Understanding Climate Variability to Improve Agricultural Decision Making

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ABSTRACT

Climatic variability occurs at widely varying time scales. Better knowledge of such variability combined with probabilistic forecasting capabilities is valuable for agricultural decision making at the farm, marketing or policy level. Agricultural simulation models can help to add value to this improved understanding of climate variability and are used to objectively assess management options. Decisions based on such tools ranges from short-term, tactical crop management options to policy decisions about future land use. At the strategic level they allow answers to questions such as: Are the current cropping systems in Australia best suited for their individual region's climate variability? How will these systems perform over the next few decades? This systems analytical approach is at the centre of several research projects that evaluate and compare current cropping systems against the background of climatic variability at various time scales. Although knowledge of likely temperature ranges (and particularly high and low temperature thresholds) can also influence agricultural decisions, our focus for this paper is on rainfall variability, which is still the major source of yield fluctuations in Australia.

Key words:
climate variability, forecasting, simulation modelling, decision making, systems analysis

INTRODUCTION

Perfect knowledge of future rainfall would fundamentally change the way agriculture is practised - Discuss.

Many research proposals in the disciplines of atmospheric sciences, oceanography, climatology and agriculture use this or similar statements to justify their proposed activities. This ingrained 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 categorical forecasting system is therefore either wrong or dishonest (23).

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 clearly the case, a similar number of cases show either negative outcomes or identify decisions that are insensitive to such information.

It is our objective to show that via a systems analytical approach, climate information and long-range climate forecasting can positively influence agricultural decision outcomes. Therefore, we will

- briefly describe the major climatic patterns that cause rainfall to vary;
- present data from case studies in Qld, SA and Vic showing the effect of climate variability at various time scales;
- discuss the importance of systems analytical tools (ie. simulation models) to progress from a rainfall forecast to improved outcomes for decision makers and
- address issues of temporal scale in seasonal forecasting ranging from bi-monthly climate patterns to climate change.

Background

Rainfall variability and its interaction with land management has shaped Australian agriculture since the beginning of white settlement over 200 years ago. In less than a century European settlers had transformed much of Australia's natural landscape. Extreme climate events combined with factors such as overgrazing resulted in major long-term resource degradation (20). High rainfall variability is also the major source of dryland yield fluctuations (10). Although most dramatic at the farm level, this effect of climatic variability is apparent throughout the entire Australian economy and can even affect macroeconomic indicators such as international wheat prices (5), employment or the exchange rate (39). Overall however, Australia's rainfall variability has resulted in cropping systems that are generally resilient, ie. they are capable of absorbing some of that variability without immediate disastrous results. Typical examples for this are the dryland wheat/cotton rotations of the Darling Downs which use stored soil moisture as a buffer against low in-season rain and the wheat/pasture rotations in Southern Australia that remain productive even under adverse climatic conditions. Although such rotations have been developed in response to the predominant climatic conditions, they are not necessarily optimally adapted. Meinke and Hammer (22), for instance, showed that the production systems for peanuts in Southern Queensland were well adapted to the above average summer rainfall conditions of the 1950s to 1970s but resulted in unrealistically high yield expectations for the changed climate patterns of the 1980s and 1990s.

To remain economically viable in an internationally competitive market, Australian farmers have to devise management options that can produce long-term, sustainable profits in such a variable environment. This requires a sound understanding of the sources of rainfall variability, their degree of predictability and objective tools to assess management options in agronomic, economic and environmental terms. *Demonstrating the **effect** of climate variability must not be confused with either the real or potential **impact** of a forecast.* Effective applications of climate information, including climate forecasts, will depend on factors such as the type of forecast provided and its suitability for influencing specific decisions (9).

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, including Australia. However, ENSO is not the only source of rainfall variability. In addition to an inherently unpredictable chaotic component there are a range of other climate phenomena varying at a wide range of time scales. It is not surprising that there is now considerable research effort to better understand these phenomena. This effort is being directed towards work on high frequency phenomena such as the Madden-Julian Oscillation (MJO, also known as the intra-seasonal oscillation or 'ISO'), to ENSO related information (eg. SOI or SST based forecasting systems), to decadal and multidecadal rainfall variability and finally to greenhouse related changes in climate patterns (Tab. 1).

