

SEASONAL AND INTER-ANNUAL CLIMATE FORECASTING: THE NEW TOOL FOR INCREASING PREPAREDNESS TO CLIMATE VARIABILITY AND CHANGE IN AGRICULTURAL PLANNING AND OPERATIONS

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Abstract. Climate variability and change affects individuals and societies. Within agricultural systems, seasonal climate forecasting can increase preparedness and lead to better social, economic and environmental outcomes. However, climate forecasting is not the panacea to all our problems in agriculture. Instead, it is one of many risk management tools that sometimes play an important role in decision-making. Understanding *when*, *where* and *how* to use this tool is a complex and multi-dimensional problem. To do this effectively, we suggest a participatory, cross-disciplinary research approach that brings together institutions (partnerships), disciplines (e.g., climate science, agricultural systems science, rural sociology and many other disciplines) and people (scientist, policy makers and direct beneficiaries) as equal partners to reap the benefits from climate knowledge. Climate science can provide insights into climatic processes, agricultural systems science can translate these insights into management options and rural sociology can help determine the options that are most feasible or desirable from a socio-economic perspective. Any scientific breakthroughs in climate forecasting capabilities are much more likely to have an immediate and positive impact if they are conducted and delivered within such a framework. While knowledge and understanding of the socio-economic circumstances is important and must be taken into account, the general approach of integrated systems science is generic and applicable in developed as well as in developing countries. Examples of decisions aided by simulation output ranges from tactical crop management options, commodity marketing to policy decisions about future land use. We also highlight the need to better understand temporal- and spatial-scale variability and argue that only a probabilistic approach to outcome dissemination should be considered. We demonstrated how knowledge of climatic variability (CV), can lead to better decisions in agriculture, regardless of geographical location and socio-economic conditions.

1. Introduction

Climatic variability (CV) occurs at widely varying temporal and spatial scales. This variability often impacts negatively on agricultural and natural ecosystems. Although floods and droughts have always been an integral part of human existence, our collective coping strategies have so far been limited by the complexity of systems responses to climate, environment and management and our inability to predict such systems dynamics. This has led to the development of conservative management approaches that usually fail to capitalise on the up-sides of CV and often only poorly buffer against the severe downsides.

The emerging ability to probabilistically forecast future seasons *in terms of climate and its consequences on agricultural systems* has started to influence decision-making at many levels. The potential benefits are substantial, but unfortunately adoption of new insights occurs more slowly and in a more haphazard way than was envisaged and is desirable. This is a consequence of the multi-faceted, multi-dimensional and cross-disciplinary nature of the problems.

It is our aim to outline the multi-dimensionality of the problems in order to assist in the process of establishing an operational framework to conduct what is sometimes referred to as 'end-to-end' applications (Basher, 2000; Manton et al., 2000). Such a framework might help us in achieving a better integration of the disciplinary components and hence better outcomes *via* improved management of agricultural systems. Much has been written about individual aspects of this subject and we would like to draw attention to some of the key publications on these issues, such as the books by Muchow and Bellamy (1991), Hammer et al. (2000), IRI (2000) and Sivakumar (2000). Further, and in addition to this special issue of Climatic Change, the following special journal issues of (i) *Agriculture and Forest Meteorology* (vol. 103, 2000) on *Agrometeorology in the 21st century*, (ii) *Agricultural Systems* (vol. 70, 2001) on *Advances in systems approaches for agricultural development* and (iii) *Agricultural Systems* (vol. 74, 2002) on *Applying seasonal climate prediction to agricultural production* need to be mentioned explicitly. We will draw on this material and cite individual contributions where appropriate.

It is important to point out that we do not explicitly distinguish between CV and climate change (CC). Instead, for the purpose of this paper, we regard CC as a low-frequency component of CV that can be managed using the same quantitative tools and approaches. This point will be made more clearly in the relevant sections, but needs to be stressed from the outset to avoid confusion.

2. Setting the Scene

In the tropics and sub-tropics, CV is a major source of agricultural production variability (e.g., Hammer et al., 1987; Dilley, 2000). Although most dramatic at the farm level, this effect of CV is apparent throughout entire economies and can even affect macroeconomic indicators such as international wheat prices, employment statistics or currency exchange rates (Chapman et al., 2000b; White, 2000a). In October 2002, media reports in Australia attributed half of the reported inflation rate to the effects of the El-Niño-induced drought.

Since humans began farming, climate variability has influenced people's experiences, which in turn resulted in agricultural systems that are somewhat resilient, i.e., systems that are capable of absorbing some of that variability without immediate disastrous results. An example is dryland winter and summer cropping in the northeastern region of Australia where water is stored in the heavy clay soils over fallow periods. This water is then used by the next crop grown and acts as a buffer

against possible low, in-season rain (similar practices exist throughout the semi-arid tropics and sub-tropics). Other examples are the wheat/pasture rotations in Southern Australia that remain productive even under adverse climatic conditions (i.e., prolonged droughts or water-logging).

Issues that we have not addressed here are the longer-term implications of CC on enterprise profitability. For instance, some horticultural enterprises, where the set-up cost is substantial and returns are realised on longer time scales, are extremely susceptible to CC. Producers making decisions on introducing such enterprises need to consider not only CV, but also the combined impact of CC and CV.

Although current systems have been developed to cope with the variable climate, they are not necessarily optimally adapted. For instance, relying on fixed fallow lengths can leave fields prone to erosion and drainage below the root zone. Production systems developed during a run of wetter seasons may not be as resilient in drier seasons. Peanut production in Southern Queensland, Australia, for instance, started during the above average summer rainfall conditions of the 1950–1970s but resulted in unrealistically high yield expectations for the changed climate patterns of the 1980s and 1990s (Meinke and Hammer, 1995).

It is important to acknowledge that, although important (and sometimes even dominant), CV is only one of many risk factors impacting on agriculture. From a decision-maker's perspective, it is the consequences of CV and/or CC on possible management responses that are of interest, rather than CV or CC *per se*. This highlights that forecasts must be appropriately 'contextualised' before they can positively influence decision-making. In other words, causes, choices and consequences must be clearly outlined and quantified (Hayman, 2001). This requires effective cross-disciplinary research and we argue here that such contextualised delivery can only be achieved through an integrated, systems analytical approach (cf. Hammer, 2000). While forecasts in terms of a seasonal rainfall or temperature outlook are often followed with interest, they ultimately may not result in subsequent action (i.e., changed practice). However, the same forecast provided, for instance, in terms of crop or pasture yields has the potential for much stronger impact by influencing the decision-making *via* the quantification and discussion of decision options (Hayman, 2001).

The picture gets even murkier when we consider that particularly policy decisions relating to agriculture are not made in isolation from other topics such as issues relating to markets, political environment and lobby groups. In this paper, we deliberately excluded this aspect and concentrated entirely on issues within the realm of agricultural production systems. We refer readers interested in these broader societal issues to publications by Buizer et al. (2000), Agrawala and Broad (2002), Agrawala et al. (2001) and IRI (2000).

At the highest level, the problem appears simple: it is about better risk management and our ability to produce food and fibre products economically and in a socially and environmentally desirable fashion.

This is where the complexity starts and differences based on socio-economic conditions emerge: effective risk management in developed countries is about profitability and the tensions associated with economic production and consequent social and environmental risks (i.e., sustainability). In developing countries, sustainability issues are often, from a farmer's perspective, secondary and only deserve attention after the most pressing needs for survival are met. We need to break the vicious cycle of poverty and hunger before we can successfully promote sustainable development in these countries.

Profitably applying climate information requires the identification of the key decision points in agricultural production systems. We must not assume that these decision points are the same in developing and developed countries. The prime need from climate forecasting in developing countries may simply be disaster management, i.e., to protect the system against the extremes of CV. For example, in Indo-China the fundamental issue related to CV is the capacity to *protect* local people, to *protect* natural ecosystems, and to *protect* national economies. The current ability to provide protection against the impacts of El Niño and La Niña in many Southeast Asian countries remains limited. This is because both effective climate forecasting systems and linkages to decision systems for this region are still in various stages of development (CERED, 2000; Hansen, 2002). There is a fundamental and urgent need to capitalise on our climate knowledge. We may achieve this by translating that knowledge into meaningful, locally relevant decision options.

