PHILOSOPHICAL TRANSACTIONS OF THE ROYAL SOCIETY B

Phil. Trans. R. Soc. B (2005) **360**, 2109–2124
doi:10.1098/rstb.2005.1753
Published online 24 October 2005

Operational seasonal forecasting of crop performance

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Integrated, interdisciplinary crop performance forecasting systems, linked with appropriate decision and discussion support tools, could substantially improve operational decision making in agricultural management. Recent developments in connecting numerical weather prediction models and general circulation models with quantitative crop growth models offer the potential for development of integrated systems that incorporate components of long-term climate change. However, operational seasonal forecasting systems have little or no value unless they are able to change key management decisions. Changed decision making through incorporation of seasonal forecasting ultimately has to demonstrate improved long-term performance of the cropping enterprise. Simulation analyses conducted on specific production scenarios are especially useful in improving decisions, particularly if this is done in conjunction with development of decision-support systems and associated facilitated discussion groups. Improved management of the overall crop production system requires an interdisciplinary approach, where climate scientists, agricultural scientists and extension specialists are intimately linked with crop production managers in the development of targeted seasonal forecast systems. The same principle applies in developing improved operational management systems for commodity trading organizations, milling companies and agricultural marketing organizations. Application of seasonal forecast systems across the whole value chain in agricultural production offers considerable benefits in improving overall operational management of agricultural production.

Keywords: operational seasonal forecasting; simulation modelling; crop management systems; decision-making systems; interdisciplinary approaches

1. INTRODUCTION

(a) *Motivation*

Agricultural businesses, associated government systems and farmers depending on agriculture for sustenance, may all be significantly responsive to fluctuations in climate, largely through the impacts of climate on production and associated management intervention. These systems involve farms, input supply businesses, marketing and government policy systems. Skill in operational seasonal forecasting offers considerable opportunities to crop managers through the potential to provide improvements in the overall system involved. This may be through increased crop production and farm profitability or through reduction in risks. However, capturing the opportunities associated with climate and crop forecasting is not necessarily straightforward as climate forecasting skill, while nevertheless improving over recent years, remains imperfect and methods used to apply this type of skill level to operational management issues in crop production have not generally been developed or tested extensively. A key issue in fitting crop forecasting systems to seasonal climate models is in dealing with differences in scale between crop models (normally developed for field-level application) with the new generation of general circulation models (GCMs), which provide output at national or regional scales. Additionally, there may be a mismatch between the temporal scale associated with output of a climate model and that required for input into an agricultural model. A further key aspect related to seasonal forecasting of crop performance is that the outputs of the combined seasonal crop–climate forecasting system must have direct application for crop production managers to apply this type of information to modify their actions ahead of likely impacts of climate variability or climate change (Hammer *et al*. 2001; Hansen 2002*b*; Challinor *et al*. 2004). In this respect, Hansen (2002*b*) emphasized that seasonal forecasts have to address a need that is 'real and perceived', and, importantly, the benefit from seasonal forecasts depends on the 'existence of decision options that are sensitive to the incremental information that the forecasts provide and compatible with the farmer's goals' (Hansen 2002*b*).

As an example of this type of requirement Everingham *et al*. (2002) found the key requirement for the sugar industry was for forecasts of total industry yield and for those forecasts to be made as early in the growing season as possible in order to better manage international market commitments. However,

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One contribution of 17 to a Discussion Meeting Issue 'Food crops in a changing climate'.

close involvement of key components of the sugar industry was needed in order for suitable development of a crop performance forecast system. This type of commitment resulted in the Australian sugar industry shifting from having the lowest proportion of users engaged in uptake of seasonal forecast information to the highest of all farming groups in Australia (CLIMAG 2001; Everingham *et al.* 2002). The use of operational seasonal forecasts of crop performance by decision-makers can be facilitated through use of decision-support systems that are capable of forecasting potential farm-level production both before the crop is planted and during critical stages of crop production management (Meinke *et al.* 2005). However, it is argued use of these systems needs to be driven by the potential capability to positively influence agricultural management practices. In this sense, so-called 'discussion support' systems may provide a novel means, whereby a simulation-based support software can act as a key vehicle for facilitating infusion of forecasting capability into practice (Nelson *et al.* 2002).

(b) *Objective*

The aim of this paper is to provide an overview of a number of techniques, especially those developed in Queensland, Australia, that are already successfully applied in operational seasonal forecasting of crop performance and to draw attention to needs and methods of integrating climate modelling systems with agricultural–economic modelling systems. Emphasis will be placed on the need for a shift towards an interdisciplinary approach where, climate scientists, agricultural scientists and extension specialists are intimately linked with stakeholders (e.g. crop production managers, policy makers) in the development of targeted seasonal forecast systems. It is suggested this framework offers the potential for application for improving crop management and production for many regions, worldwide.

2. OPERATIONAL FORECAST SYSTEMS

(a) *Operational decision making associated with seasonal crop forecasting*

Decision-makers associated with crop production, needing to prepare for a range of possible outcomes, often use conservative risk management strategies to reduce negative impacts of climatic extremes. In more favourable seasons, this can be at the expense of reduced crop productivity and profitability, inefficient use of resources, and accelerated natural resource degradation (e.g. under-investment in soil fertility inputs or soil conservation measures). Broad & Agrawala (2000) showed the value of climate forecasting in crop production management but cautioned against regarding seasonal forecasting as a panacea for solving food crises. The designated role of climate-related risk management tools for cropping systems needs to be carefully established and the chosen strategies identified must take this into account. This also requires a careful analysis and understanding of the existing overall policy framework. Policies may have been developed with the aim of alleviating the consequences of high climate variability (such as drought). In particular, policies such as income subsidies may act as disincentives for the adoption of better climate-related risk management strategies (Meinke *et al.* 2003; Meinke & Stone 2005).

Additionally, major stakeholder groups, especially those involved in agricultural planning (policy makers, regulators and large agribusinesses, including financial institutions) and those involved directly in crop production (farmers, farm managers, rural businesses and consultants) have information needs. Tactical as well as strategic decisions need to be made continuously and climate forecast-related information might only be highly relevant for some of these decisions. Furthermore, when new seasonal forecast systems are being developed there may be an implicit assumption that perfect knowledge of, for instance, future rainfall would change the way crop management is practised. However, it may be the case that such 'perfect knowledge' might be never achievable due to intrinsic chaotic elements of the climate system (Meinke *et al.* 2004). Although, there is still much to learn about the underlying physical processes in climate systems, it is now appreciated that climate systems have many chaotic and non-deterministic features, which will prevent achieving complete certainty in seasonal climate forecasting (Hunt & Hirst 2000; Meinke *et al.* 2004).

Additionally, not all seasonal forecasts will be useful and lead to improved outcomes in crop management and associated areas. Although, many examples can be found, where seasonal forecast systems have been identified as providing value to crop management systems (in addition to having 'forecast skill'), others show either negative outcomes or identify management decisions that are insensitive to such information. It is suggested that there are several conditions that must be met before a seasonal forecast will result in improved value to the management system; a seasonal forecast system must: have 'skill' (assessed by applying recognized hindcast or independent verification 'skill-testing' criteria—e.g. applying scores that measure 'linear error in probability space' (LEPS); Potts *et al.* 1996); honestly convey the inherent uncertainty (i.e. the information must be presented in a probabilistic form); be relevant, timely; be able to be 'tracked' in terms of how well the forecasts are representing the actual climate conditions; provide background information on previous forecast outputs; be of value; and the information content must have application to a user (Glantz 1996; Pulwarty & Redmond 1997; Nicholls 2000; Meinke & Stone 2005).