At the highest frequency, the MJO involves variations in wind, sea surface temperature, cloudiness and rainfall that occur regularly every 30 to 50 days. It consists of cloud clusters that originate in the Indian Ocean and move eastward with speeds of 5-10 ms^{-1}. The MJO particularly affects the intensity and break periods of the Australian monsoons and also interacts with ENSO. ENSO is a quasi-periodic interannual variation in global atmospheric and oceanic circulation patterns that causes local, seasonal rainfall to vary at many locations throughout the world (35). The physical causes of lower frequency rainfall fluctuations are still being investigated, but our understanding of these processes is also steadily increasing (1, 32, 40). This enhanced understanding of the causes and consequences of rainfall variability at a range of time scales and our increasing ability to predict these cycles has made 'managing for climate variability' an important feature of Australian farming systems.

Table 1: **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 (eg. only)***	***Frequency (approximate, in years)***
Madden-Julian Oscillation, intraseasonal (MJO or ISO)	Madden and Julian (18)	0.1 – 0.2
SOI phases based on El Niño – Southern Oscillation (ENSO), seasonal to interannual	Stone et al. (35)	0.5 – 7
Quasi-bi-annual Oscillation(QBO)	Lindesay (17).	1 – 2
Antarctic Circumpolar Wave (AWC), interannual	White (40)	3 – 5
Latitude of Sub-tropical ridge, interannual to decadal	Pittock (30)	?? – 11
Interdecadal Pacific Oscillation (IPO) or Decadal Pacific Oscillation (DPO)	Zhang et al. (41) Power et al. (32) Tourre and Kushnir (38) Mantua et al. (19) Allan (1)	13+ 13 – 18
Multidecadal Rainfall Variability	Allan (1)	18 – 39
Interhemispheric Thermal Contrast (secular climate signal)	Folland et al. (7)	50 – 80
Climate change	Timmermann et al. (37) Kumar et al. (16)	???

THE ROLE OF MODELLING IN CROPPING SYSTEMS MANAGEMENT

In managing agricultural systems, farmers make decisions that are influenced by many factors. While economic returns are of primary importance, decisions are also based on perceived risk of economic loss, weed and disease control, the risk of soil degradation, lifestyle and the existing policy framework. 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 (2, 3).

Decisions that could benefit from such targeted forecasts are also made at a range of temporal scales. These range from tactical decisions regarding the scheduling of planting or harvest operations to policy decisions regarding land use allocation (eg. grazing systems vs cropping systems). Table 2 gives a few examples of these types of decisions at similar time scales to those seen in climatic patterns.

Table 2: Agricultural decisions at a range of temporal and spatial scales that could benefit from targeted climate forecasts.

Decision Type (eg. only)	***Frequency (years)***
Logistics (eg. scheduling of planting / harvest operations)	Intraseasonal (> 0.2)
Tactical crop management (eg. fertiliser / pesticide use)	Intraseasonal (0.2 – 0.5)
Crop type (eg. wheat or chickpeas)	Seasonal (0.5 – 1.0)
Crop sequence (eg. long or short fallows)	Interannual (0.5 – 2.0)
Crop rotations (eg. winter or summer crops)	Annual/bi-annual (1 – 2)
Crop industry (eg. grain or cotton)	Decadal (~ 10)
Agricultural industry (eg. crops or pastures)	Interdecadal (10 – 20)
Landuse (eg. agriculture or natural systems)	Multidecadal (20 +)

Landuse and adaptation of current systems	Climate change

Climatic patterns translate via rainfall variability into associated production variability. However, rainfall anomalies are not the only determinant of yield and factors such as starting soil moisture, temperature, planting dates and timeliness of rainfall strongly influence final yields. Simulation models integrate all these effects in a physiologically meaningful way. Although rainfall and yield are strongly correlated, consequences of rainfall variability will differ from season to season due to these other influences on yield formation.