Decision makers, who must prepare for the range of possible outcomes, often use conservative risk management strategies that reduce negative impacts of climatic extremes. In favourable seasons, however, this can be at the expense of reduced productivity and profitability, inefficient use of resources, and accelerated natural resource degradation (e.g., under-investment in soil fertility inputs or soil conservation measures). Improvements in our understanding of interactions between the atmosphere and sea and land surfaces, advances in modelling the global climate, and substantial investment in monitoring the tropical oceans now provide some degree of predictability of climate fluctuations months in advance in many parts of the world (Goddard et al., 2001).

Broad and Agrawala (2000) showed how climate forecasting can contribute to elevating vulnerability but caution against seeing it as a panacea for solving future food crises. Clearly, 'risk management' must be seen within the context of the actual risk posed (individual survival, economic and environmental risks) and requires a clear analysis of all contributing factors. The role of climate and climate-related risk management tools must then be established and the chosen strategies must take this into account appropriately. This also requires a careful analysis and understanding of the existing policy framework. Often policies have been developed with the aim to alleviate consequences of high climate variability. Such policies (e.g., income subsidies) can act as disincentives for the adoption of better climate-related risk management strategies.

This fact needs to be considered when evaluating the potential of climate forecasting.

Even under homogenous socio-economic conditions, the requirements of potential users of climate forecast information will differ. Firstly, as the title of this paper already implies, there are at least two major stakeholder groups, namely those involved in agricultural planning (mostly policy makers, regulators and large agribusinesses including financial institutions) and those involved directly in agricultural production, i.e., farmers, farm managers, some rural businesses and consultants. Information needs for these groups differ, but even more importantly, their needs vary with on-going changes in socio-economic and market conditions. Tactical as well as strategic decisions must be made all the time and while climate-related information might be highly relevant for some of these decisions, it will be irrelevant for others. Hence, it is no surprise that we generally fail to measure a notable impact of non-contextualised climate forecasts.

When climate forecasting is discussed there is often an implicit assumption that perfect knowledge of, for instance, future rainfall would change the way agriculture is practised. This assumption is rarely challenged, but it touches on two issues that are fundamental when considering the value of climate information in decision-making:

The first issue is the notion that such ‘perfect knowledge’ might be – at least theoretically – achievable. Although we still have much to learn about the underlying physical processes, we now appreciate that climate has many chaotic and non-deterministic features, which will prevent us from ever achieving complete certainty in climate forecasting. Any deterministic forecasting system is therefore either wrong or misleading and should not be endorsed (Meinke et al., 2003).

The second issue is the implicit assumption that a forecast will be useful and lead to improved outcomes. Although many examples can be found where this is the case, others show either negative outcomes or identify decisions that are insensitive to such information. Several conditions must be met before a seasonal forecast will result in an improved outcome: a forecast

- must have some skill (see later);
- must honestly convey the inherent uncertainty (i.e., the information must be presented in a probabilistic form);
- must be relevant (neither trivial nor obvious; timely);
- must be able to be ‘tracked’ in terms of how well the forecasts are representing the actual climate;
- must be inclusive of provision of histories of previous forecasts (Pulwarty and Redmond, 1997);
- must be of value (see later);
- the information content must be applied (see also Glantz, 1977; Lamb, 1981; Nicholls, 2000).

3. Forecasting for a Purpose (Contextualised Forecasting)

As this workshop showed, climate forecasting and its applications have matured considerably over the last few decades. There is excitement about the potential benefits our societies might reap from further research and development. Hence, this paper is titled ‘Seasonal and inter-annual climate forecasting: The *new* tool for increasing preparedness to climate variability and change in agricultural planning and operations’. We asked ourselves: how ‘new’ are climate applications? To answer this question, we will quote from one of the most significant books in Brazilian literature, ‘Os Sertões’, first published by Euclides da Cunha in 1902. Our quotations are taken from the English translation (*Rebellion in the Backlands*) published by University of Chicago Press, 1995 edition:

... the drought cycles ... follow a rhythm in the opening and closing of their periods that is so obvious as to lead one to think that there must be some natural law behind it all, of which we are as yet in ignorance.

... And then, of a sudden, there comes a tragic break in the monotony of their days. The drought is approaching. Thanks to the singular rhythm with which the scourge comes on, the sertanejo is able to foresee and foretell it. He does not, however, take refuge in flight, by abandoning the region, which is being little by little invaded by the glowing inferno that radiates from Ceará. ... And he confronts them [the droughts] stoically. Although this grievous ordeal has occurred times without number ... he is nonetheless sustained by the impossible hope of being able to hold out against it.

... he has studied this affliction as best he could, in order that he might understand it and be able to bear or to avert it. ... Two or three months before the summer solstice, he props and strengthens the walls of the dams or cleans out the water pits. He looks after his fields and plows up in furrows the narrow strips of arable land on the river's edge, by way of preparing these diminutive plantations for the coking of the first rains. Then he endeavours to make out what the future holds in store. Turning his eyes upward, he gazes for a long time in all directions, in an effort to discover the faintest hints, which the landscape may have to offer him. The symptoms of the drought are not long in appearing; they come in a series, one after another, inexorably, like those of some cyclic disease, some terrifying intermittent fever on the part of the earth.

... This is the traditional experiment of Santa Luzia. On December 12, at nightfall, he sets out six lumps of salt in a row, where they will be exposed to the action of the dew; they represent, respectively, from left to right, the six coming months, from January to June. At daybreak the next morning, he observes them. If they are intact, it presages drought; if the first has dissolved

somewhat, has been transformed into a soggy mass, he is certain of rain in January; if this happens to the second, it will rain in February; if it happens to the majority of the lumps, the winter¹ will be a kindly disposed one.

This experiment is a most interesting one. Despite the stigma of superstition which attaches to it, it has a positive basis and is acceptable when one stops to consider that from it may be gathered the greater or less amount of vaporized moisture in the air and, by deduction, the greater or less probability of barometric depression capable of bringing rain.

This was written over 100 years ago, and it is only the language that gives its age away, not the content. Have we really advanced that much? Graziers and small-holder farmers in the Nordeste region of Brazil are still suffering from droughts and are hoping for divine intervention while the scientific debate about causes and predictability of droughts continues (Moura and Shukla, 1981; Ward and Folland, 1991; Kane, 1997; Folland et al., 2000).

3.1. CLIMATE VARIES AT A RANGE OF SCALES

Research and experience over recent decades has shown that the El Niño–Southern Oscillation phenomenon (ENSO) plays a critical role in partially explaining rainfall variability in many countries, particularly in the tropics and sub-tropics. However, ENSO is not the only source of rainfall variability. The Austral-Asia region is particularly strongly impacted by ENSO and we will use this region as a case study for many of the arguments presented here.

In addition to ENSO and an inherently unpredictable chaotic component there are a range of other climate phenomena varying at a wide range of time scales that determine what manifests itself as ‘climate variability’. Much of the current research concentrates on the development of credible global circulation models (GCM), with the expectation that the emerging dynamics of all these interacting phenomena, including CC, can be captured adequately. In Australia, effort is being directed towards investigating high-frequency phenomena such as the Madden-Julian Oscillation (MJO, also known as the intra-seasonal oscillation or ‘ISO’), to ENSO-related information (e.g., SOI- or SST-based forecasting systems) and to low-frequency phenomena such as decadal and multi-decadal climate variability and CC (Table I).

