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Advances in application of climate prediction in agriculture

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Abstract

Agricultural ecosystems and their associated business and government systems are diverse and varied. They range from farms, to input supply businesses, to marketing and government policy systems, among others. These systems are dynamic and responsive to fluctuations in climate. Skill in climate prediction offers considerable opportunities to managers via its potential to realise system improvements (i.e. increased food production and profit and/or reduced risks). Realising these opportunities, however, is not straightforward as the forecasting skill is imperfect and approaches to applying the existing skill to management issues have not been developed and tested extensively. While there has been much written about impacts of climate variability, there has been relatively little done in relation to applying knowledge of climate predictions to modify actions ahead of likely impacts. However, a considerable body of effort in various parts of the world is now being focused on this issue of applying climate predictions to improve agricultural systems.

In this paper, we outline the basis for climate prediction, with emphasis on the El Niño-Southern Oscillation phenomenon, and catalogue experiences at field, national and global scales in applying climate predictions to agriculture. These diverse experiences are synthesised to derive general lessons about approaches to applying climate prediction in agriculture. The case studies have been selected to represent a diversity of agricultural systems and scales of operation. They also represent the on-going activities of some of the key research and development groups in this field around the world. The case studies include applications at field/farm scale to dryland cropping systems in Australia, Zimbabwe, and Argentina. This spectrum covers resource-rich and resource-poor farming with motivations ranging from profit to

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food security. At national and global scale we consider possible applications of climate prediction in commodity forecasting (wheat in Australia) and examine implications on global wheat trade and price associated with global consequences of climate prediction.

In cataloguing these experiences we note some general lessons. Foremost is the value of an interdisciplinary systems approach in connecting disciplinary knowledge in a manner most suited to decision-makers. This approach often includes scenario analysis based on simulation with credible models as a key aspect of the learning process. Interaction among researchers, analysts and decision-makers is vital in the development of effective applications — all of the players learn. Issues associated with balance between information demand and supply as well as appreciation of awareness limitations of decision-makers, analysts, and scientists are highlighted. It is argued that understanding and communicating decision risks is one of the keys to successful applications of climate prediction.

We consider that advances of the future will be made by better connecting agricultural scientists and practitioners with the science of climate prediction. Professions involved in decision making must take a proactive role in the development of climate forecasts if the design and use of climate predictions are to reach their full potential.

Keywords: Systems analysis; Modelling; El Niño; Decision-making; Risk

1. Introduction

No one can predict what the next season will bring. Farmers, input suppliers, traders, marketers, and governments would all like to know because it is critical to their decision making. Instead they face uncertainty that delivers risk (i.e. a chance of incurring loss) to their business and livelihood. Strategies to cope with risk due to climate variability are often critical to survival of the farmer, agribusiness, or even the government in both resource-rich and resource-poor situations. At the very least, strategies to cope with risk due to climate variability significantly affect the economic, environmental and social stability of agricultural systems and associated communities. Many approaches have been developed to manage risk (either explicitly or implicitly) in these systems. These include maintaining storage reserves, diversifying production, insurance, forward selling, futures trading, government subsidies and taxation incentives. There is a body of literature on dealing with risk in decision making in agriculture and the influence of the decision maker's attitude to risk in that process (e.g. Anderson, 1991; Hardaker et al., 1997).

It is possible to predict, sometimes, that the next season is more likely to be in one end of the climatological distribution than it is in the other. This is because some of the year-to-year variations in climate are associated with patterns that are coherent on a large scale and this has provided a scientific basis for skilful prediction. The most dramatic, most energetic, and best-defined pattern of interannual variability is the global set of climatic anomalies referred to as (El Niño and the Southern Oscillation) ENSO. Cane (2000) reviews the state of understanding of the world's climate system and explains the underlying principles of the coupled ocean–atmosphere system that is ENSO (Fig. 1). Although the sea surface temperature patterns forming El Niño, the atmospheric circulation of the Southern Oscillation,

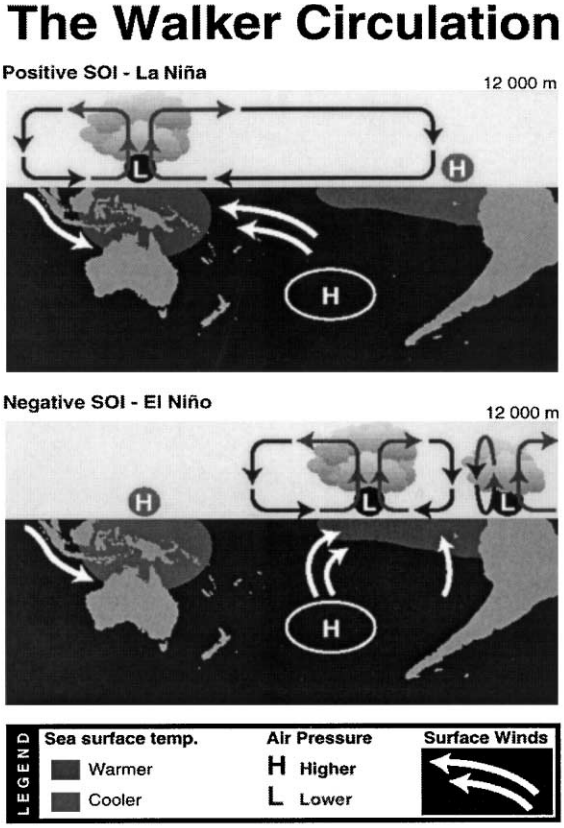

Fig. 1. Atmospheric and oceanic features of the El Niño-Southern Oscillation (from Partridge, 1994).

and their statistical associations with climate (e.g. Quayle, 1929) have been known for a considerable time, it was not until the 1960s that an explanation that depended on a two-way coupling between the atmosphere and ocean was proposed (Bjerknes, 1969, 1972). By adding the understanding of equatorial ocean dynamics introduced in the 1970s (Wyrtki, 1975, 1979), Zebiak and Cane (1987) produced the first model to successfully simulate ENSO (Cane et al., 1986).

ENSO has major effects on climate around the globe (Ropelewski and Halpert, 1987, 1996) and one indicator of the state of ENSO, the Southern Oscillation Index (SOI) has been used to forecast global rainfall probabilities (Stone et al., 1996). As a general rule, the effects of an ENSO event are strongest and most reliable in the tropical Pacific genesis region and contiguous continents (e.g. Peru and Indonesia). However, ENSO also has an influence in extra tropical latitudes, but the response is often less certain than in the tropics. By examining conditional climatologies based on phases of the SOI, Stone et al. (1996) identified predictive skill in regions beyond those identified by simple correlation analysis with indicators of ENSO (e.g.

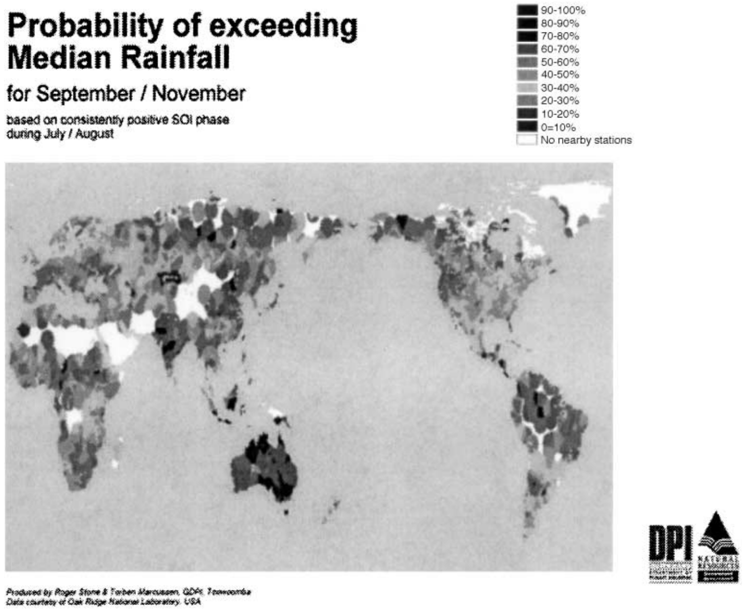

Fig. 2. Probability of exceeding median rainfall following a positive phase of the Southern Ostillation Index in September–October (copy of colour map from http://www.dnr.qld.gov.au/longpdk (after Stone et al., 1996)).

Ropelewski and Halpert, 1987; Fig. 2). Although the capacity to model the world's climate system is progressing rapidly (Hunt and Hirst, 2000), statistical forecasting systems based on the SOI or (Sea Surface Temperature) SST patterns remain the major source of seasonal forecasts used in agricultural practice. This reflects not only on current levels of forecasting skill but also on the method of forecast delivery — a point we shall return to later.

There are major climate forcing factors other than ENSO that are relevant to seasonal to interannual climate prediction. The North Atlantic Oscillation (NAO), which is usually defined by an oscillation in sea-level pressure between stations in Iceland and the Azores, has well identified connections to climate anomalies in Europe, North Africa, the Middle East, and eastern North America (Hurrell, 1995). SST variations in the tropical Atlantic have been related to droughts in the Sahel region (Folland et al., 1986) and the Nordeste region of Brazil (Nobre and Shukla, 1996). Indian Ocean SST anomalies have relationships to climate anomalies in Australia that are independent of ENSO (Nicholls, 1989). Cane (2000) notes that while statistical associations with these factors have been identified, it is not clear whether any of these modes can be predicted several seasons ahead and their interaction with ENSO is mostly not understood. There is clearly more research required before these factors can be utilised confidently in climate prediction.

There has also been recent interest in climate variations at decadal time scales. Various analyses of historical atmospheric pressure and SST compilations have isolated several modes of variability operating on decadal to secular time scales (Latif et al., 1997; Folland et al., 1998; Allan, 2000; White, 2000b). This research indicates that not only do some of these climatic modes display ENSO-like structure and rainfall relationships at these time scales (Allan, 2000), but that they interact with interannual ENSO signals to provide important modulations of the phenomenon. Consequently, protracted El Niño and La Niña event sequences, such as the 1990–1995 El Niño period, are manifest through the superposition of interannual ENSO and decadal ENSO-like modes in the climate system. While this low frequency variability can confound statistical forecasts at the seasonal time scale, it also provides considerable scope for improvement if the interactions of signals at the various time scales can be interpreted in relation to their climatic consequences (e.g. Power et al., 1999).