A simulation approach offers other advantages, too: 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 a number of combinations. Today simulation analyses have become a legitimate means of evaluating policy and resource management issues (eg., 26, 14), but they also provide valuable information for on-farm decision making (2, 24).

Traditionally simulation models have been used as “knowledge depositories” by scientists in order to describe an area of interest. Once they became available, interest quickly shifted from curiosity about the underlying principles to using models in a predictive capacity (eg. 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 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 mathematically. 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 (21). Some of the emerging challenges in genomics require a more balanced emphasis on both attributes and might show a way forward.

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. The amount of process detail contained within a model should match its intended application. However, care needs to be taken whenever the level of process detail is reduced that we can demonstrate 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 (8). In situations where multiple hypotheses are possible, one can discriminate amongst them based on their plausibility (29). 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 (6).

Biological models can never be completely verified. 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. For instance, as part of research still in progress we tested the APSIM Wheat model on data from 100 plant breeding experiments across 23 sites and several years and deemed its performance adequate (R^2 = 0.6) to characterise the environmental component of GxE interactions (Fig. 1a, unpublished data, Cooper, pers. com.; 4). These experiments were not specifically conducted for model testing and while some information regarding soil type, soil water and nutrient status were available the data set still contains a considerable amount of parameter uncertainty. Using data from a longterm soil fertility trial (36) where all the necessary input parameters and starting conditions were available a R^2 value of 0.8 was obtained (Fig. 1b). However, this dataset also highlights the deficiencies of using R^2 values as an indicator of model performance (28). When only data from a dry year were used, R^2 was zero (Fig. 1c), in

spite of the models obvious ability to capture the year-to-year variation in yield (Fig. 1b). Obvious overpredictions at high yield levels (>4000kg ha^{-1}) are generally the result of biotic stresses (ie. pests and diseases) that are not accounted for by the model (Fig. 1b). The example shows that the validity of a model does not depend on the correlation coefficient but rather on whether the inevitable difference between predicted and observed values are acceptable for the decision maker.