In developed countries, economic outcomes across the value chain associated with crop production are important, but decisions are also based on many other factors such as environmental consequences (on- and off-farm), weed and disease impact, lifestyle and the existing policy framework. At the farm-level, most management decisions have to fit within a whole farm strategic plan such that many decisions are planned months ahead and their consequences seen months afterwards. This requirement for a certain lead-time between deciding on a course of action and realizing its

Table 1. Agricultural decisions at a range of temporal and spatial scales that could benefit from targeted climate forecasts (Meinke & Stone 2005).

farming decision type	frequency (years)
logistics (e.g. scheduling of planting/harvest operations)	intra-seasonal (greater than 0.2)
tactical crop management (e.g. fertilizer/pesticide use)	intra-seasonal (0.2–0.5)
crop type (e.g. wheat or chickpeas) or herd management	seasonal (0.5–1.0)
crop sequence (e.g. long or short fallows) or stocking rates	interannual (0.5–2.0)
crop rotations (e.g. winter or summer crops)	annual/bi-annual (1–2)
crop industry (e.g. grain or cotton; native or improved pastures)	decadal (approximately 10)
agricultural industry (e.g. crops or pastures)	inter-decadal (10–20)
land-use (e.g. agriculture or natural systems)	multi-decadal (20+)
land-use and adaptation of current systems	climate change

results is a characteristic of managing cropping systems (Carberry *et al.* 2000; Carter *et al.* 2000).

Pannell *et al.* (2000) stressed the importance of getting the big decisions right in crop management, such as land purchase, machinery investment and resource improvement. They pointed out that farmers are usually better off, 'if they solve the whole problem roughly, rather than to attempt to solve part of the problem extremely well'. This issue reinforces the importance of considering climate issues across the spectrum of temporal scales. Crop management decisions that could benefit from targeted seasonal forecasts range from tactical decisions regarding the scheduling of planting or harvest operations to policy decisions regarding land-use allocation (e.g. grazing systems versus cropping systems). Table 1 provides examples of these types of decisions at similar time-scales to those seen in climatic patterns. In water-limited environments such as the semi-arid tropics and sub-tropics, rainfall variability represents the main factor determining crop production variability and environmental risk. However, other factors such as starting soil moisture, soil type, soil fertility, temperature, planting dates, rainfall intensity, and timeliness of rainfall are particularly important when operational seasonal forecasting systems are applied in practical farming system management (Meinke & Stone 2005).

(b) *Methods of operational seasonal forecasting of crop production*

Sivakumar (2000) describe agricultural modelling 'as a priority to address sustainable agricultural development in the twenty-first century'. Crop simulation models have been used as 'knowledge depositories' to describe a particular area of interest. Once simulation models became available, interest shifted somewhat from aspects associated with underlying principles to using models in a predictive capacity (e.g. to develop scenarios or as a decision-support tool) or in an explanatory capacity to investigate interactions between processes. Detailed descriptions of the underlying physiological processes and parameters values are often difficult to obtain experimentally. This parameter uncertainty may result in low predictive ability. On the other hand, models that are built explicitly to predict management responses often use phenomenological description of groups of processes with easily derived parameter values but fewer process details (Dent & Anderson 1971; Meinke 1996; Meinke & Stone 2005).

Case studies can provide useful evidence of the value of simulation models in operational crop management decision making and in operational aspects of forecasting crop performance. For example, the APSIM-wheat model (Keating *et al.* 2003) has been applied using data from 100 plant breeding experiments across 23 experimental sites. The performance in this type of model is believed to be adequate to characterize the environment of gene functions and their interactions with their environments. Using data from a long-term soil fertility trial, where all the necessary input parameters and starting conditions were measured and available, an R^2 value of 0.8 has been obtained. Measured and simulated data were in better agreement when the input parameter uncertainty was reduced. However, the same dataset also highlights the deficiencies of using R^2 values as an indicator of model performance (Oreskes *et al.* 1994). For instance, when only a sub-set (i.e. data from one dry year) has been used for testing, the R^2 was zero, in spite of the model's obvious ability to capture the climate-related year-to-year variation in yield. Further details of this model's performance are available in Meinke & Stone (2005). A simulation approach incorporating process-based crop models offers the advantage of analysing cropping systems and their alternative management options experimentally and in real-time that is not otherwise, generally, feasible. This approach also offers the capability to assess a large number of combinations suitable for scenario analysis of potential value to the crop production manager. Empirical climate forecast models that are connected to process-based crop simulation models include CERES-wheat model derivatives (Abrecht & Robinson 1996) and the APSIM-wheat simulation model (Hammer *et al.* 1987; Keating *et al.* 2003). Various scenario analysis programs and decision-support systems can be provided as output systems from this type of approach (e.g. Hammer 2000; Meinke & Hochman 2000; Gadgil *et al.* 2002; Nelson *et al.* 2002; Podesta *et al.* 2002; Meinke & Stone 2005).

(c) *Seasonal forecasting methods*

Improvements in the understanding of interactions between the atmosphere and sea and land surfaces, advances in modelling global climate, and investment in monitoring the tropical oceans mean some degree of

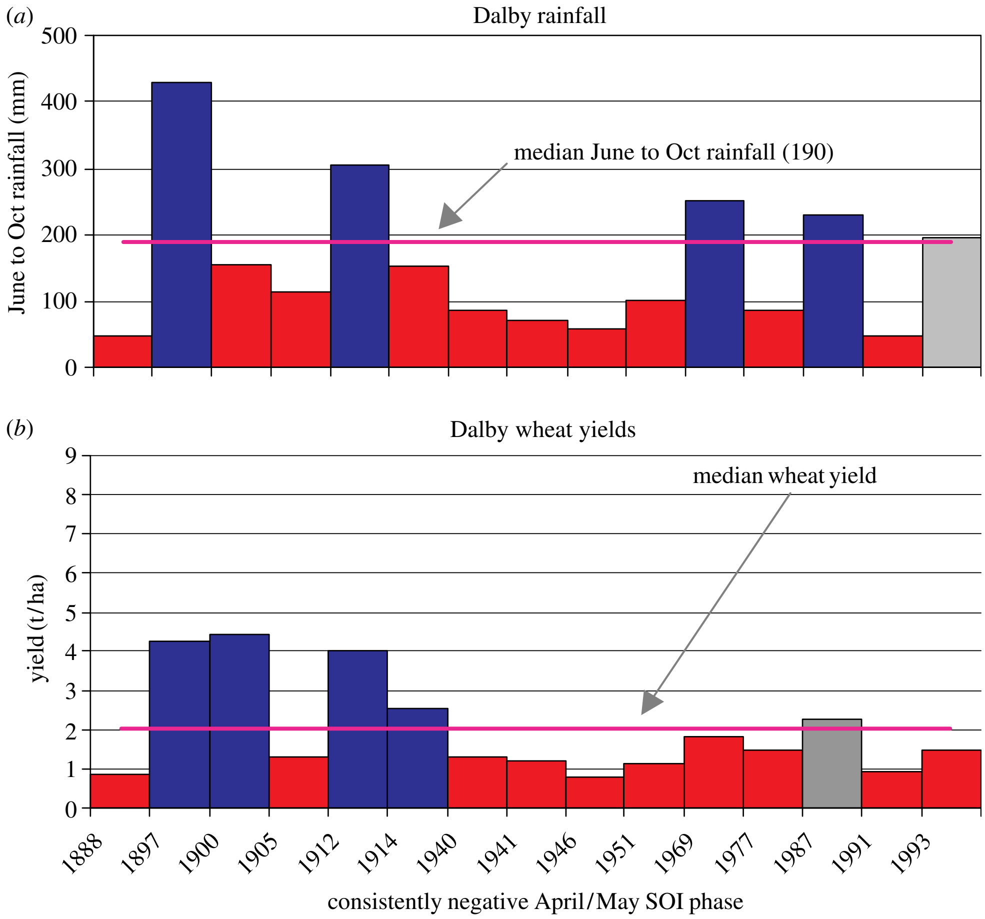

Figure 1. Example of 'hindcast' output for a cropping location in Queensland, Australia together with modelled crop yield output (hindcasts) for the same period. (*a*) The output provided here shows the actual rainfall that has occurred in history for the June–October period following a 'consistently negative SOI phase' at the end of the immediately preceding May. (*b*) Cumulative probability distributions can be produced using data obtained from this type of information (after Hammer 2000).