Along with increased understanding and predictability of ENSO, has come increased awareness of associated impacts and opportunities to utilise forecasts. However, it is vitally important to distinguish between application of a seasonal climate forecast and the impact of a particular climatic event. There is a rich literature on impacts of ENSO on agriculture and other sectors (see Glantz, 1996; White, 2000a) and a number of specific reports of impacts on crop production in various countries (Nicholls, 1985, 1986; Hammer and Muchow, 1991; Rimmington and Nicholls, 1993; Cane et al., 1994; Khandaker, 1996; Meinke and Hammer, 1997; Phillips et al., 1999). Application of a seasonal climate forecast differs considerably from impact or anticipated impact. While impact refers to the extent of effect, application of a forecast refers to the pre-emptive management response aimed at changing the anticipated impact. In this way, the forecast can acquire value. A seasonal forecast has no value unless it generates changed decisions. But for the forecast to be effective the decision changes must produce positive changes in value by improving the relevant aspect of system performance targeted (Murphy, 1994; Hammer, 2000a). A considerable body of effort in various parts of the world is now being focused on this issue of applying climate predictions to improve agricultural systems. Some studies have examined tactical changes in decisions associated with a seasonal forecast (Mjelde et al., 1988, 1997; Hammer et al., 1991; Lagos and Buizer, 1992; Keating et al., 1993; Hammer et al., 1996b; Marshall et al., 1996; Meinke and Stone, 1997). Mjelde et al. (1998) have reviewed current evidence on economic effects of use of climate forecasts in agriculture.

It is becoming clear that skill in climate prediction offers considerable opportunities to agricultural system managers via its potential to realise system improvements (i.e. increased food production/profit, reduced risks, and improved food security policy). This involves a shift from passive acceptance of climate variability and associated impacts to active response to a climate forecast (Hammer and Nicholls, 1996). Realising these opportunities, however, is not straightforward as the forecasting skill is imperfect and approaches to applying the existing skill to management issues have not been developed and tested extensively. A general lack of understanding of probabilistic information and difficulty in communicating risk and probability often impede progress (Orlove and Tosteson, 1999; Nicholls, 2000; White, 2000a).

While these difficulties are not trivial, there have been major developments in systems approaches in agriculture that provide a sound basis for research and development in applications of climate forecasting. (Hammer, 2000a) outlines concepts associated with a systems approach to management and how these concepts provide a suitable means to apply seasonal climate forecasting within a decision-making context. The systems approach highlights inclusivity of all key players and combines biophysical, economic and social considerations within a communications process that facilitates education of all players, while seeking system improvements. The actual climate forecast is a small part of this comprehensive process.

In this paper we present a selection of major recent and on-going case studies of applications of climate forecasting at field–farm and nation–global scale. The case studies involve various parts of the world, cover both resource rich and resource poor situations, and have varying degrees of sophistication and completeness. Our main objective is to synthesise the key lessons on approaches to applying climate prediction in agriculture for all involved — climate and agricultural scientists, economists, analysts, sociologists, advisers, and decision makers. Does this diversity of examples give rise to some common issues? Are there implications for a general methodology of approach to applying climate forecasts in agricultural systems? We firstly present each of the case studies as a separate vignette that gives rise to its own lessons before attempting to synthesise key lessons in a general discussion.

2. Case studies at field–farm scale

2.1. Zimbabwe — forecast application in resource poor farming

Interannual climate variability in southern Africa has been known to be related to ENSO for over a decade (Ropelewski and Halpert, 1987; Janowiak, 1988; Kiladis and Diaz, 1989; Matarira, 1990; Jury et al., 1996). Given the devastating impacts of the droughts of the 1980s and early 1990s in the region, initial thrusts of applications of seasonal forecasts were directed towards food security, with a bias toward early warning of potential famine and planning for drought relief (Cane et al., 1994; Orlove and Tosteson, 1999). More recently, focus has shifted towards food production management, i.e. ex ante interventions that would lead to mitigation of the negative impacts of poor rainfall (Phillips et al., 1998). The case of applications of seasonal climate forecasts to the agricultural sector in Zimbabwe is reviewed here, with particular focus on small farmers.

The agriculture sector in Zimbabwe is stratified into two distinctive components: commercial, high input, high production farmers; and small-scale, low input farmers, usually referred to as 'Communal Farmers' using terminology left from the pre-independence period (Masters, 1994). Communal farmers contribute roughly half of the total national grain output, and participate in markets to the degree that they cannot be strictly considered subsistence farmers. Maize is the principal grain, with millets, sorghum, and groundnuts playing an important role in food production, and cotton and tobacco being major cash crops. There is a single rainy season, occurring in summer, and amounts range from less than 500 mm annually with very poor temporal distribution in the lowlands, to over 1400 mm evenly distributed over the season in the highlands to the east. Communal farmers are disproportionately concentrated in the poorer rainfall zones and are thus exposed to greater climate-related risk than most commercial farmers.

Given the constraints imposed by the socio-economic and agro-ecological environment in which communal farmers operate, the first step in applications research was to delineate the potential role that seasonal forecasts could play in farm management for the small farm sector in Zimbabwe. A survey was conducted across a range of agro-climatic zones during the 1997–1998 El Niño season (225 households) and the 1998–1999 La Niña year (450 households). Interviews were conducted in Shona and Ndebele languages both before planting and post-harvest, returning to the same set of households each time. Specific objectives of the survey were to (1) identify and catalogue the use of traditional climate forecasting schemes, (2) assess access to seasonal climate forecasts issued by the Zimbabwe Meteorological Service, and (3) evaluate current opportunities and constraints in the farming system which may limit adoption of forecasts in decision making (Phillips et al., 2001). Additional meetings were held with farmers across all the study areas in July and August of 1999 to corroborate survey data and allow for more nuanced understanding of farmer perceptions and needs (Chester, 2000). These findings support and guide the conclusions reported here.

2.1.1. Constraints and opportunities for applying seasonal climate forecasts

2.1.1.1. Access to, and use of, credit. The farming systems found in communal areas in Zimbabwe are very much shaped by exposure to risk with much of this risk being related to climate variability (Mataruka, 1985; Mombeshora and Mudhara, 1994; Shumba, 1994). The use of credit for example is very low, especially now that government has greatly reduced support for agricultural loan programmes. Less than 20% of the survey population reported ever using credit, with fear of failure to repay and lack of knowledge on where to obtain credit being the most common reasons. Inputs requiring cash outlays such as fertiliser are only used on the most important crops (usually maize) and in extremely low quantities, with other chemical inputs almost never used. If left to the private sector, agricultural loans may be extended as a function of the expected season, with availability increasing in 'good' years and decreasing when a poor year is expected. There were unconfirmed reports in Zimbabwe of a decrease in loans extended to the commercial farm sector in 1997–1998, with a strong El Niño brewing, but even in 1998–1999, with an increased expectation of a wet year, the number of farmers in our survey population making use of loans was only 5.3%, not significantly different from the 3.2% who borrowed in 1997–1998. Until skill level and confidence in the forecasts become much improved, increases in the extension and use of credit for purchased inputs to take advantage of favourable years are not likely to be felt among small farmers in Zimbabwe. Furthermore, misinterpretation of the probabilistic nature of the forecast by the banking sector could have negative repercussions, highlighting the need for improvements in communication of the forecast.

2.1.1.2. Time of planting. Long before seasonal forecasts were available it was recognised that late planting, primarily due to bottlenecks in labour and draft animals, was one contributing factor to low yields (Mataruka, 1985; Campbell et al., 1989; Shumba, 1994). Unless winter ploughing has been done, farmers wait until enough rain has accumulated to soften soils so that ox-drawn ploughs can be operated. Poor animal health at the end of the dry season also contributes to the draft-power limitations. Furthermore, few crops are dry planted because the risk of losing seed is costly. Although forecasts of the start date of the rainy season was commonly cited as potentially helpful by farmers interviewed in this study, it seems that medium-term forecast information (7–10 day) would be more likely to be of value in helping farmers determine planting date than seasonal forecasts, given limitations in skill and temporal resolution.

2.1.1.3. Crop choice and area sown. While some of the adaptive strategies that have evolved to cope with production risks faced by communal farmers, such as minimising inputs and use of credit, are not likely to be influenced by seasonal forecasts at present, others may be well-suited for incorporation of climate forecasts if information is available in a timely manner. Communal farmers not only plant a wide variety of crops each year but the areas devoted to each vary regularly. Crop choice and percentage of arable land sown reflect both how the previous season fared [in years following a bumper harvest, grain stores are full, there is likely to be more cash for purchases, and greater production risks can be born (Scoones, 1996)], and expectations for the coming year. Based on Zimbabwe National Early Warning Unit estimates (1999), in 1998–1999, total area planted to the five major crops (maize, sorghum, finger and pearl millet, and groundnuts) increased by 16% over the area planted in 1997–1998. Among farmers surveyed in this study, 45% identified increase in area planted as the primary strategy adopted in response to the expectation of a wetter than average year in 1998–1999.

In contrast to farmers wholly dependant on saved open-pollinated seed stock, there appears to be potential to exploit the fact that virtually all communal farmers purchase hybrid maize seed (Masters, 1994; this study) by encouraging the use of varieties targeted for the forecast. Before planting in 1998–1999, farmers who expected a wet year (either as a result of hearing the forecast or through traditional forecasting schemes) more commonly cited intentions to plant later-maturing maize varieties than those who did not have a forecast. At the end of the year, many farmers had planted even later-maturing varieties than intended, potentially a result of 'real-time' decisions made after seeing how very wet the year was. In most areas surveyed, changing variety planted was the third most common suggestion regarding useful strategies, whereas in the wettest zone, where high rainfall had set records in a number of locations and flooding was common, changing crop altogether was mentioned equally often in the post 1998–1999 season survey. We found a 16% increase in the number of farmers intending to plant maize and an equal decrease in the number intending to plant pearl millet relative to what they said they 'normally plant' in 1998–1999, given improved chances of a good year. The percentage of farmers intending to add maize to their crop mix was even higher (35%) when restricted to the drier Natural Regions 4 and 5, where maize often fails even in 'normal' years, and millet and sorghum are the dominant crops. In some areas where paddy rice has traditionally been grown but seed stocks were lost during the droughts of the late 1980s and early 1990s, farmers identified rice as an appropriate crop for 1998–1999 but were unable to plant it due to lack of seed.

Access to seed, in fact, is a constraint that currently limits the use of seasonal forecasts. Even though farmers purchase maize seed annually, the number of varieties available at the village-level is not high, and in some cases no seed arrives in the local shop until quite late in the planting season. When farmers who deviated from their stated intentions for the season were asked the reason for planting something different than intended, the most common response was that they could not get seed. Reasons ranged from prices being too high to deliveries coming too late. Furthermore, the forecast presently is not issued until the month when planting begins. Farmers in most cases have already purchased their seed, and the better farmers have purchased it months in advance to avoid high prices that develop around planting time. Even if the forecast is issued early enough and seed is made available, other factors may inhibit farmers from switching varieties. The most commonly planted maize hybrid, R201, which has been on the market since the 1970s, is valued for its robust performance under rainfall variability. Unless farmers have some confidence in seasonal forecasts, they may be less likely to risk planting a hybrid with high potential under good rainfall if it cannot tolerate drought in case good rains are not realised.