At the highest frequency, the MJO involves variations in wind, sea surface temperature, cloudiness and rainfall that occur regularly every 30–50 days. Although the MJO is a tropical phenomenon (Wheeler and Weickmann, 2001), it can, *via* teleconnections, influence rain events over large parts of Australia, India and the Maritime Continent. The MJO consists of cloud clusters that originate in the Indian Ocean and move eastward with speeds of 5–10 m s⁻¹. The MJO particularly affects the

TABLE I

Known climatic phenomena and their return intervals (frequency, in years) that contribute to rainfall variability in Australia

Name and/or type of climate phenomena	Reference	Frequency (approximate, in years)
Madden-Julian oscillation, intra-seasonal (MJO or ISO)	Madden and Julian (1972)	0.1–0.2
SOI phases based on El Niño–Southern oscillation (ENSO), seasonal to inter-annual	Stone et al. (1996)	0.5–7
Quasi-biennial oscillation (QBO)	Lindesay (1988)	1–2
Antarctic circumpolar wave (ACW), inter-annual	White (2000b)	3–5
Latitude of sub-tropical ridge, inter-annual to decadal	Pittock (1975)	10–11
Inter-decadal pacific oscillation (IPO) or decadal pacific oscillation (DPO)	Zhang et al. (1997); Power et al. (1999); Meinke et al. (2005); Mantua et al. (1997); Allan (2000)	13+ 13–18
Multi-decadal rainfall variability	Allan (2000)	18–39
Interhemispheric thermal contrast (secular climate signal)	Folland et al. (1998)	50–80
Climate change (CC)	Timmermann et al. (1999); Kumar et al. (1999)	???

intensity and break periods of the Australian and Indian monsoons and also interacts with ENSO. Many farmers in northeastern Australia routinely follow the passage of the MJO for some of their tactical decision making.

ENSO is a quasi-periodic, inter-annual variation in global atmospheric and oceanic circulation patterns that causes local, seasonal rainfall to vary at many locations throughout the world. It is the best researched of all these phenomena and has attracted considerable media attention over the last decade.

The physical causes of lower-frequency rainfall fluctuations are still being investigated, but our understanding of these processes is steadily increasing (Power et al., 1999; Allan, 2000; White, 2000b). It appears that most of these low-frequency phenomena result in modifications of ENSO-related variability (Kleeman and Power, 2000; Meehl et al., 2001). Predictability of low-frequency variability is still questionable and the possibility of stochastic resonance (i.e., the phenomenon whereby noise amplifies the effect a weak signal has on its surroundings) cannot be dismissed

(Ganopolski and Rahmstorf, 2002). However, teleconnections of ENSO with rainfall patterns are clearly affected at these decadal to multi-decadal time scales (e.g., Australia: Power et al., 1999; USA: Hu and Feng, 2001).

Although anthropogenically induced CC does not oscillate, it needs to be included in this list because it (a) interacts with the ‘oscillating’ phenomena of CV and has a tendency to increase the amount of CV we already experience (Kumar et al., 1999; Timmermann et al., 1999; Salinger et al., 2000) and (b) potential management response to CC – and the tools to quantify them – do not fundamentally differ from responses to low-frequency climate variability (Howden et al., 1999, 2001, 2003).

Although Table I lists the most important known phenomena influencing Austral-Asia region, it is by no means complete. Further, we do not wish to imply that all of these phenomena might be – even theoretically – predictable (e.g., see the critical note by Storch and Zwiers, 1999, on the danger of ‘identifying’ periodicity in stochastic time series). Table I is an example of phenomena currently featured in scientific debate and we acknowledge the difficulties of clearly distinguishing between some of these phenomena. Further, other parts of the globe are affected differently and for the northern hemisphere, for instance, the North Atlantic Oscillation (NAO) is one of the most important contributor to inter-annual CV (Salinger et al., 2000).

Table I only considers time scales that are relevant from an agricultural management perspective and thus ignores known fluctuations at the scale of centuries and beyond (e.g., Dansgaard-Oeschger events at 1500 years, or multiples thereof, Milankovitch forcing fluctuations or ice ages at time scales of more than 100,000 years).

The enhanced scientific understanding of the causes and consequences of rainfall variability at a range of time scales and our increasing ability to predict some of these cycles has made ‘managing for climate variability’ an important feature of Australian farming systems. Similar developments can be observed elsewhere (Meinke et al., 2001).

3.2. THE ROLE OF SIMULATION MODELLING IN AGRICULTURAL SYSTEMS MANAGEMENT

All major agricultural decisions are made under uncertainty caused by variability in some of the key parameters (e.g., economic conditions, physical environment and many more). Decision makers need to be cognisant of the time scales that determine this variability and the possible consequences of such variability for their business. By providing new, quantitative information about the environment within which they operate and about the likely outcome of alternative management options, this uncertainty can be reduced (Byerlee and Anderson, 1982). Computer simulations can provide such information and are particularly useful to quantitatively compare alternative management options in areas where seasonal CV is high, such as

Australia, Southeast Asia, Africa, parts of the US and South America (Meinke et al., 2001; Gadgil et al., 2002; Hansen, 2002; Jones et al., 2000; Jagtap et al., 2002).

Economic outcomes are important, but decisions are also based on many other factors such as environmental consequences (on- and off-farm), weed and disease impact, lifestyle and the existing policy framework. At the farm level, most management decisions have to fit within a whole farm strategic plan such that many decisions are planned months ahead and their consequences seen months afterwards. This requirement for a certain lead-time between deciding on a course of action and realising its results is a characteristic of managing cropping and grazing systems (Carberry et al., 2000; Carter et al., 2000). Pannell et al. (2000) stressed the importance of getting the big decisions right, such as land purchase, machinery investment and resource improvement. They pointed out that farmers are usually better off, if they solve the whole problem roughly, rather than to attempt to solve part of the problem extremely well. Or, as one of our colleagues puts it: it is better to be roughly right than precisely wrong (P.T. Hayman, personal communication). This reinforces the importance to consider CV and CC across the spectrum of temporal scales.

Decisions that could benefit from targeted forecasts are also made at a range of temporal and spatial scales. These range from tactical decisions regarding the scheduling of planting or harvest operations to policy decisions regarding land use allocation (e.g., grazing systems *versus* cropping systems). Table II gives a few examples of these types of decisions at similar time scales to those seen in climatic patterns as presented in Table I.

In water-limited environments such as the semi-arid tropics and sub-tropics, rainfall variability represents the predominant force determining production variability and environmental risk. However, factors such as starting soil moisture, soil type, soil fertility, temperature, planting dates, rainfall intensity and timeliness

TABLE II

Agricultural decisions at a range of temporal and spatial scales that could benefit from targeted climate forecasts

Example of decision types	Frequency (years)
Logistics (e.g., scheduling of planting/harvest operations)	Intra-seasonal (<0.2)
Tactical crop management (e.g., fertiliser/pesticide use)	Intra-seasonal (0.2–0.5)
Crop type (e.g., wheat or chickpeas) or herd management	Seasonal (0.5–1.0)
Crop sequence (e.g., long or short fallows) or stocking rates	Inter-annual (0.5–2.0)
Crop rotations (e.g., winter or summer crops)	Annual/bi-annual (1–2)
Crop industry (e.g., grain or cotton; native or improved pastures)	Decadal (~10)
Agricultural industry (e.g., crops or pastures)	Inter-decadal (10–20)
Landuse (e.g., agriculture or natural systems)	Multi-decadal (>20)
Landuse and adaptation of current systems	Climate change

of rainfall also strongly influence the final outcomes. Although rainfall and plant growth are strongly correlated, consequences of rainfall variability will differ from season to season due to these other influences on growth. In livestock systems, these factors not only have an impact on fodder growth and availability, but also on the animals themselves, further complicating the situation. Simulation models can integrate all these effects in a physiologically meaningful way. Sivakumar et al. (2000) stressed that the development of sustainable food production strategies requires a more complete understanding of the ecosystem and the inter-relationships between crops, trees and livestock. We suggest adding 'management' to this list of interacting elements and propose that simulation modelling is the only tool available that allows easy quantification of these inter-relationships in probabilistic terms.