predictability of climate fluctuations months in advance in many parts of the world is now possible. While some of the year-to-year variations in climate are the result of random sequences of events, many climatic variations are part of patterns that are coherent on a large scale. Skilful prediction may then be possible, particularly if the patterns are forced by observable changes in surface conditions such as sea-surface temperatures (SST) (Cane 2000; Goddard *et al.* 2001).

'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 southern oscillation (ENSO)' (Cane 2000). Progress in predicting ENSO and associated climatic anomalies or values follows advances made in ocean–atmosphere modelling and the development of associated ocean–atmosphere observing systems. Predictions of the global impacts of ENSO are now often made using physical models, statistical procedures, or other empirical methods. If the physical models are global coupled GCMs they are capable of predicting global impacts as well as core changes in the equatorial Pacific. A two-tiered approach can also be employed which utilizes a simpler model that predicts tropical Pacific SSTs as boundary conditions to calculate global climate variations (Barnett *et al.* 1994).

Empirical approaches may also be 'two-tiered' deriving climate forecasts by combining a predicted ENSO index such as the southern oscillation index (SOI) or 'Nino3' region in the equatorial Pacific with the historical relationship of a local climate variable, such as rainfall at a meteorological station adjacent to a crop production region or even a farm. They may also do the entire prediction at once (as is commonly applied operationally in Australia), using observed values of an ENSO index to predict future local conditions. For example, the prediction of global rainfall of Stone *et al.* (1996) based on the 'SOI-phase' system uses clustered values of principal component scores of SOI activity at two different times to predict rainfall a season or more ahead. Figure 1 shows the amount of rainfall that has occurred in recorded history following a 'consistently negative SOI phase' in April/May for a wheat growing location in Queensland, Australia. These values are incorporated as input into subsequent cumulative probability distributions and final forecast output. Hindcast tests for discriminatory ability among the probability distributions produced from these outputs are the provided using non-parametric methods such as Kruskal–Wallis or Kolgomorov–Smirnov while (cross-validated) forecast verification skill is assessed using tests such as 'LEPS' (Potts *et al.* 1996; Maia *et al.* 2004). Considerable effort is also applied to independent verification assessment in real-time using the LEPS method and similar techniques. Potgieter *et al.* (2003)

provide a useful summary of approaches in assessing climate forecast skill.

The method of clustering similar key climatic indices also allows for the identification of analogue years or seasons. These are then employed to derive daily weather parameters for use in crop production models (Stone *et al.* 1996; Cane 2000; Hammer *et al.* 2001). Output from the crop simulation model 'APSIM' (Keating *et al.* 2003) is also provided in figure 1. Rainfall that has occurred following the 'consistently negative SOI phase' in May is provided in figure 1. Notably, this has mostly been below the long-term median. Similarly, simulated yield obtained using APSIM for the same years as the hindcast rainfall also shows most yield values are below the long-term median. However, they can be different years, demonstrating the need to employ systems that can account for the effectiveness in rainfall timing, temperature, radiation and evaporation, as well as total rainfall amount throughout a growing season. This approach demonstrates the value of simulation modelling to provide users with an improved perspective of likely potential yield under these circumstances. The model output shown here is following a consistently negative SOI phase occurring at the end of May with a two-thirds-full soil moisture profile at planting (Meinke *et al.* 2003). Regional maps of more general forecast information (e.g. probability of exceeding the climatological median) are also available for more general user application.

ENSO is not the only mode of climate variability with large-scale near-global impacts. The North Atlantic oscillation, defined by an oscillation in sea-level pressure between stations in Iceland and the Azores, is important because of 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 (Ward & Folland 1991; Nobre & Shukla 1995). From these and other developments, there is now considerable evidence supporting the substantial progress being made in the developments of operational 'seasonal weather prediction' systems, such as those outlined above and especially at the European Centre for Medium Range Weather Forecasts, the International Research Institute for Climate Prediction and the Climate Prediction Center in the United States (Challinor *et al.* 2003).

However, Podesta *et al.* (2002), in their case study of farmer's use of climate forecasts in Argentina, found a reluctance to use seasonal forecasts in management of crop production because the temporal and spatial resolution of the forecasts was perceived as not relevant to local conditions (Buizer *et al.* 2000). These types of issues must be taken into account in order to improve the relevance and potential adoption of seasonal climate or crop forecasts. For example, for effective management systems to be put into place, integrated climate–crop modelling systems need to be developed at the appropriate farm or regional scale suitable for the decision-makers needs (Meinke & Stone 2005). Challinor *et al.* (2003) make the point that reliable forecast output will not result from simply linking climate and crop models. In this respect, they suggest consideration should be given to the spatial and temporal scales on which the models operate, the relative strengths and weaknesses of the individual models, and the nature and accuracy of the model predictions. A key aspect of this approach is that on longer time-scales, process-based forecasting has the potential to provide skilful forecasts for possible future climates, where empirical methods would not necessarily be expected to perform well.

While it is recognized that statistical approaches may, in future, have limitations and it is expected that dynamic climate modelling will provide much improved forecast skill in the near future, this will require continued effort to identify appropriate solutions to solve the 'connectivity problem' between seasonal climate forecast systems and crop production forecast systems. For example, ways need to be found to convert large, grid point GCM output into something akin to point scale daily weather station data for use in farm-scale crop forecast models. The use of higher resolution regional climate models initialized from GCM data is considered an alternative option, but statistical properties of these data usually differ considerably from the observed historical climate records, requiring further manipulation (Landman & Mason 1999; Landman & Goddard 2001; Meinke & Stone 2005).

Another approach may be to apply a statistical clustering process to GCM forecast output (hindcasts) in order to derive analogue years or seasons suitable for input into crop simulation models (Stone *et al.* 2000). Alternatively, GCM output could be used to establish climate trends, which are then used to modify historical climate records for use with biological models. This approach may be taken when the impact of climate change on agricultural systems is to be assessed (e.g. Reyenga *et al.* 1999; Howden *et al.* 2001). Hoogenboom (2000) also draws attention to the different scales implicit in GCMs and biological models.

In development of the DEMETER project (Development of a European Multi-Model Ensemble System for Seasonal to Interannual Prediction; Palmer *et al.* 2004) both statistical/empirical methods and dynamical regional climate models have been used and applied for downscaling purposes with the further aim of connecting such output to crop modelling systems. In the statistical/empirical methods, a mapping technique based on regression methods, analogue techniques or neural networks is one method of application. A second method using dynamical downscaling has been based on the Rossby Centre Atmosphere model, a climate version of the HIRLAM regional weather prediction model (Rummukainen *et al.* 2001). This model has been nested to the ECMWF model output and run in a climate mode for six months. However, problems arise from propagation of systematic biases from the global to regional model. Nevertheless, an 'innovative' approach has been developed to supply seasonal forecast information to crop models by running the crop model on each member of the ensemble of climate forecast output to derive a probability distribution function of crop yield.