2.1.2. *Communicating seasonal forecast information*

Making wise strategic decisions depends on having quality information. In Zimbabwe, the media played a large role in disseminating forecast information in the 1997–1998 El Niño year, though at a cost in terms of distortion. The official forecast was quite cautious and probabilistic, calling for probabilities never exceeding 50% chance of rainfall in the lowest tercile of historical records during the December–January–February period. But the message reaching the public was interpreted as expectation of a drought, with memories of the disaster in 1991–1992 still vivid. Ultimately, survey results on perceptions of the outcome of the season, in line with observed rainfall, show that both climate and crop yields were perceived as 'good' in the northern parts of Zimbabwe and only in the typically dry south perceived as poor, which aligned more with the forecast greater expectation of low rainfall. Total area planted to maize by both commercial and communal farmers was down by 27% compared with 1996–1997, while maize yields only fell by 8% compared with the year before (FAOSTAT Data base, FAO). This discrepancy undoubtedly led to ill feelings towards the Meteorological Service, as production opportunities were missed.

In 1998–1999, the number of people reporting having heard the official forecast dropped from over 90% to less than 40%, as a result of the lack of media attention. Nonetheless, given the prevalence of traditional forecasting schemes, which are based on factors ranging from winds and flowering of trees to forecasts delivered via village spirit mediums, almost all farmers interviewed had some expectation of conditions for the season. In both 1997–1998 and 1998–1999, the majority of accounts of the traditional forecast were in agreement with the official forecast. A better understanding of local perceptions of climate phenomena and factors used in traditional forecasts would help in developing appropriate dissemination pathways and messages. Efforts are currently underway to develop a radio programme in collaboration with the Zimbabwe Meteorological Service and the Ministry of Agriculture's Extension Service to increase climate forecast awareness among the rural population with hopes of improved understanding and interpretation of seasonal predictions and potential applications.

2.1.3. Lessons

It appears that there are opportunities for resource-limited farmers in Zimbabwe (and potentially elsewhere) to utilise seasonal forecasts to improve crop production and overall farm management if quality information is available. However, given that a lack of safety nets such as insurance or robust savings define the context in which decision making is being conducted, attention to forecast skill and potential risks associated with forecasts need to be considered in defining what is meant by 'quality' information. Communicating these risks can be assisted by developing climate scenarios that represent the distributions of uncertainty, and pairing them with crop simulations focusing on the most likely strategies to be of use to farmers with system limitations such as those revealed by the survey. Applications encouraged in this context should probably be limited to safe strategies such as shifts in area planted to drought tolerant and drought vulnerable crops and changes in total area planted, with the degree of alteration being defined by the degree of certainty in the forecast. Trade-offs between various maize hybrids and the small grains available is likely to be particularly well suited to investigation with simulation models, once model parameters are developed for this context. Applications to riskier strategies, such as enhanced use of fertiliser, may become possible subsequently. However, this would likely require government support in the first instance. Ultimately, communications efforts need to focus on the probabilistic nature of climate predictions and implications for impacts under a range of management alternatives, so that final management decisions are left for farmers to decide themselves, given clear understanding of the strengths and limitations of the forecast and the consequent outcomes and risks.

2.2. Australia — manipulating crop management in sub-tropical dryland farming systems

The cropping systems of the northern grain region of Australia are characterised by the opportunity to produce a wide range of cereal, pulse, oilseed, forage and fibre crops. Both summer and winter crops are grown, with yields largely determined by water supply from either in-season rainfall or storage in the soil prior to planting. Rainfall is a key determinant of both the nature of the production system and variation in financial returns. The region experiences overlapping influences from the summer rainfall system of the tropics and the winter rainfall system of the temperate zone. While the diversity in crop choice and planting time can be seen as advantageous, the high variability in seasonal rainfall means that the prospects for any one crop is often risky (Hammer et al., 1996b). Fallowing the soil between crops in order to build-up soil moisture storage in the generally high water-holding soils is a recommended management strategy to offset the risk of low in-season rainfall. However, fallow lengths of up to 18 months result in low cropping frequencies and, in some locations, may be contributing to resource degradation through increased soil erosion or solute leaching (Freebairn et al., 1991; Turpin et al., 1996). As an alternative to rotations of fixed fallow length, opportunity cropping has become more prevalent in many parts of this region. This represents the practice of planting a crop whenever a planting opportunity is triggered, based usually on the accumulation of a minimum level of soil moisture storage and occurrence of a planting rain.

Agriculture in this region has also entered a period of perhaps unprecedented challenge. Continued profitability in the face of an unrelenting cost–price squeeze depends heavily on compensating gains in production efficiency. A current rule of thumb is that increasing yield by 15% will double profit; a similar yield decline will eliminate profit. Margins for error in decision management will continue to diminish. This is particularly relevant in these systems where most managers are risk averse (Hardaker et al., 1997). Optimising crop yields and enterprise mix, maximising efficiency in resource use, and skill in marketing have been identified as key aspects of successful farm business management (Wylie, 1996). While the profit motivation is foremost in management of these extensive and mechanised farming systems, this is within the context of community and farmer expectations on maintaining resource and environmental integrity. Cropping farms are generally large (300–3000 ha), managed as commercial businesses, attract few subsidies and support or protection schemes, and produce for global and domestic markets at world prices. Farmers are supported by private and public advisers and by mostly public research, which they influence and partly fund through a research levy on production.

Integral to management skill in these areas is the managers' understanding and perceptions of likelihood of subsequent rainfall. There is obvious potential for seasonal climate forecasts in managing these cropping systems. A number of studies have demonstrated value in seasonal climate forecasting for improving tactical agronomic management of crops and optimising yields (Hammer et al., 1991, 1996b; Marshall et al., 1996: Meinke et al., 1996; Meinke and Hochman, 2000). Other initial studies have explored possibilities in relation to crop rotation (Carberry et al., 2000; Hammer et al., 2000) and crop marketing decisions (Chapman et al., 2000). While these studies have focused on predictability derived from ENSO, mostly via the SOI phase system of Stone et al., (1996), some comparative analysis of forecasting systems has been undertaken (Hammer et al., 1996b, 2000).

2.2.1. Integrated systems approach to applying seasonal climate forecasts

There has been a rich experience of interaction among researchers, advisers (public and private), and farmers in the development of use of seasonal climate forecasting in management of these farming systems (Hammer, 2000a). Significant initial interaction was focused around the forecasting capability and communication/education processes via workshops and meetings that used rainfall analysis software such as Rainman (Clewett et al., 1994) to reinforce the concepts of ENSO, SOI, and probability shifts in seasonal rainfall. This was closely linked with simulation analyses of scenarios for crop management, giving expected outcome distributions for sets of historical analogue years (Hammer et al., 1991). The simulation approach using historical climatic analogues was built on a history of development and use of crop modelling and simulation as a general means to support decisions in this highly variable environment (Hammer et al., 1987; Woodruff, 1992; Hammer et al., 1996a). This systems approach has underpinned the development of decision analysis procedures in agriculture (Dent and Anderson, 1971; Anderson and White, 1991).

A systems approach in a problem-solving context requires on-going connections between decision-makers, advisors, modellers and researchers for effective outcomes. This integration of skills is required to achieve the balance needed between practicalities of system management, needs of decision-makers, and development and use of system simulation or expert knowledge to evaluate options. Checkland (1983) noted that the failure to be more aware of the human factor had resulted in a general failure of quantitative systems analysis approaches to influence what practitioners do. The failure of the analytical methods to adequately address the human factor has lead to the emergence of different methodologies for dealing with people-related issues, such as learning processes (e.g. Bawden and Packham, 1991). McCown et al. (1994) argued that the best prospects for developing better policy and management strategies lie with skilful use of systems analysis tools within a human systems philosophical framework. An interdisciplinary and participative approach facilitates this combination and has been found effective in farming systems activities (McCown et al., 1994).

An integrated and participative systems approach has been used in applying skill in seasonal climate forecasting in these dryland farming systems. Initial studies and analyses by researchers to introduce possibilities (e.g. Hammer et al., 1996) have been quickly replaced by analyses most relevant to farmers (e.g. Meinke and Hochman, 2000). Professional advisers have played a key-linking role in this iterative process of balancing supply (possibility) with demand (feasibility). The most relevant issues have been associated with optimising crop choice, cropping intensity and crop management. Outcomes from simulation analyses are used as a basis for discussion of scenarios being considered by farmers. The analysis provides a useful and significant input to the farmer's decision making. It must, however, be placed in the context of other factors outside the analysis that impinge on the decisions.

To facilitate discussions and meet growing demand effectively, many of the simulation analyses can be pre-packaged by awareness and anticipation of key issues, which is engendered by close interaction with advisors and farmers. This is particularly the case for crop management and crop choice issues. Where greater flexibility or specificity is required, such as in rotational issues or applications in specific fields, it is necessary to conduct simulations tailored to meet the requirements. We have combined these approaches using a range of crop models based on a generic crop model template (Hammer, 1998) that form modules of the cropping system simulator APSIM (Agricultural Production Systems Simulator; McCown et al., 1996).

Simulations can then be conducted as part of specific discussions (Meinke and Hochman, 2000) or can be used to form data bases that can be interrogated during discussions (Nelson et al., 1999, 2001). In both cases there is a focus on expected outcomes and riskiness associated with scenarios arising from discussions with farmers. A detailed example is given elsewhere in this volume (Meinke et al., 2001), so here we will outline underlying principles and tools.

2.2.2. Whopper Cropper — a crop management discussion support system

Whopper Cropper is a software tool designed to facilitate the application of seasonal climate forecasting to crop management in farmer-driven workshops (Nelson et al., 1999, 2001). It was developed in response to a demand by extension professionals for access to business critical information derived from the cropping systems modelling capability of APSIM (McCown et al., 1996) and the type of seasonal climate forecasting capability exemplified by Stone et al. (1996). It provides information on the impact of climate risk on crop yields for crop management alternatives beyond the experience of individual farmers, using historical climate records to obtain a very long-term perspective. Whopper Cropper's graphical user interface is relatively unstructured and is designed to support farmer-driven workshops that enable farmers to explore management strategies using context-specific reasoning.

An approach using crop models to develop a decision support system similar to Whopper Cropper was reported by Jamieson et al. (1992), and Whopper Cropper draws heavily on, and extends this earlier research. APSIM is a very precise daily time step model that mathematically reproduces the physical processes taking place in a cropping system, providing a capacity to simulate the effect of climate variability on crop yields. Complex research models can be made more relevant to farmers by deconstructing their output using simpler translation models (Cox et al., 1997). Whopper Cropper is a database of pre-run APSIM simulations with an easy-to-use graphical interface facilitating time series, probability and diagnostic analyses. To create the Whopper Cropper database, a team of researchers from the Agricultural Production Systems Research Unit (APSRU) have used the APSIM model to simulate a variety of crops with different starting soil conditions and management options, for 16 major cropping regions in NE Australia. Each combination of region, crop, sowing date, starting soil conditions, etc. defines a single simulation. The current Whopper Cropper data base contains somewhere around 180,000 of these simulations. Each simulation is as long as the historical climate records available for that region, and most simulations in the Whopper Cropper database are over 100 years long. This database is constantly expanding via interaction with extension professionals seeking to cover new areas, crops and management alternatives. Whopper Cropper facilitates access to simulations that generate information that is focused on discussion of farmers' immediate cropping opportunities and constraints and in a form designed by extension professionals for such discussions.