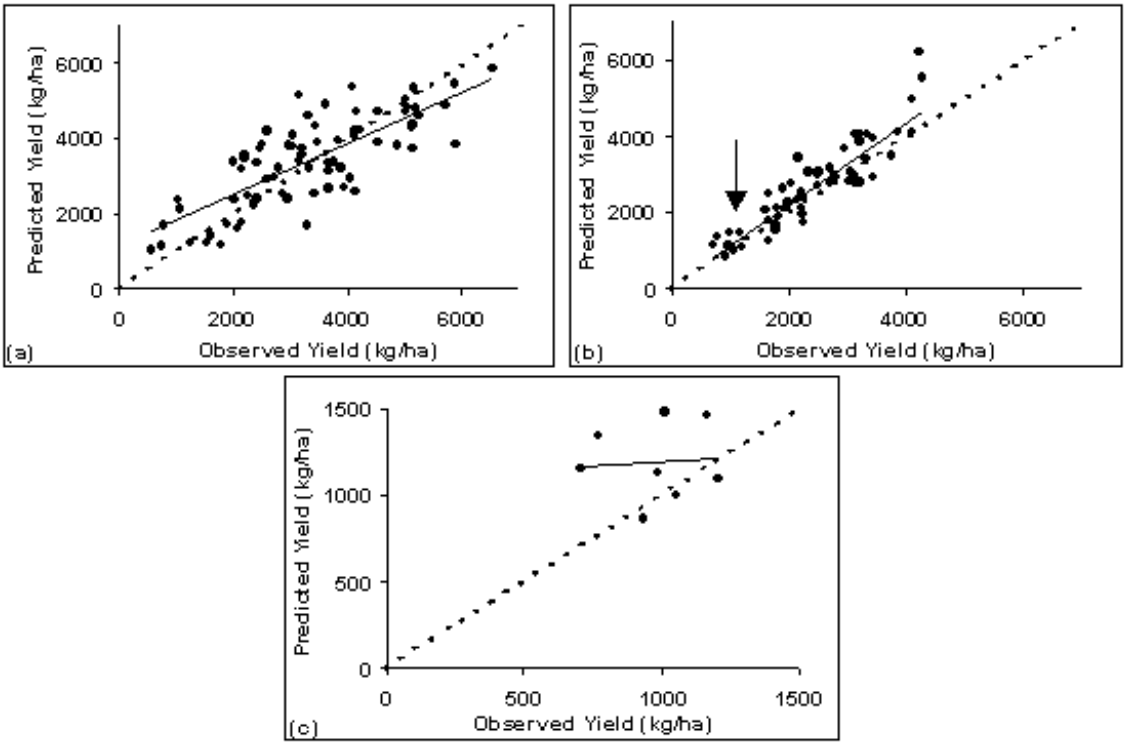

Fig. 1: Performance of APSIM-Wheat against yield data from (a) 100 plant breeding experiments from 23 locations over several seasons (R^2=0.6); (b) experimental results from soil fertility studies at a single site in Queensland over 8 years, 5 N levels and 2 surface management regimes (R^2=0.8) and (c)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

UNDERSTANDING THE EFFECT OF CLIMATE VARIABILITY

While the effect of ENSO on primary production in Northeastern Australia has been comprehensively documented (eg. 13), there is still considerable confusion about similar effects in the southern parts of Australia. When we either analysed historical district yield data from the Le Hunte district in SA (1916 – 1997; Egan, pers. com., 2000) or simulated 100 years of wheat production based on historical rainfall records for three locations in SA, Vic and Qld using the APSIM model (11), we found that years that had either a positive or rising SOI pattern in April/May always had the highest median yields while a negative or falling SOI pattern often resulted in the lowest median yields (Fig. 2). Although there are strong regional idiosyncrasies (eg. a 'near 0' phase in SA only yields about 20 - 30% of the long-term average based on either district yield or simulated data; Fig. 2a,b), ENSO effects are clearly evident at all locations (Fig. 2). For SA the patterns found in the historical district yield data were similar to the simulated data, indicating (a) that rainfall variability in SA is also influenced by ENSO and (b) that rainfall variability is the major cause of wheat yield fluctuations in this environment (Fig. 2a,b). This contradicts the commonly held belief that 'the SOI works only in Queensland'.

However, ENSO is only one element of the full spectrum of climate variability (Table 1). Meinke et al. (25) used a shire-based wheat model (34) to analyse wheat yields for decadal/multidecadal variations (DCV). At the multidecadal time scale they showed that a negative (positive) DCV pattern often enhances (weakens) any ENSO related variability in many parts of Australia. However, they also noted considerable regional differences. Their study highlighted the need to better understand the physical causes for DCV and the associated potential to predict such climate variation. They also stressed the

importance to connect such scientific developments with the information needs of decision makers in agriculture at the farm management level as well as at the policy level.