Challinor *et al.* (2004) demonstrate the value of the new crop model, the general large area model for annual crops, for the purpose of connecting numerical climate models to crop model output. The challenge for this type of approach is in its capability to capture previously unobserved weather conditions, an important consideration in operational development of these types of systems under climate change. An important aspect of this approach is in the use of 'seasonal weather forecasting' to estimate daily weather values months in advance. Importantly, seasonal weather prediction (Challinor *et al.* 2003), on scales close to 200 km is now routinely carried out using GCMs of the atmosphere and ocean. While these models provide probabilistic predictions of the seasonal mean climate they also produce daily time-series of the evolution of the weather and, therefore, provide information on the statistics of the weather during the crop-growing season. Of prime importance is that these daily time-series can be used to drive crop simulation models. The spatial structure of the relationship between rainfall and crop yield has been explored using an empirical orthogonal function (EOF) analysis that identified a coincident large-scale pattern for both rainfall and yield. Noteworthy with this approach, on the sub-divisional scale the first principal component of rainfall was found to correlate well with the first principal component of yield clearly demonstrating that the large-scale patterns picked out by the EOFs are related. However, the use of larger averaging areas for the EOF analysis resulted in lower less robust correlations. As an alternative, it is suggested the mean forecasts could be used as inputs to a weather generator that produces a time-series consistent with both the probabilistic climate scenarios and the locally observed weather patterns (Wilks 2002; Challinor *et al.* 2003).

Hansen *et al.* (2004) also applied a GCM in an experiment to forecast regional wheat yields in Queensland, Australia. To achieve this, they used a GCM-based seasonal rainfall forecast combined with a wheat simulation model that uses a stress-index, STIN (Stephens *et al.* (1989), for yield forecasting. The model calculates a stress index (SI) as a cumulative function of water demand and plant extractable soil water simulated dynamically using daily rainfall, and average weekly temperatures and solar irradiance required to calculate potential evapotranspiration. Final yields are estimated as linear regression functions of SI and year, accounting for linear trend associated with changing technology. Hansen *et al.* (2004) provide more detail on use of the atmospheric GCM ECHAM 4.5 and SST boundary conditions applied up to the forecast start time. Hansen *et al.* (2004) note prediction accuracy was, generally, better at the state scale than at the smaller district scale. It was noteworthy that the wheat simulation model accounted for 75% of the variance of the detrended state average wheat yields. However, correlations for individual districts were lower, accounting for an average of 58% of the variance. A key outcome was that for every forecast period, the GCM-based method gave better results for state average yields simulated with observed weather than those based on the empirical SOI phase-based method of Stone *et al.* (1996) and applied to the yield forecast method developed by Potgieter *et al.* (2002). A potentially valuable outcome for production managers (e.g. farmers/farm managers) was that this result was more pronounced for forecasts with longer lead-times. Also potentially importantly for managers in production and production reliant industries is that the GCM-based method appears to provide distinct advantage in the ability to improve forecast accuracy during the pre-planting period near the end of April when ENSO may be less predictable. However, the comparisons between the numerical climate forecast-based method and the empirical climate forecast-based method are difficult to determine, primarily due to the differences in number of years of available predictor data for the two systems. Additionally, certain SOI phases applied in this experiment were combined to create composite SOI phases. This resulted in SOI phases of a slightly different type to the originally designed system, again making comparisons difficult, although this approach does provide increased numbers of cases with more suitable sample sizes (Potgieter *et al.* 2002; Hansen *et al.* 2004)

In operational seasonal forecasting of crop performance, historical climate records can also be partitioned into 'year or season-types' based on concurrently prevailing ocean and atmospheric conditions (i.e. SOI and/or SST anomalies), resulting in 'SOI phases' (Stone *et al.* 1996) or ENSO phases (Messina *et al.* 1999; Phillips *et al.* 1999). Such categorization needs to be based on an understanding of ocean–atmosphere dynamics and incorporate appropriate statistical procedures to partition the data successfully. Current conditions can then be assigned to a particular category and compared to other categories in order to assess the probabilistic performance of the biological system in question (e.g. Meinke & Hochman 2000; Podesta *et al.* 2002). This rather pragmatic method of connecting climate forecasts with biological models also only requires historical weather records. Figure 2 provides an example of output of an operational crop forecast system that utilizes an integrated climate forecast system—a crop modelling system. The particular example presented here provides indication of the capability of the forecast system to provide future potential shire yield values in the early developmental stages of an El Niño event soon after the crop was planted. Probability values are for the probability of exceeding the long-term relative median yield.

The method described above has been used in other countries and has provided valuable information for many decision-makers (Meinke & Stone 1992; Messina *et al.* 1999; Hammer *et al.* 2000; Nelson *et al.* 2002; Podesta *et al.* 2002). The SOI phase system has become the dominant scheme used in Australia and neighbouring countries while ENSO phases are often used in the Americas. However, both schemes are globally applicable. Hill *et al.* (2000) and Hill *et al.* (2001) compared the value of the SOI phases versus broader 'ENSO phases' for Canadian and US wheat producers and found that, in the particular case being examined, the SOI phase system, generally, provided more valuable information for operational crop management in terms of potential for increasing gross margins.

Additionally, for broader regional-scale applications, empirical climate forecast models may be connected to the simpler (hybrid) agroclimatic model, based on moisture stress (and described earlier in this paper), developed by Stephens *et al.* (1989). The projected seasonal climate forecast is based on the 'SOI phase system' (Stone *et al.* 1996) which is combined with the agroclimatic model to generate a crop forecast that can be updated each month throughout the growing season (Stone & Meinke 1999). The moisture-SI is similar in concept to that proposed by Nix & Fitzpatrick (1969) in that it utilizes biophysical knowledge of the crop, allows consideration of soil type effects, and derives the SI by contrasting soil water supply with crop demand. The regression model has been previously fitted to historical shire wheat yields that are provided by the Australian Bureau of Statistics. The variance of wheat yield explained, using the SI, ranges between 78 and 93% at the state level and 93% at the national level (Hammer *et al.* 2001). Using this method, maps showing the probability of exceeding median yield for each wheat-producing shire are produced with predictions commencing at the beginning of the wheat-growing season (April/May in Australia). These maps are produced and updated each month as the season progresses. Figure 3 provides an example of output from this approach.

The information provided indicates the likely size of the total crop as well as highlighting those areas, where production has the highest chance of being abnormally high or low. For management considerations, this information provides forward warning in relation to logistics for grain transport, quantifies the potential need for exceptional circumstances support for farmers by government in places indicating a high risk of low yields, and provides grain traders with indication of the total size of the crop for commodity trading purposes (Stone & Meinke 1999; Hammer *et al.* 2001). A similar approach is being applied to operational maize production forecasting in South Africa, where computed maize grain yield forecasts using a crop growth model linked to the SOI phase climate forecast system are compared against long-term cumulative probability distribution functions of yield to determine their probabilities of non-exceedance. The system has wide acceptance and credibility in the Free State Province and is used by grain merchants, importers, exporters and millers (DeJager *et al.* 1998).

