Examining the value of dynamic seasonal forecasts in managing farm-level production and environmental outcomes in a variable climate

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Abstract

Australia's agricultural industries are heavily impacted by both climate variability and change. The variable nature of Australian rainfall has had a strong role to play in the location and success of many agricultural enterprises. Developing flexible, proactive strategies for managing year-to-year climate variations within farming communities, and institutions that interface with them using advanced climate information, is arguably the most concrete step that agricultural industries can take to build resilience to long-term changes in the global climate system. In recent years dynamically-based atmospheric general circulation models (AGCMs) have become a mainstream tool in seasonal climate forecasting. This is as a result of the ongoing improvement in model performance and limitations of some existing statistical forecast systems to capture changing teleconnections in response to anthropogenic climate change. In this study a number of dynamically-based seasonal prediction models have been examined to understand the production implications of using this seasonal climate information to modify on-farm management. This has been achieved by using APSIM to examine the yield implications of varying starting or top-dress nitrogen management decisions in response to seasonal climate indices. This approach has been implemented for a number of farms in northern Victoria (Birchip) and the Murray Mallee in South Australia (Waikerie). The research to date has shown that the value of varying nitrogen management in response to these seasonal climate indices is dependent on location, soils and type of enterprise. The skill of the Development of a European Multi-model Ensemble system for seasonal to interTERannual prediction (DEMETER) model predictions for these two areas is limited particularly in the ability of the models to capture the impacts of El Ni?o Southern Oscillation (ENSO) events on Australian rainfall. It is also evident that GCMs seem to represent mean rainfall more effectively (average 20% different from observed) than the deviations in rainfall (average 50% different from observed). This has a significant constraining impact on the value of the hindcast when used to vary fertiliser decisions given the region is characterised by high rainfall variability and marked seasonality.

Key Words

climate change, climate variability, adaptation, crop modelling, atmospheric general circulation models

Introduction

Australia's agricultural industries are heavily impacted by both climate variability and change (Hammer 2000; Howden *et al*., 2001). The ability of agricultural systems to adapt to climatic variability has long been recognised as a key driver in production success, with failure to adapt responsible for production variability and related resource degradation. To remain economically and environmentally sustainable under such variable climate conditions requires a sound understanding of the drivers of climate variability and the extent to which these can be predicted. In addition this knowledge must be translated into a form that allows the modification of practical management strategies for avoiding economic and environmental losses in poor seasons, and to take advantage of favourable seasons (Meinke and Stone, 2005).

In recent years dynamically-based atmospheric general circulation models (AGCMs) have become a mainstream tool to deliver seasonal climate forecasts of rainfall and temperature (e.g. Syktus *et al.,* 2003). AGCMs show much promise because many of the factors known to affect climate variability can be incorporated into these model based forecasts (Power *et al.,* 2007). There are now a number of dynamically-based seasonal prediction models which are global in extent and there is considerable

interest in developing methods for maximising and quantifying their skill and utility to potential end-users in Australia (Smith, 2005). In Smith (2005) the rainfall hindcast information was evaluated for a series of European climate models across the southern extent of the Murray Darling Basin. The suite of six models forms part of the DEMETER model hindcasts.

The models include:

- ECMWF - The European Centre for Medium-Range Weather Forecasts
- UKMET – The United Kingdom Meteorological Office coupled model
- LODYC - Laboratoire d'Oc?anographie Dynamique et de Climatologie at the University of Paris VI.
- METEO – The French Bureau of Meteorology
- CERFACS - Centre National de la Recherche Scientifique
- INGV - Istituto Nazionale di Geofisica e Vulcanologia, Italy

Whilst the DEMETER models ability to reproduce observational rainfall totals for the southern extent of the Murray Darling Basin region has already been tested as part of the South East Australian Climate Initiative (SEACI), no assessment of its value for agricultural decision making has been made until now. In this paper we have integrated the suite of climate forecast models (DEMETER) with an agricultural simulation framework (APSIM) to analyse the value of using hindcast rainfall data to inform fertiliser management decisions. Four farming systems in the Northern Victorian region were examined and a single farming system in the Murray Mallee region of South Australia (Waikerie).