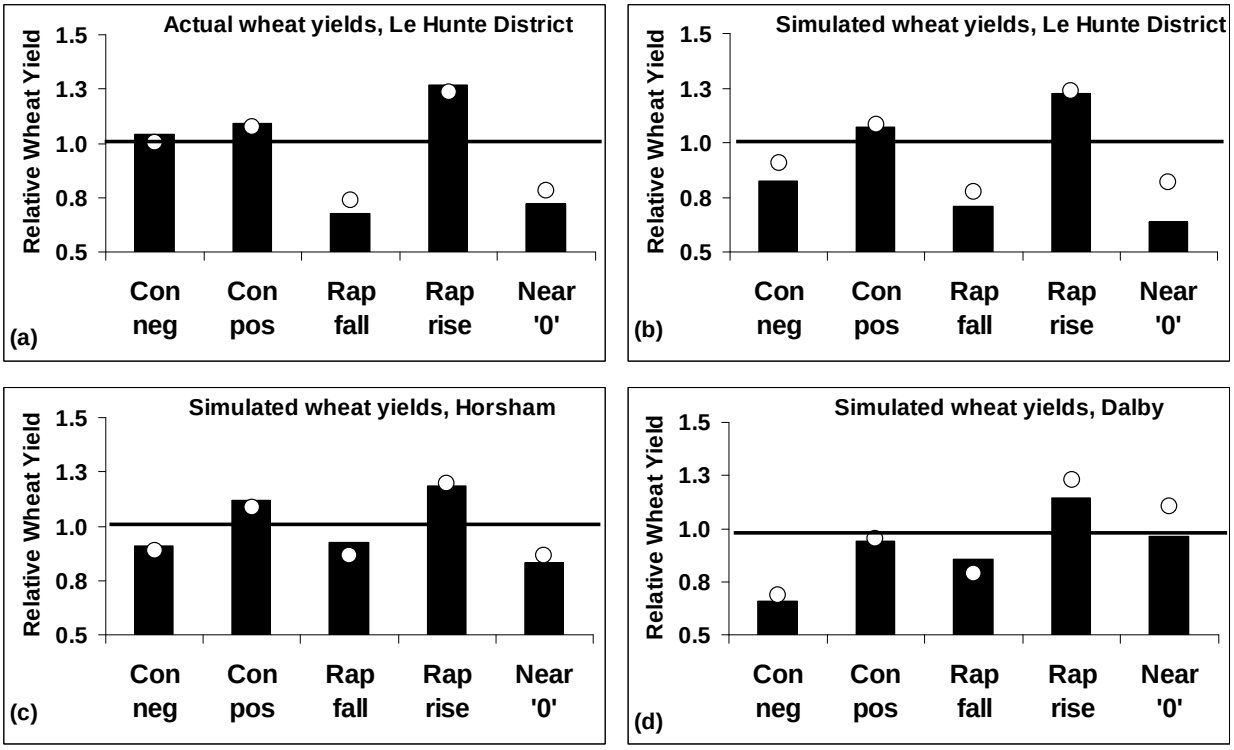

Fig. 2: Actual (a) and simulated relative wheat yields (b-d) by April/May SOI phases for the Le Hunte district (SA), Horsham (Vic) and Dalby (Qld). Solid bars represent the median, open circles the average yield for each SOI phase. The SOI phases are defined by Stone et al. (35) as: consistently negative (con neg), consistently positive (con pos), rapidly falling (rap fall), rapidly rising (rap rise) or near zero (near '0').

Using APSIM rather than a shire-based model, Pollock et al. (31) also investigated DCV effects on crop rotations in Central Queensland. They found the current trend of opportunity cropping winter as well as summer crops to be a well-adapted strategy based on the climatic patterns during the last two decades. Their results further indicated that summer cropping might be less risky and more profitable than winter cropping during times when the DCV patterns are negative.

For wheat, Fig. 3 shows a modulating but varying effect of DCV on ENSO on district yield and simulated data. The APSIM model used for this analysis assumes optimal crop management without losses due to pests or diseases and does not take negative effects of excess water into account. However, when we compared model performance with longterm yield data from the Le Hunte district in SA we found good correspondence between district yield and simulated data in terms of relative yield trends and in response to ENSO and DCV (Fig. 3a, b). District yield data from 1916 to 1997 were used without attempting to remove technological advances (unpublished data, Egan, pers. comm, 2000, Fig. 3a). The model was run using 1998 cultivar, management and technology (Fig. 3b).

For the Le Hunte district in SA both district and modelled data indicate that when DCV patterns are negative a year with a negative SOI phase often results in considerably lower wheat yields than a year with a positive SOI phase. This pattern is reversed when the DCV pattern is positive. At Wentworth, Vic, no clear effect of DCV was apparent but positive SOI phase years often result in higher yields than negative SOI years. The same SOI effect was apparent at Dalby, Qld, but here a negative DCV pattern further decreased yields when the SOI phase was negative, and often increased yields when the phase was positive (Fig. 3).