The long-term simulations in the Whopper Cropper database can be divided into groups of analogue years based on SOI phase (or phase of any other seasonal climate forecasting system). Distributing simulated yields by SOI phase enables crop management advisers to discuss with farmers the best management options for the coming season and also facilitates evaluation of forecast skill. Data for any combination of crop and management can be presented as time series and as various forms of probability distribution (cumulative, box plot, pie chart). Differences between specific scenarios can be examined similarly to facilitate comparison.

An example time series analysis (Fig. 3) shows the year-to-year variability of simulated yields for a sorghum crop in central Queensland sown in mid-November with a specified soil condition (water-holding capacity, available soil water and N at sowing) and crop management (hybrid maturity, planting density, applied N). The annual outcome for this scenario is compared with the long-term median, and the years in which the October SOI phase was positive. For this scenario, when the SOI phase was positive, 21 (or 9) of the 30 occurrences were associated with higher (or lower) than median yields. Similar graphs can be produced for each SOI phase and management strategy.

The value to crop management of skill in seasonal forecasting based on SOI phases stems from the shift in expected yield distributions associated with each of the five phases. Pie charts, box plots and cumulative probability graphs can be used to analyse the distribution of crop yields for each group of analogue years. While box plots present less information about each distribution than cumulative probability graphs, they provide a means to clearly compare a number of distributions side-by-side. For the sorghum cropping scenario, the distribution of yields for years with a positive phase at the end of September–October has a higher median and lower risk of low yields than the distributions for the other phases (Fig. 4). This shift provides a basis for targeting of management in relation to the likely outcome. For example, management intensity could be increased in years with positive SOI prior to sowing to take advantage of increased chance of higher yields and decreased risk factors.

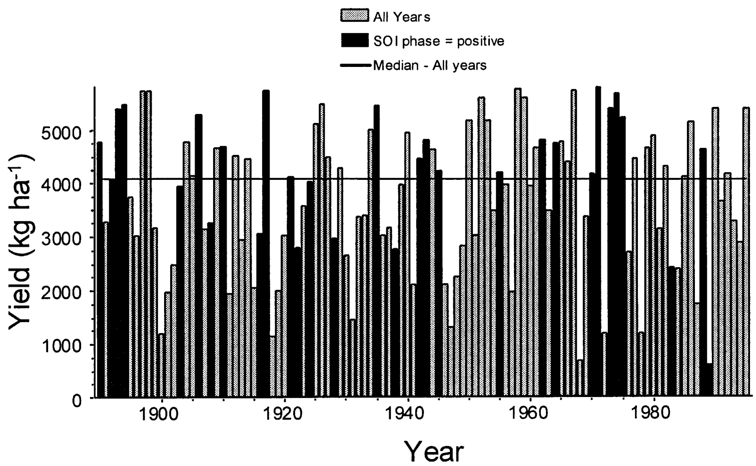

Fig. 3. Time series of simulated sorghum yields for for a mid-November sowing in central Queensland with specific soil and management conditions (see text). The horizontal line is the long-term median yield and years with consistently positive SOI phase in September–October are highlighted.

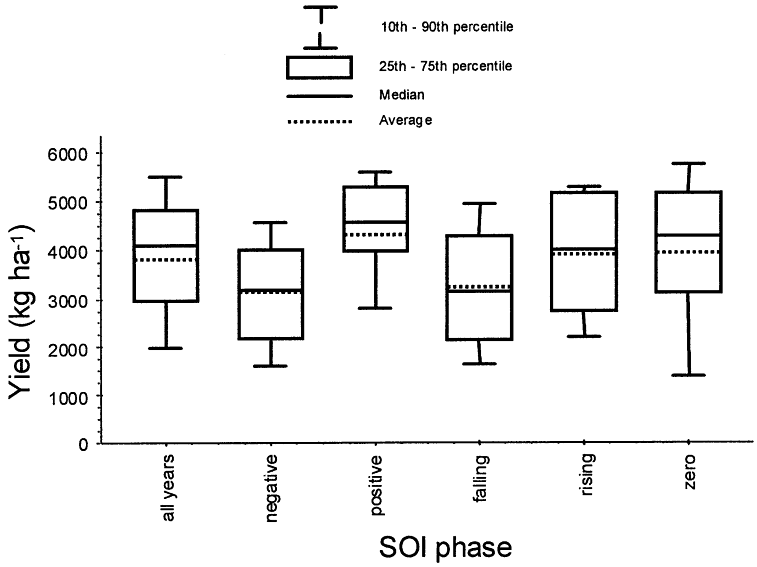

Fig. 4. Probability distribution of simulated sorghum yields for each September–October phase of the SOI for a mid-November sowing in central Queensland with specific soil and management conditions (see text).

Whopper Cropper could be used to examine outcomes associated with increased management intensity (later maturity, higher density, and increased N fertiliser) and financial payoffs and risks determined.

In the location used in this example, sorghum is usually sown in December–January. As well as having highest median yields (Fig. 5a), it often takes until this time to fill the profile with enough water for planting. However, a box plot analysis indicates that with a positive SOI phase in September–October, higher and less risky potential yields could be achieved by sowing in November–December (Fig. 5b), if the soil water was available. For the purposes of this scenario, the farmer may decide to sow in November, and then wants to know what combination of management options to employ. Whopper Cropper can be used to assess any combination of simulations in the database to pursue this question. The analysis also provides the basis for a discussion about possibilities for double cropping into a winter crop the next year — a possibility considerably enhanced by sowing the summer crop early. Hence, while shifts in distributions are not great, they provide sufficient shift to modify critical decisions. Feedback evaluations from workshops with groups of growers have indicated a range of management decisions that have been changed as a result of this process.

One of the key issues in discussing use of seasonal forecasts in management decision making concerns reliability of outcomes. We know that the forecasts are not precise and the decision-maker faces a sample of one from a possible distribution of outcomes. Previous analyses have shown that while adjusting management in response to a forecast will pay-off in the long run, it does not pay-off on every

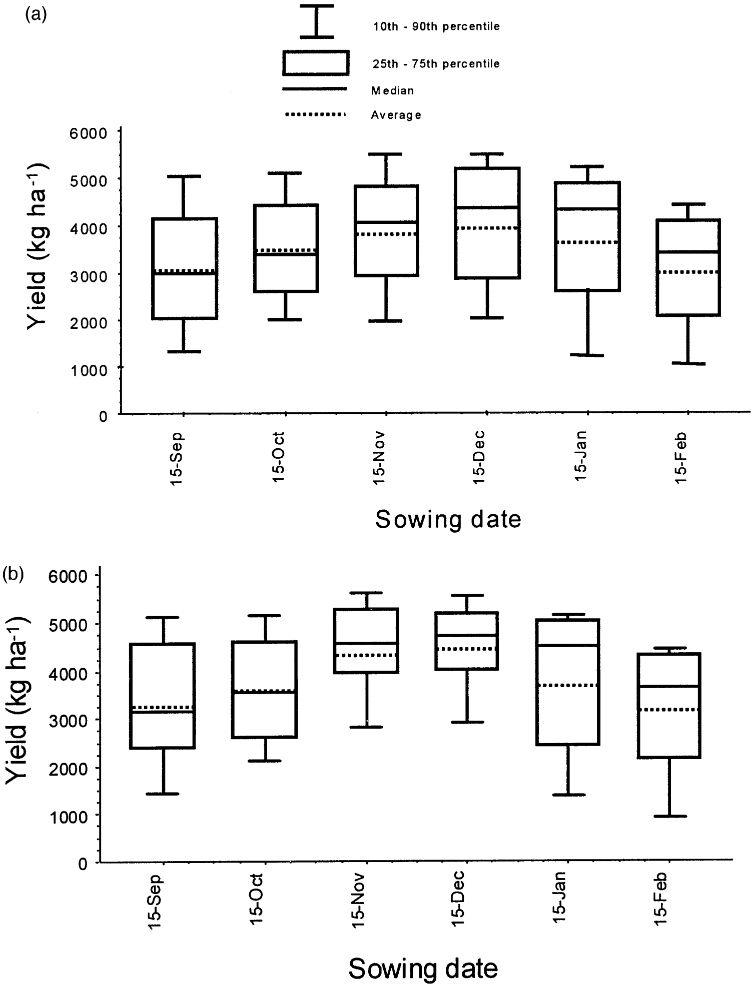

Fig. 5. Box plot of simulated sorghum yields for a range of sowing date in central Queensland with specific soil and management conditions (see text); (a) distributions derived using all years, (b) distributions derived using those years with September–October SOI phase consistently positive.

occasion (Hammer et al., 1996b; Hammer, 2000a). This point is communicated well by comparing the optimal tactical decision response (i.e. one that varies from year-to-year depending on the forecast) to the optimal fixed decision (i.e. the single best-bet decision over all years in the analysis) on a year-to-year basis. Hammer (2000a) showed in a simulation study with cotton that by adjusting row arrangement (from solid to single skip row to double skip row) in response to a seasonal climate forecast, profit could be increased by about 11% in the long term. When the tactical and fixed decisions were compared on a year-to-year basis, although the tactical approach came out ahead on most occasions, there were many years when adopting the tactical approach resulted in decreased profit, and sometimes substantially

(Fig. 6). In discussing management responses to forecasts we have found it imperative to highlight this point as we know there are no 'rights' and 'wrongs' with this technology — just shifts in distributions. Orlove and Tosteson (1999) note the credibility crises that have arisen in some countries when this approach has not been taken.

2.2.3. Lessons

There are three major lessons from the work on application of seasonal climate forecasting in NE Australia. Firstly, it is essential to include all players in the process. This includes farmers, advisers, analysts/modellers, and researchers. This helps to define the critical issues as seen by decision-makers, to introduce new possibilities from all quarters, and to generate credibility for information derived from modelling and analysis. Whether models are used directly or indirectly in this process is secondary to the discussion and the targeting attained by seeking the balance between the possible (supply) and the feasible (demand) in that dialectic.

Secondly, the leap directly from a seasonal forecast to a decision is too great to be done (well) intuitively. The use of modelling and scenario simulation and associated analysis adds substantial value by enabling information to be much more relevant to the decision in question then the general piece of information contained in the forecast. There are numerous possibilities and interactions and the insights gained from analysis of expected outcomes and risks provide a much more relevant and rich information source for the decision-maker.

Thirdly, and most importantly, it is essential to frame all discussions and analyses in the context of climatic uncertainty and the risks it generates within the target system. There are no right and wrong answers — there are just shifts in probabilities. Some of these shifts provide substantial opportunities for proactive risk management. While there is on-going concern about difficulties in communicating probabilistic information, we see little difficulty with this if it is done in a clear, simple and transparent way that is relevant to the decision maker.