Further, analysing agricultural systems and their alternative management options experimentally and in real time is generally not feasible because of the length of time and amount of resources required. Well-tested simulation approaches offer a time and cost-efficient alternative to experimentation on the physical system and results can be obtained in hours or days rather than years or decades. This provides the capacity to assess a large number of combinations. Today simulation analyses have become a legitimate means of evaluating policy and resource management issues (e.g., Nelson et al., 1998; Howden et al., 1999; Meinke et al., 2001), but they also provide valuable information for on-farm decision-making (Meinke and Hochman, 2000; Gadgil et al., 2002; Nelson et al., 2002; Podestá et al., 2002). This is strongly endorsed by Sivakumar et al. (2000) who identified agricultural modelling as a priority to address sustainable agricultural development in the 21st century.

Traditionally scientists have used simulation models as 'knowledge depositories' in order to describe an area of interest. Once models became available, interest quickly shifted from curiosity about the underlying principles to using models in a predictive capacity (e.g., to develop scenarios or as a decision support tool) or in an explanatory capacity to investigate interactions between processes usually only studied in isolation. This diverse use of models has started a debate about the appropriate way of mathematically describing biological relationships, and the level of detail needed for a 'good' model. Arguments about the 'right' way of modelling have largely concentrated on the level of empiricism acceptable when representing biological, chemical and physical processes. This debate has not been very helpful, since it has been conducted by groups interested in using models for different purposes, namely to either explain how a system operates or to predict the system's behaviour. The former objective requires detailed descriptions of the underlying physiological processes and parameters values that are often difficult, if not impossible, to obtain experimentally. This parameter uncertainty results in low predictive ability. On the other hand, models developed explicitly to predict management responses often use phenomenological descriptions of groups of processes with easily derived parameter values but fewer process details (Meinke, 1996). Some of the emerging challenges relating to genetic research and the establishment of gene

functions (G) and their interactions with environment (E) and management (M) ($G \times E \times M$) require a more balanced emphasis on all attributes and might show a way forward (Hammer et al., 2002).

Biological as well as climate models are useful because they reduce the complexity of the real system to a level that allows us to predict the consequences of manipulating the system. They also allow scientists to test whether the systems approach adequately describes the system they are dealing with. The amount of process detail contained within a model must match its intended application. However, care needs to be taken whenever the level of process detail is reduced that this simplification is based on a sound understanding of the underlying processes. To reduce number and uncertainty of parameters in simulating biological systems, a process-based approach can be replaced by a phenomenological description of that process without sacrificing scientific principles. This requires that (a) the process is already understood at the more basic level and (b) the phenomenological description is general across a wide range of conditions and of low complexity with easily derived parameter values. This will increase the predictive ability of the model and may eventually lead to a more advanced, formal framework for dealing with holistic concepts and emergent systems properties (Gell-Mann, 1995). In situations where multiple hypotheses are possible, one can discriminate amongst them based on their plausibility (Peng and Reggia, 1990). This plausibility is given by the parsimony principle, or Occam's razor, whereby the most plausible explanation is that which contains the simplest ideas and least number of assumptions (Davies, 1990).

Biological models can never be completely validated. At best, we can present case studies and examples of the models' performance and argue that this is sufficient evidence to use model output for decision-making. To illustrate this point, consider the following example:

As part of a research project we tested the APSIM-Wheat model (Keating et al., 2003) on data from 100 plant breeding experiments across 23 experimental sites and several years. We deemed the model's performance adequate ($R^2 = 0.6$) to characterise the environmental component of $G \times E$ interactions (Figure 1a, unpublished data, Cooper, personal communication; Chapman et al., 2000a). These experiments were not specifically conducted for model testing and while some information regarding soil type, soil water and nutrient status were available, the experimental data set still contained a considerable amount of parameter uncertainty. Using data from a long-term soil fertility trial (Strong et al., 1996), where all the necessary input parameters and starting conditions were measured and available, a R^2 value of 0.8 was obtained (Figure 1b). Clearly, measured and simulated data were in better agreement when the input parameter uncertainty was reduced. However, the same data set also highlighted the deficiencies of using R^2 values as an indicator of model performance (Oreskes et al., 1994): When only a sub-set (i.e., data from 1 dry year) was used for testing, the R^2 was zero (Figure 1c), in spite of the model's obvious ability to capture the climate related year-to-year variation in yield (Figure 1b).

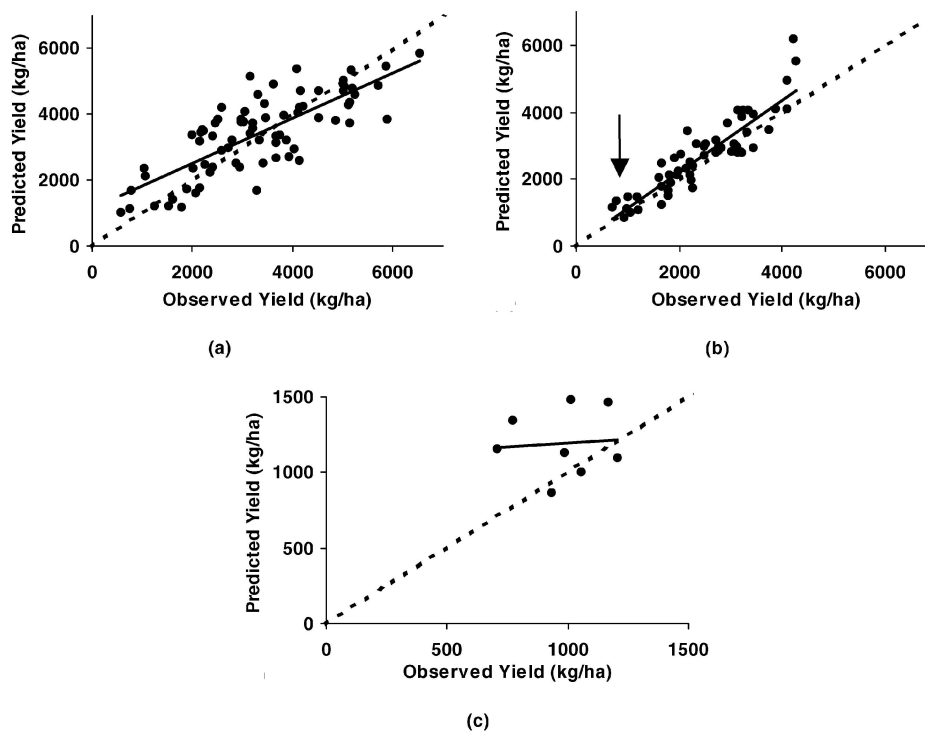


Figure 1. Performance of APSIM-wheat against yield data from (a) 100 plant breeding experiments from 23 locations over several seasons ($R^2 = 0.6$); (b) experimental results from soil fertility studies at a single site in Queensland over 8 years, 5 N levels and 2 surface management regimes ($R^2 = 0.8$) and (c) results from (b) in a dry year ($R^2 = 0$; data presented are included in (b), see arrow).

Obvious ‘over-predictions’ at high yield levels ($>4000 \text{ kg ha}^{-1}$) are generally the result of biotic stresses (i.e., pests and diseases) that are not accounted for by the model (Figure 1b).

The example shows that the validity of a biological model does not depend on a correlation coefficient (or any other, single-value performance measure) but rather on whether the inevitable difference between predicted and observed values are acceptable for the decision maker. This is analogous to Murphy (1994) and Potgieter et al. (2003), who found that there is no single statistical measure to determine ‘forecast skill’ adequately (see Section 4.4). Model performance does not only depend on scientific and technical aspects of the model, but also on the user’s experience and skill. The development of high-performance agricultural simulation platforms such as DSSAT (Jones et al., 1998), CropSyst (Stöckle et al., 2003) or APSIM (Keating et al., 2003) is costly and time-consuming. Due to modern user interfaces these modelling platforms are easy to use and it is therefore tempting to assume that the conduct of agricultural simulation analyses is a low-cost and straightforward exercise. Nothing could be further from the truth. All models require a substantial learning curve for individual users, before they can be applied appropriately.