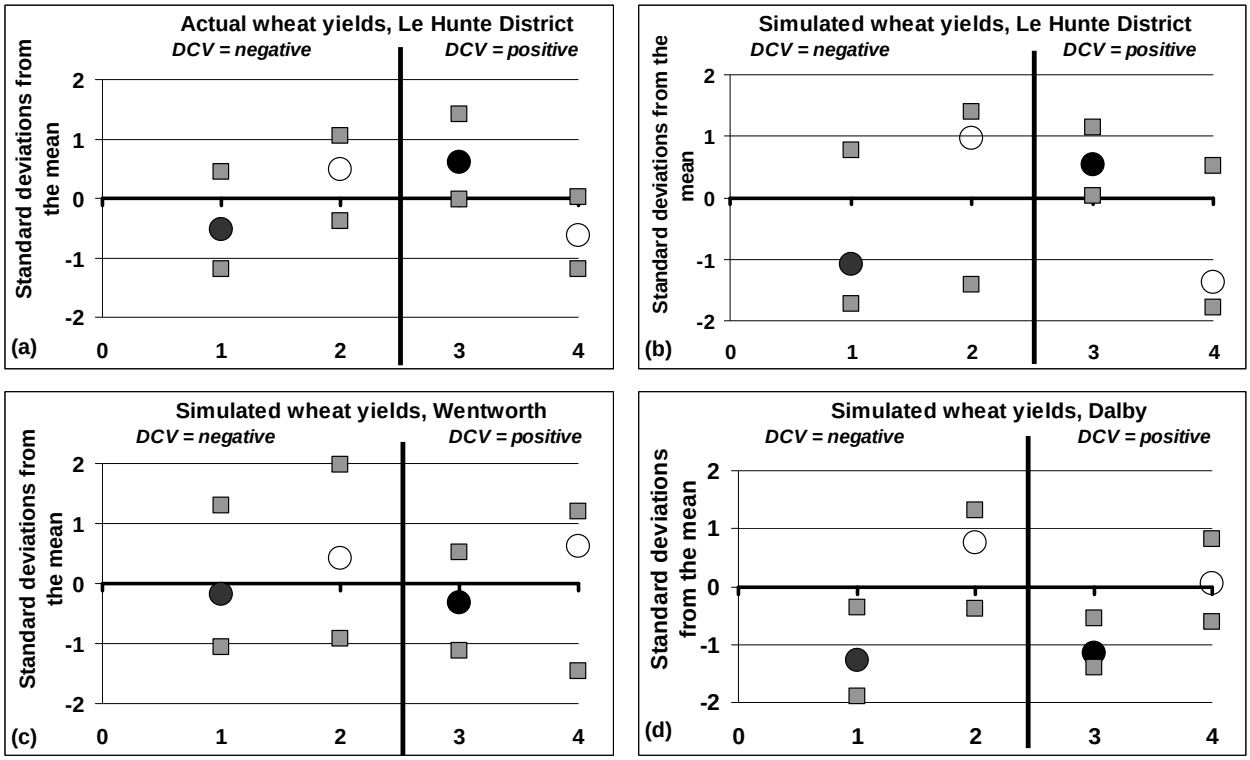

Fig. 3: Standard deviations from the mean for actual (a) and simulated wheat yields (b-d) grouped by May/June SOI phases (negative phase = 1 and 3, closed circles; positive phase = 2 and 4, open circles) and by DCV patterns (negative pattern = 1 and 2, left of the vertical line; positive pattern = 3 and 4, right of the vertical line). Data shown are for the Le Hunte District (SA), Wentworth (Vic) and Dalby (Qld). Circles indicate the median and squares the corresponding 10 and 90 percentile values, respectively.

BETTER DECISIONS THROUGH TARGETED FORECASTING: THE PROBABILITY GAME

Management decisions based on knowledge of future climatic conditions will have positive outcomes in some years and negative outcomes in others. This must not be regarded as either a 'win' or a 'failure' of the strategy employed, since each season only represents a sample of one 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. The question remains: how can this demonstrable effect and knowledge of climatic patterns be translated into impact (ie. improved outcomes)? 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 (9). 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 (9). Although modelling approaches are frequently the tools of choice, the type of model required will differ depending on geographic scale, required inputs and information needs.

