict future weather and climate patterns from present conditions and known forcings.
Non-linear, deterministically chaotic systems	The majority of natural phenomena are non-linear and often chaotic. Weather is a classical example of a non-linear, deterministically chaotic system that is predictable only for short times because the deterministic solutions depend very sensitively on initial conditions. Due to temporal and spatial scaling climate is slightly less chaotic (hence more predictable) than weather.
Open systems	Systems where energy is gained externally and dissipated internally (e.g. climate).
Probabilistic forecast	A forecast that specifies the future probability of one or more events occurring. The set of events can be discrete (categorical) or continuous.
Signal to noise ratio	The ratio between the amount of variability explained by the deterministic components versus the random variability that typically dominates non-linear, chaotic systems.
Signal intensity	The contribution of the classification system (i.e. 'forecast' system) to the overall variability of the response variable, such as rainfall, temperature, yield, drainage, runoff.
Stochastic resonance	A phenomenon in which a non-linear, chaotic system is subjected to a weak periodic but normally undetectable signal that becomes detectable due to resonances between the deterministic signal and the stochastic noise.
Strange attractors	An attractor is 'something' to which that a system irreversibly evolves, if left undisturbed. A strange attractor found in chaotic systems is a non-periodic attractor that is characterized by a set of coupled non-linear ordinary differential equations.
Teleconnections	The term used for energy transfer within the broad ocean/atmosphere system. It is a 'communication mechanism' by which usually independent weather and climate phenomena can influence each other.