Data and Methods

Rainfall data

Three different rainfall datasets were examined in this study. These were: 1) grid average monthly rainfall from the six DEMETER climate models; 2) grid average observed monthly rainfall data derived from the Bureau's climate station network; and 3) daily rainfall records from five farms in both the Northern Victorian and Murray Mallee regions. Assessments of climate model skill were undertaken, comparing the climate model and observed grid average data. Whereas a comparison of the station data with the observed grid average data was undertaken in order to examine if the skill assessments were directly applicable to the climate station rainfall. For both the May to July (MJJ) and August to October (ASO) assessment periods, correlation values in excess of 0.91 were recorded in the Northern Victoria region while in the Murray Mallee region values of 0.74 and 0.87 respectively (Table1).

Table 1: Meteorological stations – source of observed data for the region

Farm	Met Station	Lat/Long	Correlation with observed gridded rainfall (MJJ)	Correlation with observed gridded rainfall (ASO)
Farm 1	WOOMELANG	-35.68 / 142.67	0.96	0.97
Farm 2	KERANG	-35.87 / 143.80	0.91	0.93
Farm 3	HOPETOUN	-35.73 / 142.37	0.94	0.94

Farm 3	BERRIWILLOCK	-35.64 / 142.99	0.94	0.95
Farm 4	WAIKERIE	-34.18 / 139.98	0.74	0.87

Skills assessment methods (Tercile and Median)

Assessments of hindcast skill (i.e. retrospective forecasts) were undertaken for each of the six DEMETER models against grid average observed rainfall data for the period 1980 to 2001 (consistent with the shortest climate model record) for two target seasons namely May to July (MJJ) and August to October (ASO). Skill was assessed based on both a tercile and median 'hit rate' analysis. Tercile hit rates were calculated as follows:

- The three-month rainfall totals from the BoM Gridded data and GCMs was assigned a tercile 1, 2 or 3 value, depending on percentage rank of the rainfall amount (i.e. less than the 33.3% rank – tercile 1, between 33.3% and 66.6% rank – tercile 2 and greater than the 66% rank – tercile 3) calculated from the entire period (1980 to 2001).
- If the GCM tercile values matched the observed tercile values then a 'hit' was declared.
- The total number of hits was summed across the period 1980 to 2001 to determine the 'hit rate' for each model.

The median hit rates were also calculated based on the GCMs' ability to match the variation of three-month rainfall totals above or below the median. The results of the tercile analysis are given in the Table 2. In the case of the tercile hit rates, a value of close to 33% would indicate little or no skill. Similarly, a success rate of close to 50% at forecasting above/below median values also indicates little or no skill. Values in excess of these thresholds indicate potential skill.

Table 2: Percentage time for the period 1980 to 2001 that each climate model predicted the correct observed 3-month rainfall tercile category (values greater or equal to 50% are in bold).

Climate Models	**Northern Victoria**		**Murray Mallee (SA)**	
	MJJ (%)	**ASO (%)**	**MJJ (%)**	**ASO (%)**
CERFACS	32	45	5	36
ECMWF	36	18	32	27
INGV	**55**	36	32	32
LODYC	**55**	41	**55**	36
METEO	27	**50**	27	18
UKMET	18	36	32	27

APSIM model benchmarking

The potential economic value derived from using climate information to adapt crop management was estimated using the APSIM cropping systems model. The APSIM model was benchmarked against representative paddocks and actual rotations on each of the five farms. The benchmarking against farmer observations revealed a good agreement with observed wheat, canola, barley, and oat yields (further details available in Crimp *et al*, 2007).

Two on-farm management decisions were the focus of the evaluation, namely the amount of fertiliser at sowing and the subsequent top dressed fertiliser amount. The amount of fertiliser applied at sowing was varied according to the rainfall amount indicated for the MJJ period. If the GCM hindcast indicated rainfall in tercile 3 then the amount of nitrogen applied at sowing was increased. If the GCM hindcast indicated rainfall in tercile 2 then long term average amount of nitrogen was applied. If the GCM hindcast indicated rainfall in tercile 1 then the amount of nitrogen was reduced. An example of this management strategy is given below (Table 3). Top dressing fertiliser rates were varied in a similar way, based on rainfall over the ASO period. In this study the soil mineral nitrogen content is reset to a fixed amount at the start of each year (60kg/ha) to eliminate any carryover effects from the previous year which might cloud the assessment of the forecast value in determining applied fertiliser rates.