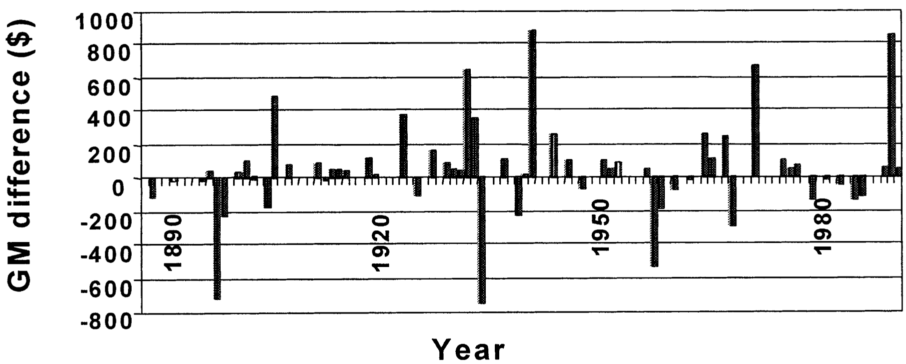

Fig. 6. Difference in gross margin between tactical (responsive to seasonal climate forecast) and fixed (non-responsive) row configuration management strategies for each year of the cotton simulation study (from Hammer, 2000a). The mean annual gross margin difference was $+\$28$ ha^{-1} year^{-1}.

2.3. Argentina — adjusting cropping mix in temperate dryland farming systems

The temperate Pampas region is the main agricultural region of Argentina, and an important contributor to the world supply of wheat and oilseed crops. The region is characterised by extensive rainfed production of field crops under highly variable (CV = 28%) rainfall (Hall et al., 1992). Climate risk increases toward the western part of the region due to an east–west gradient (1000–600 mm year^{-1}) in mean precipitation. The CV of crop yields in the western districts ranges from 11% for sunflower to 20% for soybean. Median crop losses (i.e. planted area that is not harvested) range from 15% for wheat to 35% for sunflower. Farmers are well organised, and benefit from a capable network of public- and private-sector researchers and advisors.

The El Niño-Southern Oscillation (ENSO) accounts for much of the interannual variability of the climate of the Pampas (Kiladis and Diaz, 1989; Halpert and Ropelewski, 1992; Ropelewski and Halpert, 1996). During La Niña events, maximum temperatures and solar irradiance tend to be higher, and minimum temperature and rainfall tend to be lower than normal. El Niño events show an opposite but weaker influence. ENSO influences crop yields in the region through its influence on precipitation, temperatures and solar irradiance (Podestá et al. 1999a; Magrin et al., 1998). Maize, soybean and sorghum yields tend to be lower than normal during La Niña events. Sunflower yield shows a weaker and opposite response. Maize is clearly the most responsive of the major field crops to increases in rainfall during El Niño events.

The predictability of climate and yield variability associated with ENSO suggests a potential to tailor agricultural production decisions to either mitigate the negative impacts of adverse conditions or to take advantage of favourable conditions. Late in 1996, researchers from the Florida Consortium of Universities (Podestá et al., 1999b) and INTA (Instituto Nacional de Tecnología Agropecuaria) began a collaborative effort to improve management of agricultural production in the Pampas using ENSO-based climate forecasts. Early interactions with stakeholder organisations in the region indicated that farmers perceived more flexibility to change allocation of land among crops than to change crop management. Therefore, one facet of the research has been to explore the potential for tailoring farm-scale crop mix to expected conditions associated with ENSO phases. In this case study we explore application of seasonal climate prediction to land allocation on farms and outline some of the lessons learned. Because details of the model study are in Messina et al. (1999), we present only a brief overview.

2.3.1. Land allocation modelling

An economic optimisation model was used to explore the potential for managing climatic risk through land allocation conditioned on ENSO phase. The model identifies the crop mix that maximises expected utility of wealth based on given costs and prices, risk preferences, and crop yields simulated for each of a given set of weather years. It assumes that farmers allocate land to cropping enterprises in a way that maximises the expected utility of wealth at the end of a 1-year planning period for given expected weather conditions. Although the fairly standard formulation (e.g. Lambert and McCarl, 1985; Chavas and Holt, 1990) is flexible enough to handle a variety of linear constraints such as availability of labour or equipment, the study considered only non-negativity and farm size constraints to land allocation. Aversion to risk is encapsulated in the degree of curvature of a non-linear utility function. The power function,

$$U(W_{\mathrm{F}}) = W_{\mathrm{F}}^{1-R_{\mathrm{r}}}/(1 - R_{\mathrm{r}})$$

used in this study implies constant relative risk aversion, R_{r}, and decreasing absolute risk aversion with increasing initial wealth, W_0 (Hardaker et al., 1997). Calculation of expected utility for a given crop mix and climate expectation is based on distributions of yields of each crop predicted by dynamic, process-oriented crop simulation models using historic daily weather data. The models used were those in version 3.5 of DSSAT (Jones et al., 1998) — Generic-CERES (Ritchie et al., 1998) for maize and wheat, CROPGRO (Boote et al., 1998) for soybean, and OILCROP-SUN (Villalobos et al., 1996) for sunflower. Co-operating INTA scientists have had extensive experience calibrating, testing and applying these models in the Pampas (e.g. Baethgen and Magrin, 1995; Travasso and Delécolle, 1995; Meira and Guevara, 1997).

The optimisation model was applied to representative farms in two contrasting environments. Pergamino is in the climatically favourable eastern humid region, where the dominant crops are maize, wheat and soybean. Santa Rosa is in the drier western region, where yields are more variable due to years with water deficits. More drought-tolerant crops — wheat, sunflower and sorghum — dominate in this region. Table 1 summarises the main features of the two case-study farms.

To assess implications of ENSO for optimal land allocation, the model was solved separately for El Niño, neutral and La Niño years from within the period 1930–1931 to 1997–1998. The difference in returns to optimal land allocation tailored to ENSO phases and land allocation optimised for all years provides a measure of the potential value of climate information embodied in ENSO phases.

Table 1
Characteristics of representative farms in Santa Rosa and Pergamino

Location	PESW[a] (mm)	Annual precip.		Crop area (ha)	Land value (ha^{-1})	Fixed cost (US$ ha^{-1})	Fixed costs of production (US$ ha^{-1})				
		Total (mm)	CV (%)				Maize	Wheat	Sunflower	Soybean	
										Sole	Double[b]
Santa Rosa	251	644	30	600	827[a]	71[a]	216	103	142	202	175
Pergamino	305	932	26	630	2200	133	234	139	145	202	175

[a] Plant extractable soil water.
[b] Double crop with wheat.

Model-based analyses of decisions for hypothetical farms necessarily entail many assumptions that are difficult to verify, and that may impact results substantially. We therefore analysed the sensitivity of predicted optimal crop mix and potential information value to risk aversion, initial wealth, prices, and initial soil conditions.

One test of an economic decision model is how well it predicts observed behaviour. For both locations, predicted optimal crop mix under moderate aversion was quite similar to the reported mean land allocation among the five cropping systems in the surrounding districts (Fig. 7). The model predicted increasing diversification with increasing risk aversion. In general, diversification reduces farm-scale income risk when yields show low or negative correlation among crops.

Differences in optimal land allocation among ENSO phases (Fig. 8) were consistent with known influences of ENSO on precipitation, and differences in sensitivity to water availability among crops. Crops that either tolerate water stress (i.e. sunflower in Santa Rosa) or avoid periods of water shortage during critical development states (i.e. wheat and soybean in Pergamino) dominate the optimal crop mix for La Niña events. Maize — generally the most profitable crop under adequate rainfall — consistently dominated the optimal crop mix for El Niño in Pergamino.

Tailoring optimal land allocation to ENSO phase increased predicted mean farm income between \$5 and \$15 ha^{-1} year^{-1}, depending on location, risk aversion and initial wealth (Fig. 9). Potential information value was not a simple, monotonic function of risk aversion, as predicted by Hilton (1981). Predicted value increased in Pergamino but decreased in Santa Rosa with R_r increasing above 1.0. Crop mix and potential information value also varied with crop prices and initial soil moisture assumptions. Prices in 1987, 1988, and 1997 favoured soybean monocultures for all

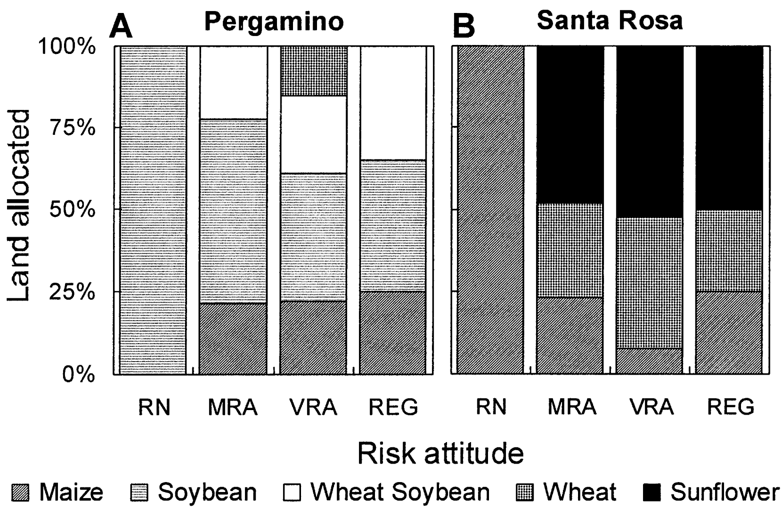

Fig. 7. Predicted optimal crop mix at (A) Pergamino and (B) Santa Rosa for risk-neutral (RN), moderately risk-averse (MRA) and very risk-averse (VRA) farmers, and mean land allocation in the surrounding district (REG).

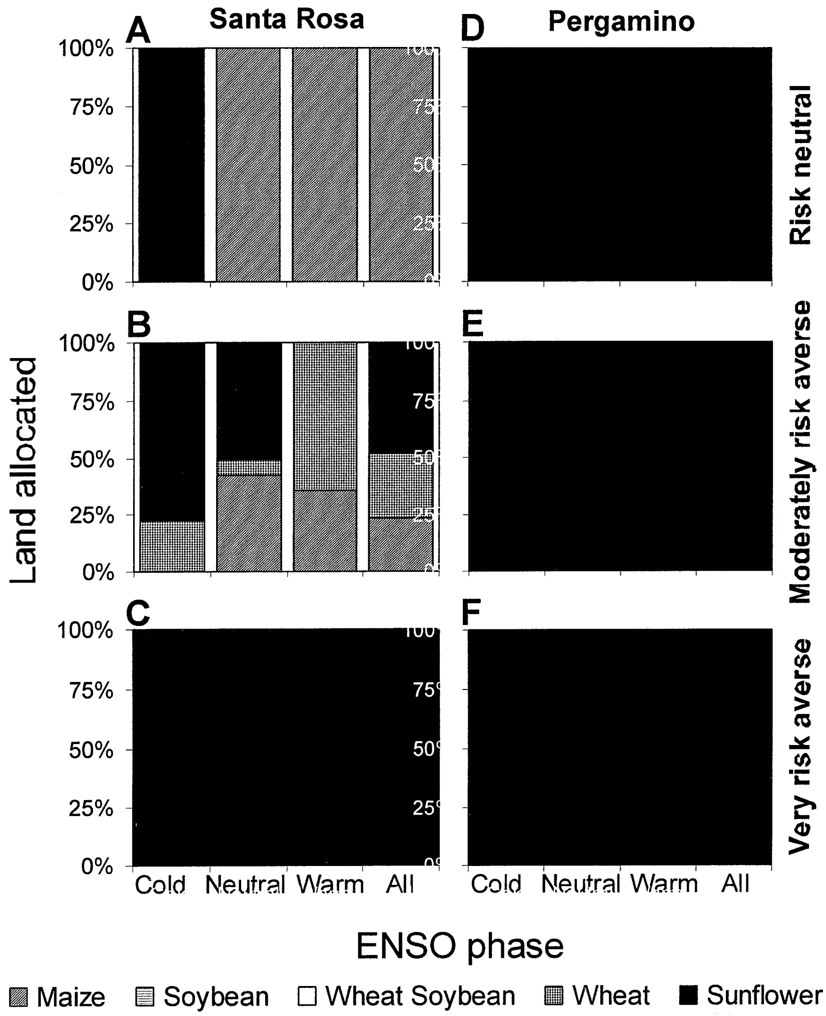

Fig. 8. Crop mix optimised for each ENSO phase for (A–C) Santa Rosa and (D–F) Pergamino for (A, D) neutral, (B, E) moderate, and (C, F) high levels of risk aversion.