Unfortunately, we encounter evidence of inappropriate model use far too frequently, which highlights the need for substantial and adequate user training. Further, many climate applications do not rely on straightforward simulations, but require modifications to the model that can only be implemented by highly skilled staff who are intimately familiar with the development pathway of the model in question.

Very similar issues arise in relation to General Circulation Models (GCMs). It is understandable why the most rigorous and successful climate applications are usually achieved by cross-disciplinary teams containing experts from each of the key scientific areas using mature simulation platforms. We should not expect agronomists to develop and run GCMs, nor should we expect climate scientists to become experts in biological model development and applications (there are, however, some rare, but notable exceptions!). Not only must the degree of detail considered in a model be congruent with the intended application, we must also ensure that the level of attention given to the climatic component of an application is of similar resolution and quality as the effort that goes into the agricultural modelling. Unfortunately, donors and funding bodies frequently fail to recognise the importance of such balance and generally provide support for either one or the other, very rarely for both.

3.3. OPERATIONAL ASPECTS – CLIMATE FORECASTS, AGRICULTURAL MODELS AND PROBABILITIES

There is an emerging consensus amongst many climate scientists that statistical, ENSO-based forecasting methods are approaching their limits of predictability. Hence, there is increased emphasis on the development and application of GCMs and regional climate models (RCMs). Connecting GCMs with agricultural simulation models is a potentially powerful approach for climate applications. However, the two methods are difficult to connect and the most successful climate applications to-date still rely on statistical climate forecasting approaches, rather than on dynamic climate modelling. Generally, biological models require daily point scale weather data as input (see Hoogenboom, 2000, for a more detailed discussion on these issues). Often, GCMs suffer from an inability to provide skilful predictability at the type of resolution needed for input into biological models.

Chaos plays a large role in climate systems and the atmosphere frequently acts like a ‘random number generator’. This means that deterministic statements cannot justifiably be made. Scientists have a responsibility to communicate their degree of ignorance, as well as their knowledge. Only if uncertainties are clearly quantified can improved risk management practices be developed. Murphy (1993) discussed the need for uncertainties inherent in judgements to be properly reflected in forecasts. He stated that the widespread practice of ignoring uncertainties when formulating and communicating forecasts represents an extreme form of inconsistency and generally results in the largest possible reductions in quality and value. Most public institutions, and an increasing number of private service

providers, now acknowledge the necessity to communicate the known level of uncertainty *via* probabilistic statements. In part, this trend has been accelerated by the increasing awareness of potential liability (corporate risk) that organisations expose themselves through the provision of inadequate or misleading advice, be it real or perceived (Meinke et al., 2003).

Probabilistic forecasts are more valuable than deterministic forecasts (Moss and Schneider, 2000). This holds true even for events that are, by definition, rare (e.g., extreme events, such as a one-in-60-year flood) and hence have considerable uncertainty associated with them. The likely future introduction of predictions based on output from GCMs may allow more versatility in climate prediction than is currently the case, including better opportunities to predict extremes. Palmer and Rätsänen (2002) have quantified the additional value of probabilistic forecasts over a single, deterministic projection in their study of greenhouse scenarios and found that the economic value of probabilistic forecasts was significantly greater and never less than for the deterministic case.

3.3.1. *Analogue Year Approach*

Historical climate records can 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 (Messina et al., 1999; Phillips et al., 1999). Such categorisation must be based on an understanding of ocean–atmosphere dynamics and good statistical procedures to partition the data successfully. Current conditions can then be assigned to a particular category and compared to other categories in order to assess the probabilistic performance of the biological system in question (e.g., Meinke and Hochman, 2000; Podestá et al., 2002). This is an easy and convenient way of connecting climate forecasts with biological models, because it only requires historical weather records. The method has been used extensively throughout the world and provided valuable information for many decision makers (Meinke and Stone, 1992; Messina et al., 1999; Hammer et al., 2000; Nelson et al., 2002; Podestá et al., 2002). The SOI phase system has become the dominant scheme used in Australia and neighbouring countries while ENSO phases are often used in the Americas. However, both schemes are globally applicable. Hill et al. (2000) compared the value of the SOI phases *versus* the broader ENSO phases for Canadian and US wheat producers and found that in this particular case the SOI phases generally provided more valuable information than ENSO phases. However, the authors stressed that in some regions neither method had any value for their specific application and that forecasts need to be targeted to industries and regions.

3.3.2. *GCMs and RCMs*

Statistical approaches have considerable limitations and it is expected that dynamic climate modelling will provide much improved forecast skill in the near future. This will require appropriate solutions to solve the ‘connectivity problem’ we addressed

earlier. Ways must be found to convert large, grid point GCM output into something akin to point scale daily weather station data. The use of higher resolution RCMs initialised from GCM data is considered an alternative option, but statistical properties of these data usually differ considerably from the observed historical climate records, requiring further manipulation. Another approach may be to apply a statistical clustering process to GCM forecast output (hindcasts) in order to derive analogue years or seasons suitable for input into agricultural simulation models, as described above (Stone et al., 2000b). 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 CC on agricultural systems is to be assessed (e.g., Reyenga et al., 1999; Howden et al., 2001). Hoogenboom (2000) also draws attention to the different scales implicit in GCMs and biological models. There are a number of promising approaches to using other forms and formats of forecasts with crop models, but they have not yet been widely tested. This issue is a high priority for most agricultural scientists using crop simulation for forecast applications (Jim Hansen, personal communication).

3.4. 'QUALITY' VS. 'VALUE' OF A FORECAST

Murphy (1993) argued that a good forecast requires three different attributes, namely consistency (correspondence between forecasts and judgments), quality (correspondence between forecasts and observations, often also referred to as 'skill') and value (the incremental benefits of forecasts to users). He further stated that this quality/value relationship is fundamentally non-linear. Some fundamental 'skill' and 'performance testing' is required before any forecast or prediction scheme can be applied. Most of the performance testing procedures originated from testing weather forecasting skill and are relatively transparent when dealing with deterministic prediction schemes. However, matters get more complex when probabilistic approaches need to be tested in climate-forecasting systems. Murphy (1994) and Potgieter et al. (2003) clearly showed that in order to measure the performance of probabilistic forecasting scheme, any assessment scheme must at least measure the two basic components of the system, namely (a) the shift in the forecast mean and median from the reference distribution, as well as (b) the change in the dispersion of forecast *versus* the reference distribution. Based on case studies of forecasts of regional wheat and sugar yields, they concluded that no single scheme tested was able to measure both attributes well and consequently there is no single statistical procedure available that measures forecast performance adequately.

This must be taken into account when developing internationally acceptable verification schemes for climate forecasts. We stress that verification of climate forecast output remains a fundamental requirement for both users and climate scientists in order to gain an assessment of real 'forecast' skill as opposed to historical 'hindcast' skill (Murphy, 1993; Elsner and Schmertmann, 1994; Nicholls, 2000).

A further concern is the issue of ‘artificial skill’, which arises particularly when a multitude of possible, statistical forecasting schemes can be employed and a number of ‘best’ performing schemes are selected on the basis of some test statistics, rather than first principles. This issue is complex and goes beyond the realm of this paper. However, we feel that we must at least flag it as a problem that needs to be addressed as an increasing number of potential forecasting schemes are promoted around the world.

The users perspective of forecast quality often differs considerably from that of mathematicians or statisticians. One of the most common problems leading to considerable confusion is the failure to differentiate between the quality of a forecast and its value or impact (Murphy, 1993). Climate information only has value when there is a clearly defined benefit, once the content of the information is applied. In other words: the information must lead to a changed decision, which must ultimately result in an improved outcome (Hammer et al., 1996, 2000; Weiss et al., 2000). Hence, a forecast can be extremely skilful, but still have no value whatsoever. Conversely, even a rather moderate forecast skill can translate into high value and impact under the right circumstances and if applied appropriately.