Additionally, Verdin & Klaver (2002) have developed useful techniques for monitoring crop performance and estimating crop (maize) yields during the establishment of the crop growing season and throughout the subsequent performance of the crop in southern Africa by applying remote sensing, modelling and geospatial analysis through a regression technique. The approach is especially valuable when large gaps in rainfall station coverage exist. Verdin & Klaver (2002) provide an alternative grid-based cell-based formulation for water requirement satisfaction (WRSI), which can provide a useful alternative as a means of inferring water limitation impacts on yield. WRSI is a useful indicator of crop performance based on the availability of water during the crop growing season (see also Frere & Popov 1979; Senay & Verdin 2001).

3. LINKING FORECASTS AND DECISION SYSTEMS

(a) *Requirements for successful application of seasonal forecasts of crop production*

Hansen (2002*b*) carefully articulated the prerequisites for potential benefits of seasonal forecasts if they are to be applied by growers and industry decision-makers. First, forecasts have to address a need that is real and perceived. Very importantly, the benefit from crop and climate forecasts also depends on the 'existence of decision options that are sensitive to the incremental information that the forecasts provide and compatible with the farmer's goals' (Hansen 2002*b*). Additionally, farmers need to be able to correctly interpret relevant aspects of crop and climate forecasts, which also have to be made with sufficient lead-time to affect their decisions. Hansen also notes that institutions must provide commitment to providing forecast information and support for its application to decision-making and policies that favour beneficial use of climate/crop forecasts by farmers and associated institutions. The minimum skill for seasonal forecasts to affect decision making depends on the cost and benefit of the different decision options (Hansen 2002*a*,*b*; also from Katz & Murphy 1987; Gadgil *et al.* 2002).

This key point is reinforced by Nicholls (1991, 2000) in that while the value of seasonal forecasts to farmers will depend on their accuracy, the value will also depend on the management options available to the farmer to take advantage of the forecasts. Indeed, the value of seasonal forecasting to the grower may never have been demonstrated to the farming community by the institution developing and promoting the forecast information. This aspect is reinforced by Sonka *et al.* (1987) who states that for benefits to occur in farming practice it is necessary to identify those areas, where tactical changes can be made either to take advantage of predicted (probabilistic) conditions or to reduce losses in predicted (probabilistic) below-average conditions. In other words, seasonal forecast systems, including those now incorporating coupled GCMs and process-based crop models, may have absolutely no value unless they are capable of affecting key management decisions that, ideally, have been identified through close interaction between climate scientists, agricultural scientists and crop production managers (Hammer *et al.* 2001).

(b) *The value of a participative approach with crop production managers*

Crop production managers may need to participate in the development of the appropriate response strategies and in deciding what decisions related to seasonal forecast information are best for themselves (Patt & Gwata 2002). The key advantage of developing a participative approach with users is that the approach tends to moderate against the frequent 'mismatch' between the knowledge systems of both seasonal climate and crop forecast developers and the knowledge systems of users. Additionally, this approach

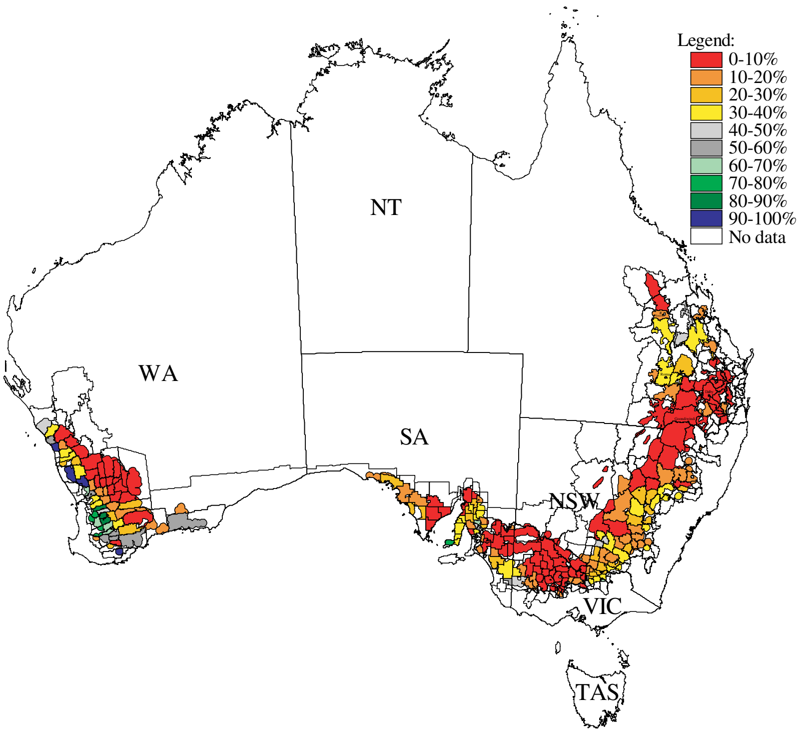

Figure 2. Example of an operational forecast system for wheat production on a shire (county) basis with particular example of the seasonal forecast provided in June 2002 in Australia. The method (Potgieter *et al.* 2002) employs an empirical climate forecast model (Stone *et al.* 1996) connected to a hybrid agroclimatic model, where an index is derived from water stress relative to plant available water (Hammer *et al.* 1996). The legend refers to the probability of exceeding long-term median yield, relative to each shire's value.

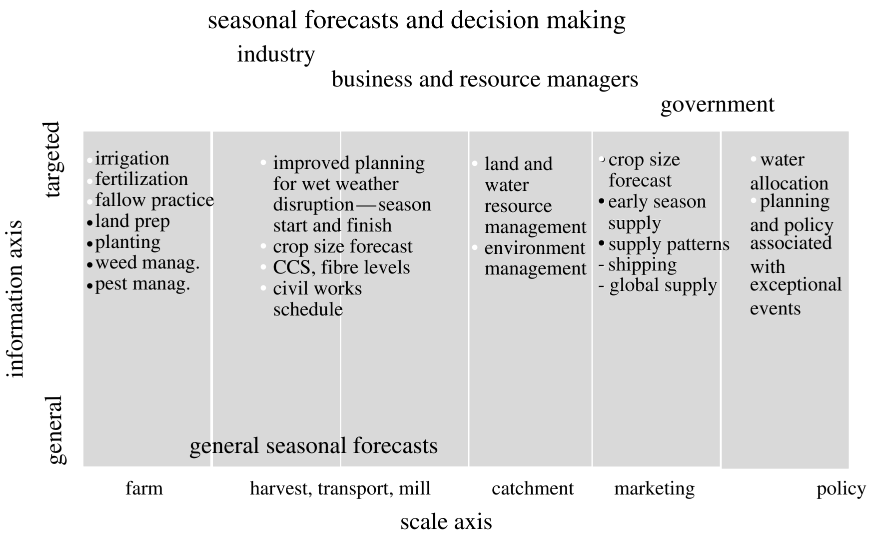

Figure 3. The relationships between scale, information content and decision-makers in defining relevant systems and the systems approach to applying seasonal forecasts in agricultural systems—example for the sugar industry (after Hammer 2000; Everingham *et al.* 2002).

greatly facilitates the integration and adoption of these scientific outputs to deliver broader industry benefits (Everingham *et al.* 2002).