ENSO phases for the moderately risk-averse farmer in Pergamino, eliminating the flexibility needed to benefit from ENSO information.

2.3.2. Farmer perceptions

An early project-planning workshop with stakeholder groups (i.e. producer organisations, input suppliers and marketing co-operatives) revealed general interest in exploring climate prediction applications, but scepticism about the reliability of forecasts, and limited flexibility to change crop management in response to forecasts. Participants, however, suggested that farmers would change crop mix if given reliable forecasts.

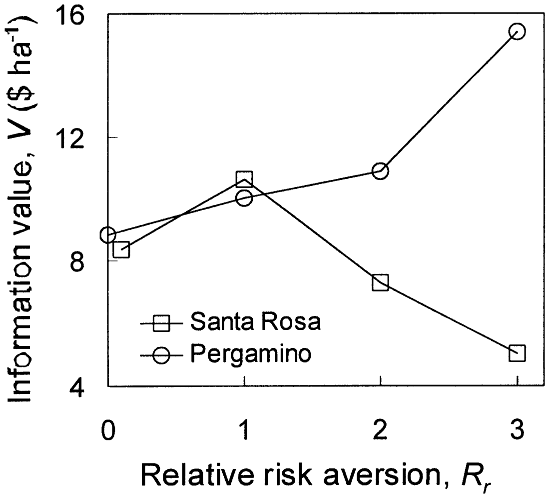

Fig. 9. Predicted potential value of ENSO information as a function of relative risk aversion at Pergamino and Santa Rosa.

The 1997–1998 El Niño event received a great deal of media coverage in Argentina. Of 11 farmers and farm managers interviewed in November 1997, most indicated that they would vary crop mix if given a reliable seasonal forecast. Two of the farmers had already modified their normal crop mix in response to media coverage of the El Niño, increasing areas devoted to maize in anticipation of abundant rainfall. The accuracy and publicity of predictions associated with the 1997–1998 El Niño, and the experience of those who had modified crop mix based on those predictions, generated enthusiasm and raised high expectations.

As the 1998–1999 summer crop season approached, many farmers were eager to apply seasonal forecasts to their operations. A farmer co-operative hosted presentations by two meteorologists. One, a well-known INTA scientist, provided a probabilistic analysis of the potential effects of La Niña on the region's climate, urging appropriate caution. The co-op farmers, apparently dissatisfied with the inconclusive prediction, invited a meteorologist from the private sector to a subsequent meeting. He predicted, with confidence that the rains that had just passed (in October) would be the last they could expect for some time. Many took his advice to minimise the area planted to maize in favour of more drought-tolerant crops. The ensuing growing-season precipitation was near normal. As the season progressed and they watched their 'uninformed' neighbours' maize prosper, the farmers' enthusiasm turned to disillusionment.

2.3.3. Lessons

Tailoring land allocation to seasonal climate forecasts appears to be a viable option for managing climate risk and increasing mean income. The methodology and model are general enough to be applied in other regions, provided adequate data are available. Because the economic model was implemented in a spreadsheet, it is quite portable and easily modified to account for additional enterprises, constraints and decision criteria.

Application of climate forecasts to farm-scale land allocation decisions is a fairly simple example of the linkage of different types of models traditionally associated with different disciplines: from seasonal climate forecast to distributions of crop yields simulated with biophysical models, to distributions of predicted outcomes, to an economic optimisation model of farmer behaviour. Uncertainty analysis is already built into the process of using historical weather years in each ENSO phase, and into the economic objective function. Climate prediction formats other than ENSO-phase categories might require additional steps to disaggregate regional, seasonal forecasts to plausible realisations of local daily weather, and to represent uncertainty correctly.

Our analyses benefited from good sources of regional soil, climate, cultivar and economic information, and from prior experience of scientists and producers in the region with prediction and decision-support applications of crop models. Sensitivity analysis revealed the importance of information and assumptions that are likely to vary among farms and among years. As expected, predicted optimal crop mix was very sensitive to commodity price variability. Ratios of prices among commodities do not have to shift very far before they favour the same monoculture in each ENSO phase, thereby eliminating the flexibility to respond to climate variability by adjusting crop mix. Results were also sensitive to differences in initial soil moisture conditions associated with the preceding year's crop and ENSO phase. These results highlight the importance of obtaining current information about prices and soil conditions. Farmers' aversion to risk is more difficult to measure than most of the other information required by the models.

Several co-operating farmers have been testing model-derived field-scale crop management strategies, tailored to ENSO phases, in small plots on their farms. Because land allocation is necessarily a farm-scale decision, model-derived crop mix cannot be tested on a small scale with minimal risk to the farmer. Farmer behaviour does, however, seem to support model results, both in the case of district-average crop mix, and in the case of individual farmers who adjusted land allocation based on recent ENSO-based forecasts.

Farmer enthusiasm after the 1997–1998 El Niño and disillusionment following the 1998–1999 La Niña suggests several lessons. Enthusiasm from the 1997–1998 El Niño was useful for promoting public awareness and co-operation. However, that same enthusiasm may have distorted public perceptions of forecast skill, and generated unrealistic expectations. A gap apparently exists between researchers' and farmers' concepts of the probabilistic nature of climate forecasts and decision outcomes. Methods of presenting probabilistic forecasts to decision-makers, and the ability of decision-makers to process that information remain important research questions. In one case, a private sector forecast provider and advisor apparently misunderstood and miscommunicated the uncertainty of seasonal climate expectations associated with La Niña, resulting not only in unexpected financial loss for a group of farmers, but also in a loss of credibility of seasonal climate forecasts. Elimination of maize from the crop mix in 1998–1999 is consistent with near indifference to risk. However, it is also consistent with perceived risk (i.e. the perceived dispersion of possible outcomes) differing markedly from quantitative estimates of risk (i.e. the modelled dispersion of possible outcomes). Wise use of climate forecasts requires a clear understanding of the uncertainties involved, and recognition that a wise decision will not necessarily result in a superior outcome every year.

3. Case studies at national–global scale

3.1. Regional commodity forecasting in Australia

The logistics of handling and trading Australia's grain commodities, such as wheat, are confounded by huge swings in production associated with climate variability. Advance information on likely production and its geographical distribution is sought by many industries, particularly in the recently deregulated marketing environment. Such information is also sought by government in relation to policy interventions triggered by the degree of exceptional circumstances (e.g. drought). Recent research has pointed to the potential to improve forecasting of the Australian wheat crop and its spatial distribution using regional crop yield models combined with seasonal climate forecasts (Stephens et al., 2000), but this information is not widely available or used in government or industry. In this case study we present a regional commodity forecasting system, examine its effectiveness in forecasting regional wheat yields for the 1999 season and consider more general possibilities for use of the information.

3.1.1. Regional commodity forecasting system (RCFS)

The RCFS combines a simple agro-climatic model for wheat, with near real-time climate data, and projected seasonal climate based on the SOI phase system of Stone et al. (1996) to generate a crop forecast that can be updated each month through the growing season. The potential of agro-climatic yield models to explain most of the variation in wheat yield across Australia has been demonstrated by Stephens (1995). The agro-climatic model (Stephens, 1995) uses a weekly soil water balance to determine the degree of water stress experienced by the crop. This index is used in a simple regression model to predict wheat yield for each wheat-producing shire (local government area) in Australia. The index is similar in concept to that proposed by Nix and Fitzpatrick (1969). It utilises biophysical knowledge of the crop, allows consideration of soil type effects, and derives the stress index by contrasting soil water supply with crop demand. The regression model was fitted to historical shire wheat yields (Australian Bureau of Statistics, 1975–1993). The variance of wheat yield explained, using the stress index, range between 78–93% at state level and was 93% at national level.

Near real-time daily rainfall data sets for over 800 recording stations are collated and used in running the model up to the end of a particular month. Historical climate data from SOI-phase analogue years (i.e. years in history most like the current year) are then used to project likely yields for each wheat-growing shire. Depending on the SOI phase, this may involve from 15–20 individual projections. Summary statistics are derived from the projections. The map in Fig. 10 shows the probability of exceeding median wheat yield for each wheat-producing shire as predicted at the beginning of the wheat season (end of May) using the RCFS. This shows good chance of above median yield in parts of Western Australia and poor chance of above median yield in much of NSW, Queensland and South Australia. This map is updated each month as the season progresses and as well as indicating the likely size of the total crop, it highlights those areas where production has greatest chance of being abnormally high or low. This provides forward warning in relation to logistics for transport and quantifies the potential need for exceptional circumstance support from government for producers adversely effected by drought. This product was based on a similar concept that had been developed from a spatial modelling system for grazing lands in Queensland (Carter et al., 2000). The motivation in both cases was largely driven by demand from government in relation to drought policy implementation.