Demonstrating the effect of CV is often confused with either the real or potential impact of a forecast. Effective applications of climate forecasts (*impact*, I) depend on the *quality* of the forecast (Q), timing and mode of forecast delivery (*communication*, C) and its *suitability* for influencing specific decisions (S).

$$I = \delta * f(\alpha Q, \beta C, \chi S)$$

Coefficients α , β , χ and δ will vary and depend on individual circumstances (range: 0–1). Hence, the impact of a forecast is maximised when all coefficients approach unity. This, however, is unlikely to be ever achieved, because each coefficient is the product of sub-components whereby α is, amongst others, a function of a shift in the distribution’s mean and the dispersion compared to the reference distribution (usually the ‘no-skill’ scenario; Potgieter et al., 2003), β depends on timing, mode of delivery of the forecast and background knowledge of the user, χ describes the relative relevance of the forecast for a specific decision that could be altered based on the information provided by the forecasting scheme and δ measures the importance of the forecast quality for the overall systems performance. This, of course, implies that even low values of α can result in high impact (or value), providing the other parameters have high values. Conversely, even a α -value of unity can result in little or no impact (or value) of the forecast.

3.5. TARGETED FORECASTING AND PARTICIPATORY APPROACHES

Unless a forecast has ‘relevance’, i.e., it addresses issues in a way that will positively influence decision-making, the forecast will remain without impact (Hammer,

2000; Hansen, 2002). Perception, rather than facts, often influence such relevance. Podestá et al. (2002), in their case study of farmers in Argentina, found an apparent reluctance to use forecasts because the temporal and spatial resolution of the forecasts was perceived as not relevant to local conditions, indicating that the desired resolution of forecasts is not necessarily consistent with the outlooks that are produced (Buizer et al., 2000). Such issues of perception, whether they are justified or not, must be taken into account in order to improve the relevance (and hence the adoption) of forecasts.

Management decisions based on knowledge of future climatic conditions will have positive outcomes in some years and negative outcomes in others. Ideally, this should not be regarded as either a 'win' or a 'failure' of the strategy employed, since each season only represents one sample from a not very well-defined distribution of possible outcomes. To assess the true value of such probabilistic information requires comparison of results in each season against outcomes that would have been achieved in the absence of such information.

Development of appropriate management systems that are able to withstand undesired outcomes associated with the low-probability event remains a considerable challenge.

Decision-making in agriculture happens at many levels and involves a wide range of possible users. To provide these clients with the most appropriate tools for decision-making requires a clear focus on their specific requirements and needs. This is an important component of an effective systems approach that ensures the on-going connections between decision makers, advisors and scientists (Hammer, 2000). The importance of such participatory research approaches is now widely acknowledged (e.g., Meinke et al., 2001; Gadgil et al., 2002; Jagtap et al., 2002). Although farmers are one obvious client group, they are not necessarily the ones most responsive to a forecast. This responsiveness depends very much on the socio-economic and political circumstances, local infrastructure and the agricultural system in question. To clearly identify clients and their decision points, it is helpful to classify them according to geographic scale and information needs. Such a conceptual framework assists in identifying the information needs of decision makers, it also assists in selecting the most appropriate and efficient tools to use (Hammer, 2000). Modelling approaches are frequently the tools of choice, but the type of model required will differ depending on geographic scale, required inputs and information needs.

Some specific Australian examples of the beneficial use of forecasting in decision-making across the temporal scales are:

1. cotton growers in Queensland, many of whom are now scheduling the timing of their cotton harvests based on the expected passing of the next MJO;
2. farmers in northeastern Australia who use ENSO-based information to tailor their rotations and crop management based on local conditions at the time and rainfall probabilities for the coming months (Meinke and Hochman, 2000);

3. sugar growers and millers in Northern Queensland who use targeted climate forecasts in management decisions involving harvest strategies, planting decisions, and mill throughput operations (Everingham et al., 2002);
4. bulk handling and marketing agencies, which require accurate regional commodity forecasts to assist them in storage, transport logistics and export sales well before harvest (Hammer et al., 2000; Potgieter et al., 2002);
5. government agencies, which require objective assessments of the effect and severity of CV on production (e.g., Keating and Meinke, 1998); and
6. policy makers, who require impact assessments of greenhouse scenarios for input into international treaty negotiations (e.g., Howden et al., 2001).

3.6. FARMER DECISIONS

Hammer (2000) demonstrated the basis for effective application and valuing of seasonal climate forecasting using a simple example of tactical management of row configuration in a cotton crop grown in Queensland, Australia. He asked: Is it possible to improve profitability by tactically manipulating row configuration in dryland cotton in response to a seasonal climate forecast? Using a simulation approach and 100 years of historical rainfall data, he determined the most profitable option for row configuration (solid, single skip or double skip) for either all years or those years associated with each SOI phase prior to sowing. The 'all-years' case relates to the situation where no notice is taken of the forecast each year. In this case (fixed management), the most profitable option over the 100-year period was to employ the solid row configuration every year. The other case takes account of the SOI-based forecast at the time of sowing. The analysis showed that with some forecast types it was on average more profitable to adopt either single or double skip row configurations (responsive management). To examine the value and risks over all years associated with adopting responsive management, he then calculated the gross margin difference for each year between the responsive (tactical) and non-responsive (fixed) management options.

On average, the tactical management approaches increased gross margins (profits) by 6% (11%). However, there were a number of specific years in which responsive management was inferior. Understanding this point about outcome risk is critical in effective applications of climate forecasting. While a significant advantage will often result over a period of years (as in this simple example), there can be no guarantees that this will occur in any particular year and in fact the decision maker will sometimes be worse off. This process is described as 'prototyping' decision rules that are relevant to the decision maker and generate collective learning (Hammer, 2000). Although the modelled predictions do not cover all aspects of the system involved, they behave essentially as 'discussion' support systems in

dealing with the complexities and risks associated with some decisions (Nelson et al., 2002).

This simple example demonstrates how the value associated with knowledge of shifts in rainfall probabilities can be determined for production management. The balance of probabilities dictates that users of this information will be better off in the long term. However, it does not eliminate production risks associated with a tactical response to a forecast nor does it eliminate the need for a farmer to make a decision. The analysis does not provide a rule for best row configuration management in cotton. Such rules can only be developed by taking account of the very specific physical and economic circumstances of a specific enterprise; they must also account for current production costs, commodity prices and soil condition.

Recent studies with selected farm managers in Queensland, Australia, indicate that by using climate information in conjunction with systems analyses producers can become less reliant on climate forecasts. By identifying decisions that positively influence the overall farm operation in either economic or environmental terms, these producers have gained a better understanding of the system's vulnerability and started to 'climate proof' their operations. Examples of actions taken when a forecast is for 'likely to be drier than normal' are: maximising no-till area (water conservation), applying nitrogen fertiliser early to allow planting on stored soil moisture at the most appropriate time; planting most wheat later than normal to reduce frost risk. In seasons that are likely to be wetter than normal, management options include: sowing wheat earlier; applying nitrogen to a wheat cover crop grown on a dry profile after cotton (normally not expected to produce a harvestable yield) and applying fungicides to wheat crops to minimise leaf diseases (Meinke and Hochman, 2000).

3.7. MARKETING DECISIONS

Based on SOI phases (Stone et al., 1996) and a regional (shire-based) wheat model (Stephens, 1998), Hammer et al. (2001) developed a regional commodity forecasting system. It allows the examination of the likelihood of exceeding the long-term median shire yield associated with different season types from the beginning of the cropping season. This system is now run operationally for Queensland, Australia, by updating the projection each month based on the actual rainfall to date and any change in the SOI phase from month to month. Although there appear to be commercial applications, this system was primarily designed to inform the Queensland Government of any areas that might be more likely to experience poor crops in any year. This information provides an alert for exceptional circumstances issues associated with potential drought in the same manner described for pasture systems in Queensland by Carter et al. (2000). Anecdotal information received from marketing agencies based on their experience with the 2000 regional wheat outlook showed that seasonal crop forecasting can be beneficial for their decision-making processes when it is used in addition to their current approaches. Possible decisions

to be taken when the outlook is for 'likely to be drier (wetter) than normal' are, for instance, forward buying (selling) of grain or shifting of resources from good yielding areas to poor yielding areas. Obvious links that exist between production volume and price need to be taken into account (Stone and Meinke, 1999; Jagtap et al., 2002).