Cash & Buizer (2005) 'emphasize that effective systems should ground the collaborative process of problem definition in the users' perspectives regarding the decision context, the multiple stresses bearing on the manager's decisions, and ultimate goals that the knowledge-action system seeks to advance'. In this instance, (following Cash & Buizer 2005) this would mean *shifting the focus* towards the promotion of broad, user-driven risk-management objectives, rather than emphasizing the uptake of particular seasonal forecasting technologies. Hansen (2002*b*) also identifies this point as a core and urgent need to bridge the institutional and cultural gap that exists between providers of seasonal forecast information and agricultural support institutions if users are to gain from improvements in developments in operational seasonal forecasting. A key point from Hansen (2002*b*) is that institutions responsible for development of seasonal climate forecasts tend to regard forecasts as stand-alone *products*, whereas the users, in assessing seasonal forecasting as an aid to increasing farm productivity, regard seasonal forecasting as a *process*. To help overcome this problem in ensuring that the objectives of the process are more user-driven, it has been suggested that a knowledge-action system needs to be evaluated relative to the achievement of the users' ultimate goals (e.g. more effective crop management), rather than the goals of the developers of seasonal forecasts (e.g. more or better understanding and use or non-use of forecasts, with the goal of improving content, format and distribution in order to increase use and impact) (Hansen 2002*b*; Cash & Buizer 2005).

Thus, a further key focus for achieving future advances in seasonal forecasting science for the benefit of crop production will be through making better connections between agricultural scientists and the developers of climate forecasting systems. Also, those professions involved in decision making in industry may need to take a proactive role in the development of seasonal forecasts if the design and use of these systems are to reach their full potential (Hammer *et al.* 2001; Hansen 2002*b*). Emphasis on a participative approach with users in order to better appreciate more precisely their decision systems may help overcome issues associated with institutional and cultural barriers. For example, through a very strong emphasis on a participative approach with users, Everingham *et al.* (2002) found that sugar growers' requirements for seasonal forecast systems were not for the 'standard' three month seasonal climate forecast period but for two months (i.e. better management of the harvesting period) and preferably for the data to be produced as numbers of 'wet days' rather than total rainfall in millimetres. Following lengthy participative interaction with crop marketers, Everingham *et al.* (2002) found the key requirement for this industry sector was for forecasts of total industry yield to be made as early in the growing season as possible in order to better manage international market commitments. Following this close involvement of industry in development of suitable crop performance forecast systems, the Australian sugar industry shifted from having the lowest proportion of users engaged in uptake of seasonal forecast information to the highest of all farming groups in Australia applying seasonal forecasting to their crop production planning (CLIMAG 2001; Everingham *et al.* 2002).

Cash & Buizer (2005) point out that designing fully 'end-to-end' systems means that seasonal forecast developers should begin their process *by going into the field and listening to farmers and their consultants*, learning their perspectives, their problems, and their needs. As Everingham *et al.* (2002) and Ingram *et al.* (2002) also imply, these conversations with users reveal that they need climate information as one type in a suite of information that can help them manage a broad array of risks. Initiating conversations with lead innovators within the farming community appears to be a key factor to success. Such farming leaders ('local champions') can lay the groundwork for broader participation of other farmers and a greater connection between science producers and farmers (Glantz 1996; Cash & Buizer 2005).

4. THE VALUE OF MORE INTEGRATED, SYSTEMS APPROACHES

The emphasis in a systems approach is to develop targeted information for influencing the most relevant decisions in the system of interest. This concept is relevant across the wide range of scales and issues associated with cropping systems and their associated business and government systems. Hammer (2000) points out the 'emphasis needs to be on the analysis required to target the seasonal forecast information to the issue and the decision-maker'. Generalized seasonal forecasts, which have information relevant across all systems, are likely to have little value if their targeting is not considered. Importantly, the relevant decision-maker at each scale must be included as part of the systems approach to ensure clear problem definition and understanding of relevant decisions and information needs. The systems approach will usually involve systems modelling as a means to move from general to targeted information (Hammer 2000). Everingham *et al.* (2001, 2002) provide an example of the range of scales and issues associated with seasonal forecasting of sugar cropping systems (figure 3).

In the example for sugar crop performance management, Everingham *et al.* (2002) described the impact of climate variability on the sugarcane production system at the farm-level, where climate variability directly determines the process of yield accumulation and the amount of sugar produced. Additionally, climate conditions influence the development and spread of fungal diseases, insects, pests and weeds, which can restrict crop growth. Further, rainfall sets the potential for runoff and deep drainage with possible environmental impacts associated with the movement of nutrients and pesticides. Beyond the farm-level, knowledge of seasonal forecasts can allow harvest managers to enhance and better plan harvesting strategies for the coming season. Knowledge of the chance of high rainfall towards the end of the harvest season allows harvest operators and farmers to alter typical harvesting strategies. At the mill level, mill scheduling, which is subject to considerable disruption because mechanical harvesting requires dry conditions, can be considerably improved through use of targeted seasonal forecasting. Furthermore, if there is likely to be rain interruption during the harvest period then sugar marketers can factor this aspect into their planning so as not to overcommit sugar supplies to customers (Everingham *et al.* 2002).

A major issue for all sectors of the sugar industry value chain is predicting the total size of the crop. Developments of sugar crop yield forecast systems are allowing farmers to better plan fertilizer and irrigation regimes. Additionally, forecasts of crop yield are allowing harvest operators and millers to better plan for the likely start and finish of the season. Appropriate forecasts of the size of the crop (incorporating seasonal climate forecasts based on the SOI phases) (Stone *et al.* 1996) and the method outlined by Everingham *et al.* 2001 in which Monte Carlo procedures were used to determine which of the five SOI phases were most useful for indicating when Australian sugarcane yields were likely to be above or below the long-term median for eight mill locations of relevance to the Australian

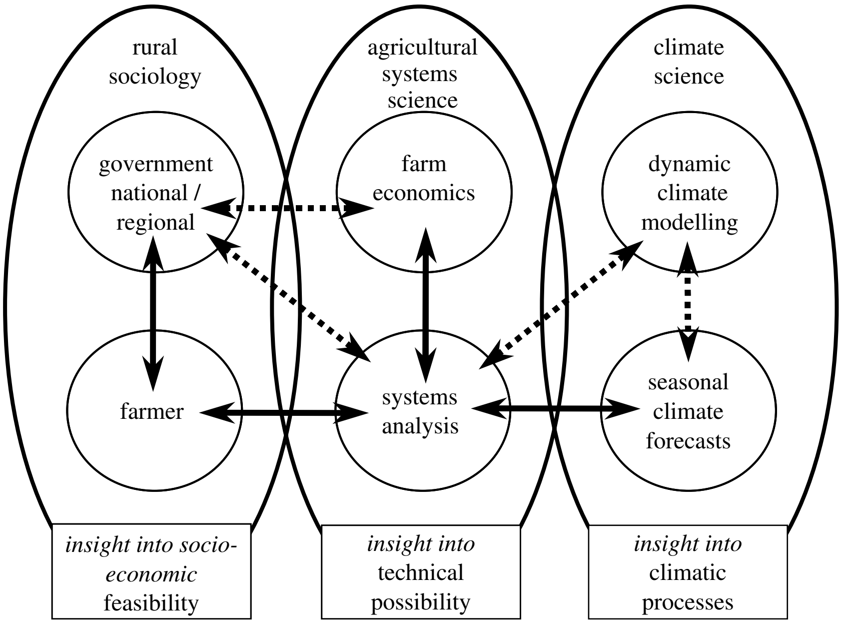

Figure 4. Outline of the RES AGRICOLA concept (Meinke *et al.* 2001). The diagram shows the disciplines, relationships and linkages needed for effective delivery of seasonal forecast information for improved decision making in managing crop production. Operational links are indicated by the solid arrows and show connections that have proven useful for managers and developers of seasonal forecast systems (i.e. in Australia, USA and South America). The dashed arrows indicate areas where operational connections still need to be developed (reproduced from Meinke & Stone 2005).

sugar industry. This approach is permitting the harvest period for sugar cane to be brought forward and is also facilitating forward selling strategies for marketing plans (Everingham *et al.* 2002).