3.1.2. Potential of seasonal climate forecasting

To examine the potential utility of seasonal climate forecasting, the monthly update throughout the 1999 season was done using projections based on all years as

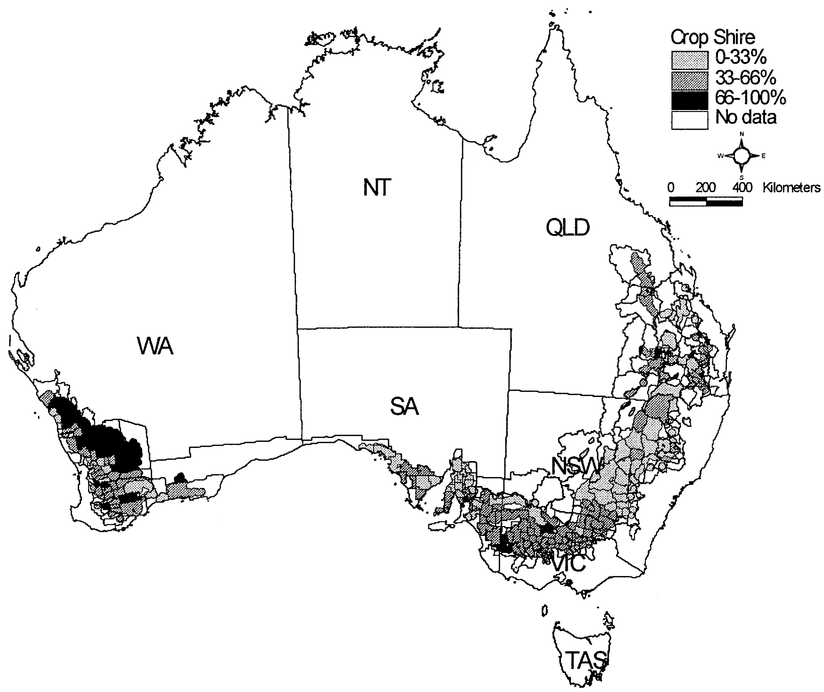

Fig. 10. Probability of exceeding median wheat yield in 1999 for all wheat-producing shires in Australia. Probabilities were calculated at end of May 1999 based on seasonal projections using SOI-phase analogue years (April–May SOI phase rapidly falling).

well as on the subset of years associated with the current SOI phase. The distributions generated were compared at state and national levels (Fig. 11).

Although, there was no strong ENSO signal in effect during 1999, the projections based on the historical analogue years associated with SOI phases tended to have narrower distributions early in the season and shifted towards the final outcome sooner than the projections based on use of all years for a number of states. A greater sample of seasons is required before any general conclusions about utility of forecasts can be drawn. Hindcasting studies are currently underway so that a more robust comparison can be made.

Historically, forecasts have not been produced in a probabilistic manner. Agencies responsible derive single estimates based on adjustment from knowledge of previous year(s) or from projections of median rainfall. This approach retains simplicity, but at the expense of any information on production risk.

3.1.3. Implications and lessons

This case study indicates potential for use of seasonal forecasts in commodity forecasting for government policy support and for decision making in industry. The system was designed primarily in relation to policy needs and is about to become operational for this purpose. It provides the quantification in time and space required to assist government decision making in relation to implementing drought policy. More specific products, such as maps identifying areas at extremely high risk will likely be developed as the interaction with policy users develops. The

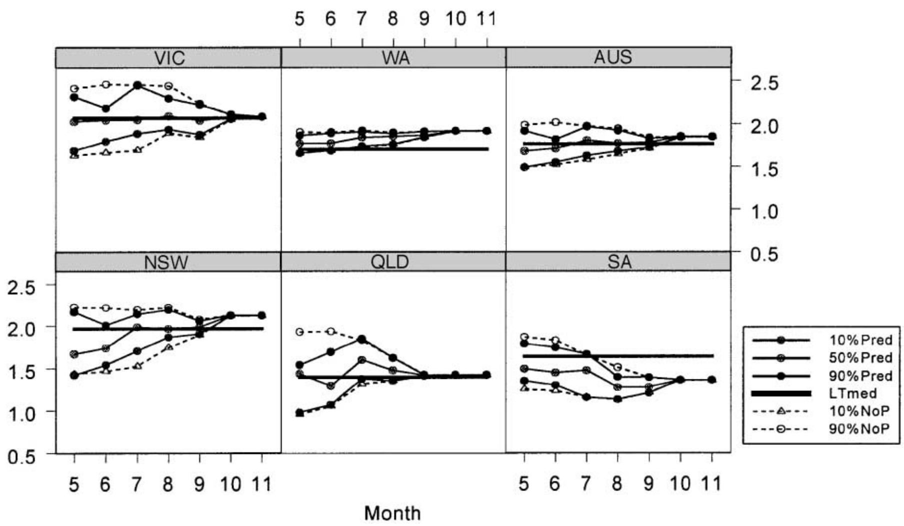

Fig. 11. Wheat yield predictions for Australia (AUS) and each state in Australia in 1999. Predictions are updated at the end of each month. The solid lines show predicted median and top and bottom decile for predictions based on the remainder of the season projected using a SOI-based forecast. The dashed lines show the top and bottom decile of the predicted values at the end of each month when all years in the historical record are used for projection. The horizontal line is the simulated long-term median yield (over all years).

presentation and interpretation of information on production risk and degree of 'exceptionality' is of prime importance. In addition, credibility of the forecasting/information system must be high for its effective use in this arena. This requires scientific rigour, accuracy and repeatability.

Although this system has not yet been interfaced with industry decision-makers in any detailed manner, it is sufficiently advanced to provide a useful basis for dialogue. One of the issues to emerge in preliminary discussions relates to the output of distributions. There is a range of awareness of risk management concepts in the business sphere. Where this is well developed, rapid utilisation of possibilities seems most likely. Otherwise, greater effort is required to develop awareness of the gap between what is possible and what is expected.

3.2. International wheat trade

International wheat (*Triticum aestivum* L.) trade is presented as a case study to illustrate the possible influence of improved climate forecasts on societal benefit in a global context and the distribution of that benefit between producers and consumers. Consumers derive benefit (consumer surplus) when the effect of technology advance results in lower prices, whereas producers derive benefit (producer surplus) when the effect results in increased returns to producers. Wheat production is selected for several reasons. First, wheat is an agricultural commodity that is particularly vulnerable to climate variability, because it is typically grown in relatively arid regions of the world. Second, some of the largest wheat producing regions in the world are in areas in which consistent weather patterns associated with the El Niño-Southern Oscillation (ENSO) have been identified. Third, within the global economy, wheat is the largest traded agricultural commodity. During the 11-year period, 1986–1997, an annual average of 97.454 million metric tons of wheat was traded worldwide. The USA is the largest exporter of wheat with an average market share of 34.5%. Canada and Australia are two of the remaining largest exporters with an average of 20 and 12% of the world wheat trade. Third, wheat is grown in areas in which few substitute crops exists. In addition, wheat use has few substitutes unless prices are abnormally high or low. These aspects allow for wheat to be considered in isolation of other crops as a first approximation.

3.2.1. Trade model

The model used in this analysis is a stochastic-dynamic model representing wheat production, consumption, inventories, and trade for three major exporting countries: United States, Canada, and Australia (Hill, 2000). Argentina, a fourth major exporter, is modelled in much less detail in this first version of the trade model than the United States, Canada, and Australia. Importing nations are treated as an aggregate called the rest-of-world. Imports are modelled as the difference between behaviourally specified consumption and production equations.

Production in each exporting country is determined as the product of cropped area and yield. Area response is determined through econometric methods using historic price and cropped area data. Because ENSO-based climate forecasts, however, are a recent development, few producers currently use this information to adjust their production practices. Consequently, historic production data based on the use of ENSO-based forecasts are not available. A proxy for actual producers' behaviour must be used. Biophysical simulation models are used to obtain estimated yield effects that result from the use of ENSO-based climate forecasts of local climate. This entails simulating crop yields under a range of climatic conditions, input combinations, and expected output price levels for representative sites across Australia, Canada, and the United States. The simulated output is then validated with historic yield information. Aggregate yield estimates with and without improved climate forecasts are then obtained. Simulated yields are regressed on assumed expected prices to obtain estimated yield response to expected price changes. Hill et al. (2000) provide details on the simulation and aggregation procedures. Argentina's production is based on historical yields and climate conditions, but producers are assumed to not adjust inputs based on forecasted climate conditions as is the case with the other three major exporters.

A major challenge to estimating the effects of improved climate forecasts on supply is incorporating forecast information into price expectations. With the availability of ENSO-based climate forecasts, producers may adjust their inputs, which will alter production. Producers' rational expected price, therefore, must be based on expected production that uses a different production distribution than the historic distribution. ENSO-based climate forecasts may lead to increases or decreases in wheat supply of an exporting country. Such changes shift that country's excess supply (wheat available for trade). These shifts cause a change in the equilibrium price. Consequently, the model considers ENSO-based forecasts' effect on both producers' price and yield expectations. The effect of climate forecasts on price expectations is included by adding historic weather information into a model of price expectations that assumes quasi-rationality. Quasi-rational price expectations assume that producers efficiently utilise available information and provides a method for adjusting the price in anticipation of shifts in the excess supply curves because of the use of improved climate forecasts. Price expectations are obtained both with and without ENSO-based climate forecasts. Each country's production is determined using the estimated cropped area response and yield functions and producer price expectations.

Each exporting country's production is incorporated into a balance equation. The balance equation consists of carryover stocks from period $t-1$, the respective country's current production, the country's consumption, exports, and storage for the following period. Aggregate consumption is modelled as a behavioural equation as a function of price, income, and population. Storage is determined via an intertemporal equation that equilibrates marginal storage cost with the expected marginal revenue from future sales. Future wheat price is based on the quasi-rational expected price equation. The USA's inventory equation is inverted to obtain a price equation. All other prices are related to the USA's price through a price adjustment equation that includes exchange rate adjustments and transportation differentials. Exports are determined as the difference between current production plus beginning inventory and current consumption plus ending inventory. USA exports are equal to rest-of-world import demand minus Australian, Canadian, and Argentinean exports. These equations insure that the equilibrium price equates supply and demand and balances international trade.

The dynamic model simulates wheat production and trade for a 25-year time horizon. Expected present values of changes in producer and consumer surplus caused by the use of climate forecasts are calculated for each 25-year simulation. Climate forecasts are based on the five phases of the Southern Oscillation Index using the approach of Stone et al. (1996). Given the possible number of climate forecasts over a 25-year horizon, changes in producer and consumer surpluses are computed using Monte Carlo techniques. Simulations are based on random draws of climate observations from an empirical distribution of observed weather patterns. Results presented are based on 1000 simulations.

3.2.2. Results

By using Monte Carlo techniques, distributions of percentage changes in the present value of consumer and producer surplus are obtained. Producer and consumer surplus are measures of aggregate net benefits. As noted earlier, the model simulates 25 years of world wheat trade. All results are placed in present value terms, which explicitly acknowledges a dollar today is worth more than a dollar in the future.

Expected percentage change in consumer surplus for Australia, Canada, and the USA are 0.7, 0.6 and 1.0%. Producers in Australia, Canada and the USA can expect to gain 15.7, 5.3 and −5.1%. Distributions of the present value of percentage changes in producer and consumer surplus by country are presented in Figs. 12 and 13. As shown in these figures, not only does the mean differ by country, but the distributions vary around the mean changes. The standard deviation of the percentage

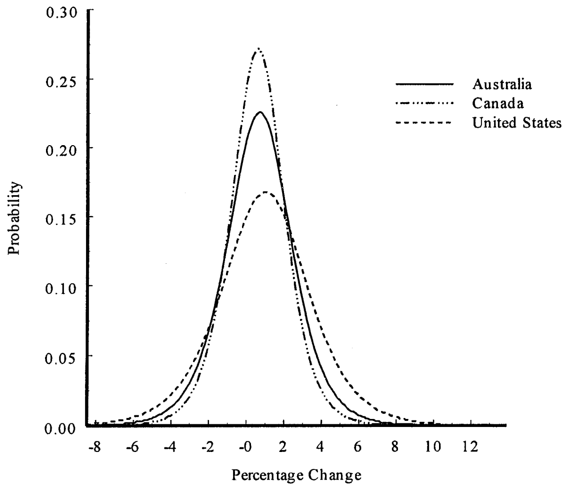

Fig. 12. Present value of percentage changes in consumer surplus associated with the use of ENSO-based climate forecasts in Australia, Canada, and the USA.