Potgieter et al. (2002) used this regional model to investigate the relationship between spatial and temporal patterns of Australian wheat yields with ENSO. They found that the SOI phase system showed significant skill in discriminating among most wheat year types. 'Skill' in this instance refers to both hindcast and forecast skill using established numerical techniques. Together with the findings by Hill et al. (2000), this shows the global applicability of the SOI phase system for commodity forecasting. Results by Potgieter et al. (2002) are also consistent with findings at the field and farm scale (Hammer, 2000). However, they concluded that there is potential for considerable improvement in predictive ability and stated that *it may be possible to identify climate system or ocean-atmosphere features that may be causal and would be most useful in improved predictive schemas* [sic].

3.8. POLICY DECISIONS

For the seasonal to inter-seasonal time scale, Keating and Meinke (1998), Stephens (1998), and Hammer et al. (2000) have shown how point-source and regionally based production models can be used to quantify exceptional circumstances and drought impacts. Howden et al. (1999) gave an example of the value of model applications to guide policy decisions for global warming scenarios. They investigated key adaptation options for wheat such as choice of cultivars and sowing windows and found significant regional differences for 10 sites throughout the Australian wheat belt. Specifically, they found likely impacts not only on production but also on grain quality characteristics such as protein content. Their findings imply that nitrogen fertilisation rates need to be increased in future if current grain quality levels are to be maintained.

Using the same modelling approach, Reyenga et al. (2001) found that by 2100 changes in temperature, CO₂ levels and rainfall patterns could lead to a movement of the 'cropping frontier' in eastern Australia by about 100 km to the west. Such studies are likely to influence future land use policy decisions.

Phillips et al. (2002) found for Zimbabwe that seasonal climate forecasting tends to increase production volatility. They suggested that in future appropriate market or policy interventions may need to accompany information targeted at farmers in order to increase societal benefits from the forecast. Meinke et al. (2001) pointed out that while there are many case study examples of simulation approaches that could inform the policy process this is rarely achieved and the challenge remains to actually integrate such approaches into policy frameworks that result in improvements.

There are many examples how climate knowledge can influence policy setting. However, to ensure that actions by resource managers and policies are 'in tune' will

require a more coherent approach that allows to simultaneously influence policy and risk management decisions based on common data sources and tools.

4. The Bigger Picture: Applying Climate Forecasts Across the Value Chain

To be useful and valuable, climate forecasting must not only individually address relevant problems at farm or policy level, but be flexible enough to take a whole value chain perspective to ensure that benefits achieved at one level are not undone at the next (IRI, 2000).

An example of this approach is an assessment of the value of seasonal climate forecasting for the Australian sugar industry (Everingham et al., 2002). Australian sugarcane industries go across an integrated value chain comprising cane growing, harvesting, transport, milling, marketing and shipping. Sugarcane industries worldwide are exposed to uncertain variable climatic conditions, which have large impacts across all industry sectors. It is believed seasonal climate forecast systems offer the potential for improved risk management and decision-making across all these sectors, leading to enhanced profitability and international competitiveness.

Such a 'whole value chain approach' can:

- identify, in partnership with all relevant sectors of that industry, the key decisions influencing sustainability and profitability that are impacted by climate;
- identify the key vulnerabilities within the value chain related to CV and CC;
- develop the necessary and appropriate databases of climate and industry sector performance;
- establish the role of climate forecast systems for different geographical regions and key industry decisions;
- assess the benefits and costs of tactical decision-making based on climate forecasting across all the different components of the sugar industry value chain; and
- effectively facilitate the appropriate implementation and delivery of climate systems for enhanced risk management and decision-making (Everingham et al., 2002).

The application of the above approach is provided for those decisions relating to yield forecasting, harvest management, and the use of irrigation. There are key lessons to be learnt from this approach that can be considered generic in terms of preparedness for all agricultural industries. These include

- the absolute need for a participative R&D approach with stakeholders,
- the need to consider the whole industry value chain,
- the need for climate forecast systems with appropriate skill and underlying mechanistic foundation appropriate to different regions and different decisions (Stone et al., 2000b; Everingham et al., 2002).

In a recent example of an assessment of the economic value of seasonal climate forecasting, Antony et al. (2002) analysed the value of climate forecasting to management systems in just one sugar milling region in Australia. They determined that in one case study season (austral winter, 1998) the value of a probabilistic climate forecasting system amounted to in excess of AUD \$1.9 million for one relatively small cane growing region. The assessment was made incorporating decisions at both the farm and mill scale. However, they point out that if prior 'perfect knowledge' of rainfall patterns for that season had been possible, the value to industry would have amounted to AUD \$20 million, 10 times the value achieved through existing climate forecasting technology.

There is compelling evidence that during recent El Niño events media reports (often factually wrong or distorted) influenced factors such as bank lending policy and agribusiness advice in Australia. Better contextualised information appears to be required. Brennan et al. (2000) discussed how agribusiness might be able to use information about CV. The same issue exists to an even greater degree for CC issues. In 2001, a major Australian insurance company withdrew its insurance coverage for cyclone damage as a result of indications of more intense cyclones in a warmer world. Brennan et al. (2000) concluded that there is considerable potential to use simulation approaches to improve bank lending policies, crop insurance policies, product inventories and marketing advice. Specifically, they found that model predictions can reduce claimant disputes and cut legal costs. They also provide the option for individually tailored financial packages. They stated that . . . *while discussions with agribusiness indicate keen interest in such tools and information, they have yet to have impact on policy and operations. While clear outcomes have been seen in some areas of engagement (e.g., insurance/loss assessment), other collaborative efforts have only progressed some way to exploring the role for seasonal climate forecasts and simulation models in their business operations (e.g., banking, portfolio analysis) (sic).*

Chapman et al. (2000a) provided a further example of the powerful combination of simulation modelling and climate forecasting: Timing and severity of water limitation affect crop growth and yield differently. In order to screen germplasm for broad adaptation to drought, plant breeders conduct large-scale multi-environment trials for several seasons, where seasonal conditions vary spatially and temporally. These trials are conventionally analysed by assuming that each location is representative for an environment-type. However, it is unlikely that the few seasons encountered at these locations during a trial represent the true frequency of all possible season types at this location (particularly when considering some of the low-frequency variability discussed in Table I). Using a simulation model for sorghum, Chapman et al. (2000a) characterised the stress environments for each location and season (e.g., early, mid or late stress) and then analysed the results by environment type rather than location. This resulted in a considerable amount of additional information that was previously attributed to 'environmental noise'. Hence, this environment-type classification can lead to more rapid improvement in the

selection process, thus improving the efficiency of a breeding program leading to a more rapid development of better-adapted cultivars. Once such improved cultivars are available, seasonal climate forecasting can help farmers to select the appropriate cultivars for the most likely environment type at a location.

5. Pathways of Integration and Delivery

The global impact of climate variability has contributed to the establishment of pilot programmes around the world that brought together climate scientists, agronomists, crop modellers and farmer representatives. Examples are the initiatives by the Queensland Government in Australia or the International Research Institute for Climate Prediction (IRI) at Columbia University, NY. The number of groups is steadily increasing and interested readers are referred to publications in special issues of *Agriculture and Forest Meteorology*, vol. 103 and *Agricultural Systems*, vols., 70 and 74 for further details. Most of these groups are partly supported by state and national government sources, and also attract considerable amounts of industry funds and farmer support. Further, the issue has been recognized by international bodies such as the WMO, who through the International START Secretariat (Global Change System for Analysis, Research and Training, co-sponsored by IGBP, IHDP and WCRP) have initiated the CLIMAG projects (Sivakumar, 2000). CLIMAG aims to utilize the growing ability to predict forthcoming climate variations to improve cropping systems management and decision-making and increase production at local, national and international scales.