Most management decisions 'on-farm' in crop production have to fit within a whole-farm strategic plan so that many decisions are planned months ahead and their consequences seen months afterwards. This requirement for a certain lead-time in seasonal forecasting to enable more efficient planning in deciding on a course of action and realizing its results is a characteristic of managing and farming cropping systems (Carberry *et al.* 2000; Carter *et al.* 2000). Effective operational seasonal forecasting of crop performance has the capability of improving the 'big decisions' in farm management such as land purchase, machinery investment and resource improvement (Pannell *et al.* 2000).

Interaction with farmers and technical experts can help define 'typical management practices' (and key decision points) in crop management by farmers. Through development of operational seasonal forecasts of potential crop production and performance, farmers could be encouraged to plant crops in seasons that may have not even been considered without knowledge gained from seasonal forecasting (Amissah-Arthur *et al.* 2002; Phillips *et al.* 2002). Additionally, the value of integrated climate/crop modelling efforts can be seen when probability distributions of a large number of simulated yields and gross margins can be produced and incorporated into risk assessment tools. The large number of simulations using the modelling approach allows the exploration of climate influences such as ENSO on extreme outcomes, a difficult approach with purely historical series that are typically short in duration (Podesta *et al.* 2002).

Hammer *et al.* (2001) stress the most useful lessons lie in the value of an *interdisciplinary systems approach* in connecting knowledge from particular disciplines in a manner most suited to decision-makers engaged in crop production. The RES AGRICOLA network is an evolution of the 'end-to-end' concept proposed by Manton *et al.* (2000). It distinguishes three discipline groups that need to interact closely if crop production systems are to benefit from seasonal forecasting: (i) climate sciences, (ii) agricultural systems science (including economics) and (iii) rural sociology. Figure 4 provides insight into the linkages needed to operationally connect research projects and through the establishment of cross-disciplinary teams for the benefits of farmers (after Meinke & Stone 2005).

Improved pay-offs across industry scales are significantly facilitated when such an integrated systems approach is employed that includes decision-makers and scientists across the various disciplines as a participatory approach which ensures that the issues that are addressed are relevant to the decision-maker (Meinke *et al.* 2001). Hansen (2002*a*) stresses that the sustained use of such a framework requires institutional commitment and favourable policies. An example, where the links shown in figure 4 could be strengthened is in the area of connecting seasonal crop forecasting with both whole farm economic analyses and broader government policy analyses (Ruben *et al.* 2000; Hansen 2002*a*).

(a) *Case studies in operational aspects of seasonal forecasting of crop production: the use of scenario analysis, crop models and 'discussion-support' tools*

Decision-support systems that encompass databases of forecast crop simulation output together with a graphical user interface to generate analyses of risks

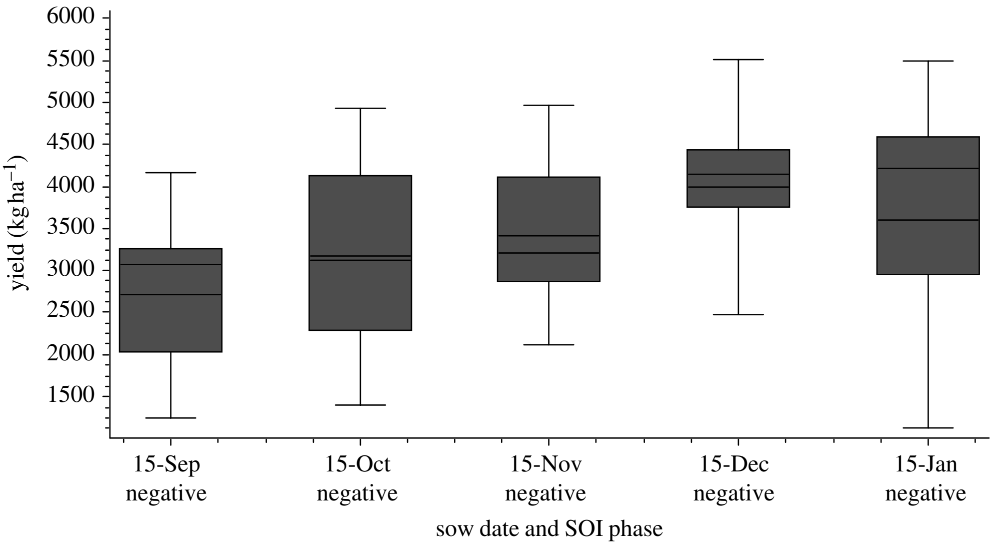

Figure 5. Example of scenario analyses of crop production for a farm in Queensland, Australia, provided by the integration of a climate forecast model with a biophysical model and known, existing, soil-moisture conditions (two-thirds soil moisture level) and the relevant soil water holding capacity. Output from the 'discussion-support system' *Whopper Cropper*. The median potential yield is indicated by a dashed line while the 'boxplots' describe the 20th and 80th percentiles (Nelson *et al.* 2002).

associated with crop management options are particularly useful for development of discussions with users in relation to the significant crop management decisions they make. Examples of these decision systems include 'Wheatman' that supplies seasonal crop forecasting information for wheat crop management (Woodruff 1992), 'Whopper Cropper' (Nelson *et al.* 2002) (incorporating key output from APSIM; McCown *et al.* 1996; Keating *et al.* 2003), that currently provides targeted seasonal crop production forecasts of wheat and sorghum crops for use in scenario analyses, 'flowcast' (Abawi *et al.* 2001; Ritchie *et al.* 2004) that provides integrated climate forecast, irrigation allocation modelling, and cotton yield information, CLIMPACTS (Campbell *et al.* 1999) providing integrated climate/crop production information, and CropSyst (Stoeckle *et al.* 2003) and DSSAT (Jones *et al.* 2003) that provide sophisticated crop simulation platforms useful for integrating and simulating future climate systems scenarios. Challinor *et al.* (2003) also point out there have generally been two approaches in development of crop models: process-based crop models which seek to represent many of the processes of crop growth and development ((e.g. CROPGRO model; Boote *et al.* 1998); APSIM; Keating *et al.* (2003)) and empirical models which use observed relationships to predict the variable of interest (e.g. Parthasarathy *et al.* 1992). Stephens *et al.* (1989), Hammer *et al.* (1996) and Potgieter *et al.* (2005) also describe 'agroclimatic models' that use simple moisture SI approaches.

There are some key but more general lessons that may be derived in applying seasonal forecasting to improving management of crop production. In this respect, case studies may represent many diversified agricultural systems and various scales of farm operation. To facilitate case study development a key activity over recent years is to provide scenario analyses based on simulation with credible agricultural–climate models (e.g. through use of crop simulation models such as 'APSIM' (McCown *et al.* 1996; Keating *et al.* 2003) or its derivative 'Whopper Cropper' as a valuable aspect of the learning process for farmers and the cropping industry. Figure 5 provides an example of output tailored to local soil and climate conditions, where the output describes forecasts of potential yield for a sorghum crop associated with a particular 'phase' of the SOI ('consistently negative') and outcomes associated with differing planting dates.