Some specific examples of the value 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 Madden–Julian oscillation (18);

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 (24);
3. bulk handling and marketing agencies which require accurate regional commodity forecasts to assist them in storage and transport logistics and export sales well before harvest (12);
4. government agencies which require objective assessments of the effect and severity of climate variability on production (eg. 15) and
5. policy makers who require impact assessments of greenhouse scenarios for input into international treaty negotiations (eg. 14).

Other applications are currently under development and will incorporate climatic patterns associated with, for instance, the latitude of the subtropical ridge (30), the Antarctic Circumpolar Wave (40) and decadal and multi-decadal climate signals (25).

Farmer decisions

Hammer (9) 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 on the Darling Downs, Qld. 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 more profitable on average 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 (Fig. 4).

Comparing the tactical and fixed management approaches over the complete historical climate record gave an average gross margin increase about 6% (or 11% in profit; calculated by deducting fixed costs) when using tactical management. 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 generates collective learning (9). 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.

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 producer 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; it must also account of current production costs, commodity prices and soil condition.

Recent studies with selected farm managers in Queensland indicate that by using climate information in conjunction with systems analyses producers can become less reliant on climate information. 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 for 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 (24).

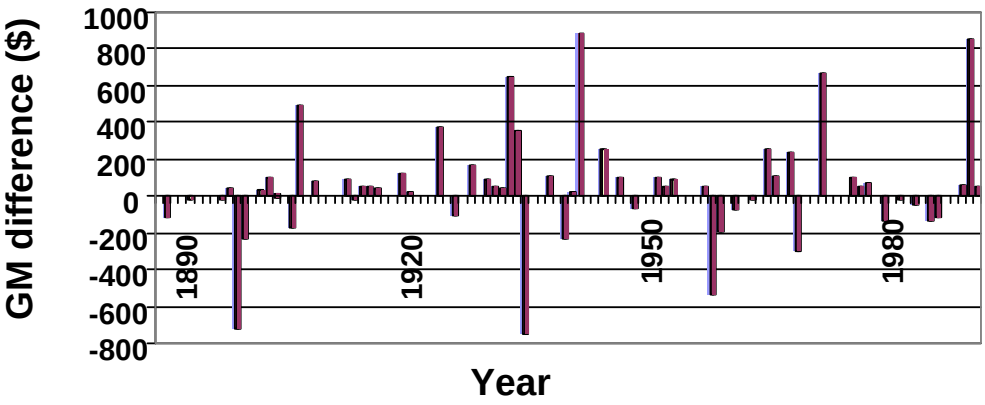

Fig. 4: Differences in gross margin between a tactical (responsive to seasonal forecast) and fixed (non-responsive) row configuration management strategies for each year of a cotton simulation study. Reproduced from (9).

Marketing decisions

Based on ENSO information (35) and a shire-based wheat model (34), Hammer et al. (12) 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 at the beginning of the cropping season. This system is now run operationally for Queensland by updating the projection each month based on the actual rainfall that has occurred and any change in the SOI phase from month to month. Although there appear to be commodity forecasting applications, this system was designed to inform government in Queensland 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. (3). Anecdotal information received from marketing agencies based on their experience with the 2000 regional wheat outlook showed that seasonal crop forecasting in their decision making processes can be beneficial 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.

Policy decisions

For the seasonal to inter-seasonal time scale, Keating and Meinke (15), Stephens (34) and Hammer et al. (12) have shown how point-source and regionally based production models can be used to quantify exceptional circumstances and drought impacts. Howden et al. (14) give 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. (33) found that by 2100 changes in temperature, CO_2 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.

SUMMARY

We demonstrated how knowledge of climatic variability, its frequencies and its causes can lead to better decisions in agriculture regardless of geographical location. Amongst the most important tools are probabilistic climate forecasting capabilities and agricultural simulation models that allow objective evaluation of alternative decisions at the farm, marketing or policy level. To achieve such improved outcomes requires effective interdisciplinary research to develop holistic analytical approaches that adequately capture our ever increasing understanding of the physical systems. 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.

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