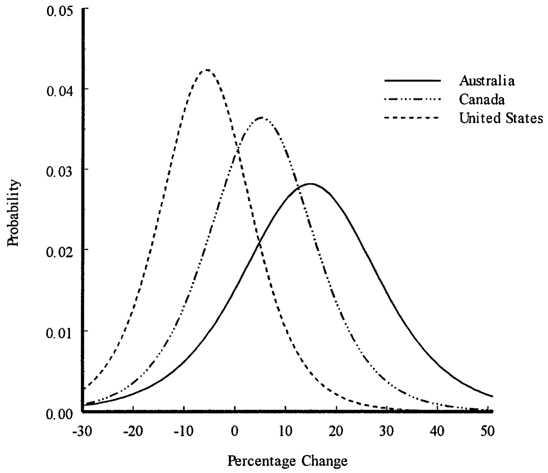

Fig. 13. Present value of percentage changes in producer surplus associated with the use of ENSO-based climate forecasts in Australia, Canada and the USA.

changes for Australia, Canada, and the USA are 2.0, 1.6 and 2.6% for consumer surplus and 30.8, 13.0 and 21.9% for producer surplus.

Expected increases in consumer surplus are approximately the same in each country. Benefits to producers, however, differ between the countries. As illustrated, on average producers from Australia benefit more in percentage terms than producers in either the USA or Canada. Several reasons contribute to Australia's gain. Firstly, the ENSO signal is stronger in Australia than in the wheat producing areas of Canada and the United States. Secondly, Australia has a smaller share of the world wheat market. Changes in production in Australia have a smaller impact on world price than in the other countries. Australian producers also have the largest distribution of gains. Canadian producers can expect the smallest distribution of benefits from the use of climate forecasts. Canadian results may be caused by a relatively concentrated area of wheat production and an ENSO signal weaker than associated with Australia. Coupling the magnitude of production in the United States, geographically disperse production, and a weaker ENSO signal than Australia explains the negative percentage changes in producer surplus.

As illustrated in Figs. 12 and 13, for all countries, there is a non-trivial probability of receiving a negative percentage change in either producer and/or consumer surplus over the 25 years. This probability is much larger for producers (especially in Canada and the USA) than for consumers. As expected these results reinforce the notion that actual benefits to producers and consumers will depend on the realised climate outcomes over the relevant time frame. Studies presenting only a long-run expected value to the use of climate forecasts ignore this issue. This issue is especially important in the policy area where decisions are made on shorter time frames than some long-run expected value to society. The distributions in Figs. 12 and 13, illustrate that various regions of the world will be effected differently. Further, even within a region, consumers and producers will be effected differently.

3.2.3. Implications and lessons

Although there are many simplifications in this initial analysis of effects of seasonal climate forecasts on international grain trade, it is clear that consumers benefit in the long run through the balance of effects on production and price. Long-run gains to producers depends on the country, that is the size of the wheat market share and the strength of the ENSO signal will affect the magnitude of the gains. The distribution of benefits is not uniform and it varies greatly from year-to-year. Questions concerning trade policy and research funding are raised by these results. For example, can trade policy in any country be modified to capture additional consumer and producer surplus? These results provide a basis for development of trade policies with such targets. In addition, given the distribution of likely benefits, who should fund research and education on the use of and improvement of climate forecasts? Capture of some benefits by consumers is likely, providing some justification for public funding of research and development. The analysis highlights the need to consider aggregate effects on price when examining value of forecasting to the producer. As in the previous case study, this analysis provides a starting point. It is needed to derive information in a form appropriate to enhance interaction and discussion with decision-makers or others that may be influenced by the results. In turn, further research and analysis will become better targeted to needs as awareness of possibilities is raised.

4. Discussion

4.1. Synthesis of key lessons

We set out the vignettes on application of climate prediction to examine intentionally the approaches and experiences associated with a diverse array of situations and scale. We wanted to synthesise the key lessons on approaches to applying climate prediction in agriculture for all involved — climate and agricultural scientists, economists, analysts, sociologists, advisers, and decision-makers.

There are a number of lessons arising when the case studies are considered together. The three major lessons that emerge are related to understanding and communicating risks, applying forecasts over a range of scale, and the interdisciplinary systems approach as a general methodological model.

4.2. Understanding and communicating risks

Perhaps the most obvious issue arising relates to understanding and communicating risks associated with the probabilistic nature of the climate forecast. This was highlighted in the case studies in Zimbabwe and Argentina, but was mentioned in all other cases as well. We know that it is not possible to predict precisely what the next season will be like. We know that not all El Niño events bring dry (wet) seasons. Yet there remains an acceptance of perceptions that seasonal forecasts can do this. And these perceptions are not only with system managers! Intermediaries, such as the media and some professional advisers, and some climate scientists continue to present forecasts in a categorical manner. The case studies highlight the difficulties introduced by simplifying, sometimes distorting, a probabilistic statement to a categorical one. It is a guarantee for loss of credibility as the distorted perception inevitably transfers to an over-reaction in decision adjustment, as noted in the Argentina case.

Understanding and communicating risks is critical to successful applications. While there are known impediments to communicating probabilistic information (Nicholls, 2000; White, 2000a), the Australian case study indicates a way to proceed. By focusing on targeted information about risks of outcomes in a manner developed by inclusive discussion, many of these issues can be resolved. The leap directly from a climate forecast to implications on management decisions is too great in an agro-ecosystem consisting of many non-linearities and biological and physical buffers and feedbacks. The case studies identify and demonstrate the considerable value-adding provided by modelling and analysis in exploring decision options and their risks. The results are not always intuitively obvious. Further, simple bar graphs, such as those produced by Whopper Cropper, provide probabilistic information on outcomes just by inspection. Chances of consequences are implicit in the presentation format and the critical point that even the decision leading to improved average outcome in the long run, will not result in a superior outcome every year, is highlighted. It is vital that this point be understood by all involved. While discussions with decision-makers invariably lead to aspects of risk management and exploration of options aligned to acceptable levels of risk, a degree of persistence and community education will likely be required for less focused activities, such as media releases of climate forecasts.

4.3. Applying forecasts over a range of scale

The case studies on commodity forecasting and global wheat trade identify potential applications of seasonal climate forecasting beyond on-farm decisions. It is notable, however, that the same systems concepts are relevant. Systems analysis and modelling provides the means to generate the information required by decision-makers at the relevant scale of operation. It is likely that interfacing information at broader scale with decision making in industry and government will provide substantial developments in applications of seasonal forecasting in the future.

The global wheat trade case study highlights the need to consider interactions across levels of scale. Implications identified at farm scale may be modified by aggregate effects on markets and commodity price. At a global scale this is complicated by the reality that the ability to forecast climate differs between regions in the world and that crop calendars are off-set by 6 months between hemispheres. While the study suggested there may be a global benefit to consumers in reduced price (if all producers react optimally to a climate forecast) the likely benefit to producers depends on their location. There is also a considerable range of outcomes so that, similarly to the farm level case studies, the outcome in any particular situation (consumer, producer, location) will vary from year to year, sometimes changing sign. Distributions of gains and losses geographically and between consumers and producers are often ignored or misunderstood when the effects of the use of improved seasonal climate forecasts are discussed. Distributions of gains and losses raises important issues concerning the public funding of climate forecast research and has policy implications at both national and international levels.

4.4. Interdisciplinary systems approach as a general methodological model

Applying seasonal climate forecasts effectively is not simple and neither scientists nor decision-makers know it all. The perspective each brings adds value beyond what can be achieved in isolation. This is demonstrated in the case studies by the role of linkages between scientist/analyst and decision-maker in seeking relevant decisions for introduction of this new technology. A balance is struck between what is most relevant and feasible given constraints operating in the system and what is possible with the forecast. In essence, this is the rationalisation of demand and supply via informed dialogue. As each player learns the limitations and possibilities, the questions become more focused and effectiveness is enhanced. The problem becomes clearly formulated and includes key aspects of the decision-makers role in the system and the various socioeconomic forces at play. The concepts of inclusivity and connectivity are critical to effective applications and form a key component of the integrated systems concept, which is outlined as part of the Australian case study. This concept has been applied to varying degrees in all of the case studies. The case studies presented here reinforce the utility of this approach as a general methodology for applying seasonal climate prediction in agricultural systems. This was noted by Hammer (2000b) in synthesising lessons from a number of detailed applications studies in Australia.

One of the strengths of the case studies presented here, is in the manner that information is targeted so that it is of more direct relevance to issues in the systems being managed and, hence, to decision-makers. The information of most relevance relates to likely outcomes in the target systems of viable decision options. A seasonal forecast on its own is not very useful to a manager of an agricultural enterprise. A probabilistic statement about the forthcoming season is often too far away from the implications on decision options facing the decision-maker for informed and effective application. In addition, an above (below) average rainfall season will not always convert to an above (below) average cropping season. There is a critical role for agricultural systems analysis and modelling in converting raw information on climate to information on likely outcomes of decisions. This is clear in all the systems and scales of activity examined in the case studies. Credible scenario analysis is essential to underpin discussions and provides the key link between climate forecast and its application. This point, which is also relevant to the communications issue (as noted above) is often overlooked, yet it involves often more research and development, and as much modelling, as for the development of the climate forecast. By combining targeted information in an inclusive approach the technology becomes effective by moving beyond knowledge and information to wisdom. There is a degree of learning that enables infusion of the technology into the decision-making milieu and generates improved focus in research.

It is instructive to note that all of the case studies presented use statistical forecasting systems that identify historical analogues as a means to derive seasonal forecasts. This is because of the importance of risk in applying the forecast, as discussed earlier. The spread of likely outcomes from a decision is at least as important as the likely shift in the mean, and is often more important. Hence, in addition to the likely mean anomaly, a credible seasonal forecast must give reliable information about the variability in the forecast anomaly. Beyond this, the analysis of outcome and decision risks often relies on simulation with agricultural models requiring daily climatic data as input, and historical analogues provide a logical means to make this connection. While it may be possible to develop agricultural models with simpler input requirements for some purposes, it is likely that the need for daily climate data will remain for many applications.

These issues require greater consideration in the design, development and delivery of seasonal forecasting systems than they have received to date. Effective applications in the future will depend on better connecting agricultural scientists and practitioners with the science of climate prediction. Professions involved in decision making must take a proactive role in the development of climate forecasts if the design and use of climate predictions are to reach their full potential.

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