Operational seasonal forecasts of crop production facilitated through use of decision/discussion-support systems (such as the above system) are capable of forecasting potential farm-level production before the crop is planted. This allows the farmer to use the forecast potential crop yield scenarios to adjust inputs to achieve optimal yields. Additionally, forecasts of crop performance may be derived during the crop-growing period allowing the farmer, miller, or grain trader to assess final yield or grain quality levels for marketing purposes. In applying seasonal forecasts of crop production operationally, the development of associated decision-support tools (as described above) may be very important in order to provide evaluation of the consequences of alternative farm management decisions. Decision-support tools may be valuable and made available to farmers and, importantly, to their advisors. (Nelson *et al.* 2002).

It is important to point out that examples of successful integration of seasonal climate forecast systems with agricultural modelling systems to provide forecasts of crop performance are not restricted to developed countries. Selvaraju *et al.* (2004) provide an example for India, where an integrated, interdisciplinary, participatory systems approach for application of an ENSO-based climate forecast systems approach is being used with smallholder farmers and their agricultural production systems. In particular, they show case study results that demonstrate use of integrated climate–crop simulation forecast systems for application in crop choice management involving cotton and peanut cropping. Figure 6 provides an example of output of simulated cotton yield for an early

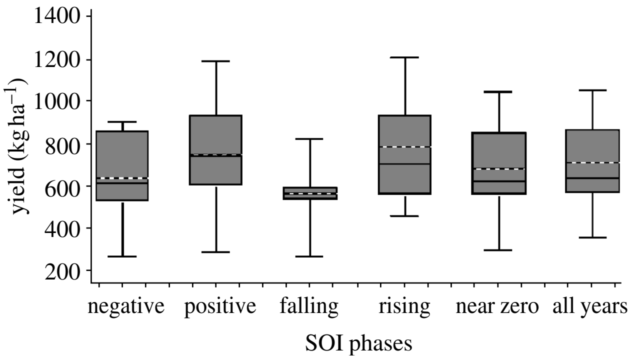

Figure 6. Distributions of simulated cotton yield for a crop grown in Tamil Nadu, India. The figure shows distributions of simulated cotton yield for an early sowing window at Avinashi for years associated with each of the five SOI phases in April/May together with the 'all-years' distribution (Selvaraju *et al*. 2004).

sowing in Tamil Nadu, India. Such output is useful in farm management decisions where, in this example, choice needs to be made between cotton and peanuts in terms of the likely most profitable crop for the coming season. Thus, there are, to some extent, parallel developments of such integrated approaches in seasonal forecasting taking place in both developed and developing countries that may help overcome some of the issues highlighted in, for example, Zimbabwe, where considerable constraints currently exist in effective application of seasonal climate forecasting in crop management (Patt & Gwata 2002). Such approaches may have even more uptake in developing countries, where it can be shown that simulation modelling outcomes match farmers' local rules of thumb (Selvaraju *et al*. 2004).

To facilitate uptake of operational seasonal forecasts of crop performance by users it may be beneficial to regard 'decision-support systems' that incorporate crop forecast systems as an integral component as 'discussion-support' systems where users can engage in discussions regarding climate, potential crop yield and crop management scenarios but maintain ownership of the processes and final decision making. In this way, discussion-support systems move beyond traditional notions of supply driven decision-support systems and can compliment the participative action research process. The critical role of dialogue among the key participants (farmers, advisors, crop modellers and climate scientists) is paramount (Nelson *et al*. 2002; Podesta *et al*. 2002) Additionally, in order to aid the decision-making process, use of operational crop forecast systems must reduce complexity rather than proliferate choices for users. Cox (1996) argued that these types of crop management decision-support systems usually impose structure on-farm management decisions that correspond poorly to the decision style of farmers and the context in which they operate. However, the research, development and extension programmes associated with delivering these programmes have facilitated social interaction between climate/crop modelling researchers, extension officers and farmers so that simulation-aided discussions about crop management incorporating seasonal forecasting has underpinned advances in farming systems analysis as a vehicle for improved farmer management (Keating & McCown 2001; McCown *et al*. 2002; Nelson *et al*. 2002).

It is suggested cross-disciplinary teams containing experts from each of the key scientific areas using mature simulation platforms usually achieve the most rigorous and successful climate applications. It should not be expected that agronomists should develop and run GCMs, nor should it be expected that climate scientists should become experts in biological model development and applications. Not only must the degree of detail considered in a model be congruent with the intended application, but it must also be ensured that the level of attention given to the climatic component of an application is of similar resolution and quality as the effort that goes into the agricultural modelling (Meinke & Stone 2005).

Furthermore, as chaos plays a large role in climate systems and the atmosphere frequently acts like a random number generator, deterministic statements in seasonal forecasting cannot justifiably be made. Only if uncertainties are clearly quantified can improved risk management practices be developed. Murphy (1993) pointed out the need for uncertainties inherent in judgments to be properly reflected in forecasts. He stated that the widespread practice of ignoring uncertainties when developing and communicating forecasts represents an extreme form of inconsistency and generally results in the largest possible reductions in quality and value. Probabilistic forecasts are more valuable than deterministic forecasts (Moss & Schneider 2000). This applies for events that are rare (e.g. extreme events) and which have considerable uncertainty associated with them. The likely future introduction of predictions based on output from GCMs may allow more versatility in climate prediction than is currently the case, including better opportunities to predict extremes. Palmer & Ratsanen (2002) have quantified the additional value of probabilistic forecasts over a single, deterministic projection in their study of greenhouse scenarios and found that the economic value of probabilistic seasonal forecasts was significantly greater and never less than for the deterministic case (Meinke & Stone 2005).

5. CONCLUSIONS

Both empirical and numerical climate forecast systems offer remarkable opportunity to improve crop performance worldwide. Both process-based and hybrid 'agroclimatic' crop simulation models are capable of providing very useful outputs of likely yield before the crop is planted or during crop growth stages. A somewhat pragmatic approach in some countries, notably Australia, has led to the development of systems that incorporate empirical climate forecast models integrated with crop simulation models. These systems can be used as a benchmark from which to determine relative increase (or otherwise) in forecast capability and value of numerical GCM-based integrated crop forecast systems. Further improvements in seasonal climate forecast capability, especially those from numerical systems that include important aspects of long-term climate change, combined with significant developments in crop simulation models offer the opportunity for major advances to be made in improving operational management of crop production. However, we strongly suggest a core commitment to an *interdisciplinary approach* in the development of seasonal forecasting systems of crop performance is needed, where climate scientists, agricultural scientists, systems modellers, economists and farm management specialists are intimately linked. Although, improvements are taking place in the development of numerical climate–crop production prediction systems, these improvements will have no value unless they are capable of changing management decisions. This requirement especially applies to agricultural systems, including crop management systems, where climate variability accounts for a significant amount of yield variability and resultant profitability. For subsistence farmers in developing countries seasonal forecasting of crop production offers enormous potential to improve production in the potentially favourable seasons and to reduce risks in the potentially poorer seasons. Production of appropriate decision/discussion-support systems promotes the output of scenario analyses of crop production at a farm or shire level, which facilitates appropriate tactical and strategic decision making by the farmer, grain trader, miller and exporter. Indeed, considerable benefits apply when seasonal forecasting of crop performance is applied across the whole value chain in crop production.

The authors are particularly grateful to Prof. Graeme Hammer and Mr Andries Potgieter for their valuable suggestions during the preparation of this manuscript, and to the National Managing Climate Variability Research Programme, and to the Queensland Department of Primary Industries and Fisheries for their financial support to this work programme over many years. We are especially grateful to the reviewers for their incisive comments and suggestions for this manuscript.

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