One of these CLIMAG projects used locations in southern India and northern Pakistan as case studies to demonstrate the utility and feasibility of combining seasonal climate forecasting with a structured, agricultural systems research approach in developing countries. With the help of the international agricultural modelling community, the project provided a means to assess the potential value of seasonal climate forecasting to agricultural producers in these regions. The project established links between research groups in Australia (APSRU; Keating et al., 2003), the International Research Institute for Climate Prediction (IRI, 2000) and partner institutions in India and Pakistan (e.g., Gadgil et al., 2002). The project team conducted agronomic and climatological systems analyses of cropping systems and provided recommendations on where additional research efforts are needed according to a general framework (Figure 2). This has led to the development of a loose network, known as RES AGRICOLA (Latin for Farmers' business), that draws on the collective expertise of the global research community to develop resilient farming systems. 'Resilient systems' allow farmers to draw on systems resources (e.g., water, nutrients, reserves) at times of need without causing permanent damage as long as these 'debts' are 'repaid' once conditions improve.

The multi-dimensionality of the problems requires effective cross-disciplinary research and communication. Interdisciplinarity and the human dimension are at the core of this approach whereby technically possible solutions will be evaluated

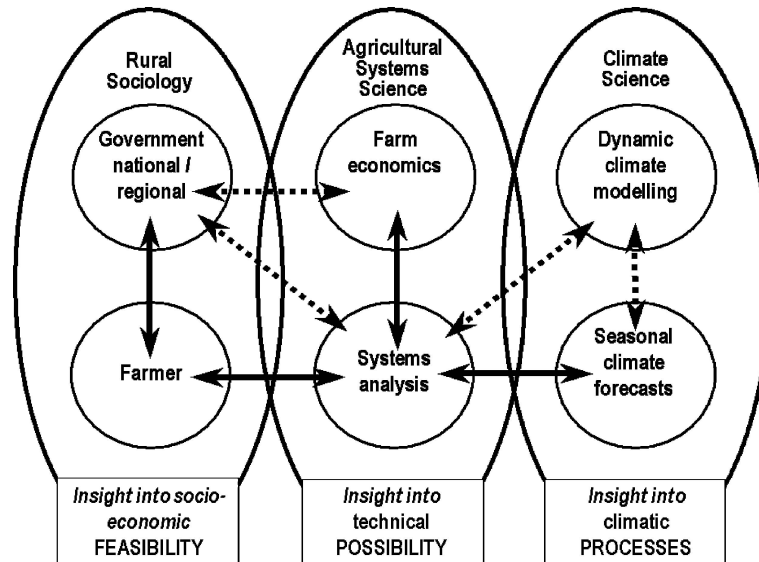


Figure 2. Outline of the concept behind the RES AGRICOLA network (adapted from Meinke et al., 2001). The diagram shows disciplines, relationships and linkages for effective delivery of climate information for decision-making in agriculture. Operational links are indicated by the solid arrows and show connections that have already proven useful; dashed arrows indicate areas where operational connections still need to be better developed. The basic principle of the concept (i.e., the requirement of cross-disciplinary research for effective delivery of climate forecasts) is generic and independent of the specific target discipline.

in terms of their socio-economic feasibility. RES AGRICOLA is a logical evolution of the 'end-to-end' concept proposed by Manton et al. (2000). To deliver benefits within agriculture, the concept distinguishes three discipline groups that need to interact closely, namely (i) climate sciences, (ii) agricultural systems sciences (including economics) and (iii) rural sociology (Figure 2). By operationally connecting research projects and through the establishment of international, cross-disciplinary teams, such a network will be able to convert insights gained into climatic processes *via* systems analysis and modelling into insights into the socio-economic feasibility of decision options.

Pay-offs are more likely when a truly integrated systems approach is employed that includes decision makers and scientists across the disciplines as equal partners and guarantees that they have ownership of this process. Such a truly participatory approach ensures that the issues that are addressed are relevant to the decision maker. This process will also ensure that there is sufficient scope for decision makers to alter their behaviour or management based on the information provided. This 'ability to move' might be constrained by external factors such as current policy settings or international market forces (Meinke et al., 2001). Hansen (2002) stressed that the sustained use of such a framework requires institutional commitment and favourable policies.

An example where the links shown in Figure 2 could be strengthened is in the area of connecting agricultural simulation approaches with whole farm economic analyses and policy decisions. Using a case study, Ruben et al. (2000) reviewed the available options for adapting land use systems and labour allocation for typical households in a region in Mali. They showed that consequences of climatic patterns and climate shocks could at least partially be offset by compensatory policy devices. Better-informed price policies would enable welfare-enhancing adjustments for better-endowed farm households, while poor farmers would benefit from reductions in transaction costs, particularly under dry conditions when dependency on market exchange tends to be intensified. *Contrary to most expectations, vulnerable households can benefit strongly from market reform policies and thus structural adjustment programmes might provide an adequate framework for containing adverse effects from climate shocks* [sic]. However, to influence policy requires operationalising the components outlined in Figure 2 *via* a participatory research approach, whereby economists and policy informants also become valued members of the research team.

This formal connection across disciplines must go hand-in-hand with an evolutionary strategy for climate applications, as proposed by Hansen (2002): (1) an exploratory phase (basic capacity building, gaining understanding of the system), (2) a pilot phase (co-learning through intensive interactions between researchers and decision makers) and, conditional on a successful pilot phase, (3) an operational phase that focuses on engaging, equipping and transferring ownership to those groups and institutions that will provide forecast information and support to a larger target audience on a sustained basis. The long-term aim is to achieve 'level 3' in all countries where CV impacts on agriculture. This requires a global and sustained commitment to the R&D process just outlined. We need to use the demonstrated successes where 'phase 3' is already operational (e.g., some places in Australia, US, and several demonstration projects in South Asia, South America and Africa) in order to initiate 'phase 1' activities at locations where such an infrastructure does not yet exist.

So far, we have outlined the global, scientific capacity to forecast future climate patterns probabilistically and shown how this capability can be translated into socio-economically feasible management options *via* a systems analytical approach and participatory action research. The question remains: how can these capabilities positively influence agricultural management practice? Nelson et al. (2002) addressed this issue by introducing the notion of 'discussion support' (rather than decision support). They provided an example of a simulation-based discussion support software that acts *as a key vehicle for facilitating infusion of forecasting capability into practice* (sic). This demand-driven analysis tool that allows decision makers to compare options either in terms of yield or economic returns is a consequence of years of simulation-aided discussions about crop management in northeastern Australia. This created the necessary demand for such a tool as well as the capacity to implement insights gained from this tool, hence improving outcomes. It is a clear example how we can progress beyond the intensive, case-study-based, participatory

research approach that by definition only reaches a small number of possible beneficiaries. However, its implementation was only possible because this region of Australia is one of the few places that has reached 'level 3' as proposed by Hansen (2002).

6. Conclusions

During the last decade substantial progress has been made in climate science and knowledge delivery. It is now time to consolidate the insights gained. Decision makers in developing and developed countries can benefit from climate knowledge through improved risk management practices or better-targeted policies. However, this can only be achieved if the broad disciplines of climate sciences, agricultural systems sciences and socio-economic sciences adopt a common, integrated framework for research and delivery.

We demonstrated how knowledge of CV and CC can lead to better decisions in agriculture, regardless of geographical location and socio-economic conditions. Amongst the most important tools are probabilistic climate forecasting capabilities and agricultural simulation models that facilitate objective evaluation of alternative decisions at the farm, marketing or policy level. An interdisciplinary systems approach to research and development will assist in capturing our ever-increasing understanding of the physical and biological systems components. This must be complemented by participatory communication methods that ensure the on-going connections between decision makers, advisors and scientists. Examples of decisions aided by simulation output ranges from tactical crop management options, to commodity marketing and to policy decisions about future land use. Any scientific breakthroughs in climate forecasting capabilities are much more likely to have an immediate and positive impact if they are conducted and delivered within such a framework.

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Note

¹In the Nordeste region of Brazil, the word 'inverno' (winter) is used to refer to the rainy season, February–June.

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