Table 3: The sowing fertiliser rule for the Barclay farm implemented in APSIM

		Fertiliser at Sowing (Units of N)
IF “GCM predictions for May” >= Observed May-June-July 66 tercile	THEN	170
IF “GCM predictions for May” < Observed May-June-July 66 tercile AND > Observed May-June-July 33 tercile	THEN	130
IF “GCM predictions for May” < Observed May-June-July 33 tercile	THEN	90

Results

The impact of varying fertiliser for sowing or top-dress fertiliser applications in response to each DEMETER model hindcast has been assessed in terms of gross margins (GMs) (i.e. gross production income minus input costs specific to each farm - derived from 2007 values). This is compared against a ‘Control’ case defined as a system whereby a farm specific optimum rate (calculated for the period 1980 to 2001) of fertiliser is applied at sowing or to top-dress.

In case of the Farm 1, using the CERFACS hindcast information to modify sowing fertiliser amount resulted in a modest $4 per hectare benefit over using the optimum fixed fertiliser rate every year (1980 to 2001 mean of $195) (Table 4). In this case the CERFACS model provided higher GMs in 32% of years, the same GMs in 45% of years and lower GMs in 23% of years compared with the control. For top dressing decisions only marginal benefits of up to $2 per hectare were achieved on this farm (Table 5), with the INGV model providing higher GMs in 36% of years, the same GMs in 18% of years and lower GMs in 45% of years. In the case of Farm 2, use of the GCM hindcast data provided average GM benefits of between $1 and $8 per hectare more than the control (1980 to 2001 mean of $247) (Table 4). Using the CERFACS hindcast data produced gross margin benefits in 68% of years when used to inform sowing fertiliser rates and in 50% of years for top dressing decisions with the same gross margins as the control simulation in 9% and 5% of years respectively. In the case of Farm 3 and 4 the GCM hindcast data provided no GM benefits for either sowing or top-dress fertiliser decisions (Table 4 and 5).

Table 4: Gross Margin benefits or losses ($ per hectare difference from the control) for four farming systems in Northern Victoria for sowing fertiliser applications.

Farms	(GM difference in $/ha from the control)					
	CERFACS	ECMWF	INGV	LODYC	METEO	UKMET
Farm 1	4.09	-5.31	-5.93	-4.72	-3.52	-6.39
Farm 2	8.40	1.15	0.81	2.57	3.44	-1.23
Farm 3	-0.75	-3.47	-5.21	-3.91	-2.23	-6.79
Farm 4	-6.05	-16.95	-16.37	-13.80	-12.72	-18.55

Table 5: Gross Margin benefits or losses ($ per hectare difference from the control) for four farming systems for systems in Northern Victoria for top-dress fertiliser applications.

Farms	**(GM difference in $/ha from the control)**					
	CERFACS	ECMWF	INGV	LODYC	METEO	UKMET
Farm 1	0.40	-0.43	1.45	1.79	0.86	1.40
Farm 2	1.02	0.54	5.07	2.23	2.89	2.23
Farm 3	-6.71	-6.71	-4.24	-6.71	-4.71	-6.71
Farm 4	-14.44	-14.60	-8.35	-14.60	-10.19	-14.60

Conclusion

The difference (with Control simulation) in GMs achieved with or without El Ni?o years was examined for the farming system most responsive to the hindcast information. In this analysis El Ni?o years were removed from the subset of years in order to examine the difference in mean gross margins. The El Ni?o years removed included 1982, 1987, 1991, 1993, 1994 and 1997. A re-examination of gross margins revealed a considerable improvement over the control for both sowing fertiliser and top-dress fertiliser decisions. The positive impact of removing El Ni?o years from the analysis suggests that the GCMs do not simulate the impact on regional rainfall well. A comparison of rainfall in the MJJ period during El Ni?o years showed an overestimation of rainfall of the order of 85-200%. From this analysis, when the climate information is processed through this evaluation framework it provides a more user-relevant and integrative measure of the skill of the different models. Critically we find that this skill is much less than what would be indicated by examining at rainfall outputs alone.

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