Invited paper: Towards Better Seasonal Climate Forecasts for Farmers

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Abstract
Two approaches to obtaining more valuable seasonal climate forecasts for farmers are described. The first involves obtaining a better understanding of the climate system by exploring the individual weather events that make up seasonal climate. The synoptic decomposition of rainfall events in NW Victoria indicates that there is one dominant synoptic system that is responsible for the majority of useful rainfall: the cutoff low. An exploration of the dynamics of these systems reveals that the moisture sources are most likely to be from the oceans north of Australia, while the frequency and intensity might be controlled by ocean temperatures to the south. The second approach involves simulation of the growth of a wheat crop in NW Victoria, and examination of the potential value of different forecast systems. It is concluded that a rainfall forecast is likely to provide less than half the potential value of a forecast system.

Key Words
Sea surface temperature, grains, management decision

Introduction
Farmers universally would love to know when it is going to rain. Rainfall forecasts up to a week ahead are now routinely available from a number of sources. Useful as this short-term knowledge is, farmers also want a forecast of rainfall for the coming season or two. This is problematic for a number of reasons. First, such longer term predictions can only be probabilistic due to the chaotic nature of the atmosphere. Second, the skill of these predictions is dependent on region and time of year. Third, the skill may not be sufficiently high to be of value to a farmer. Finally, even if the forecast is skilful, a farmer may not be able to alter a management decision to take advantage of the forecast.

There are just a few seasonal climate forecast systems in Australia. The Bureau of Meteorology produces a monthly seasonal climate outlook based on a statistical analysis of sea-surface temperature (SST) in the Pacific and Indian Oceans (Drosdowsky and Chambers 2001). The skill of this outlook, averaged over many rainfall stations throughout Australia, has been questioned recently by Vizard et al. (2005). The Queensland Centre for Climate Applications (QCCA) provides rainfall probability information based on the Southern Oscillation Index (SOI) “phase system” (Stone et al. 1996). The utility of this statistical system varies considerably across Australia, and has the greatest skill in north-east Australia (Hammer et al. 2000), where the El Niño/Southern Oscillation (ENSO) phenomenon has the greatest impact. The ENSO sequence system (Stephens et al. 2006) is another statistical system based on ENSO physics in a more complicated form than the SOI phase system. It is too early to really assess the skill of this system, and while it shows promise, it is likely to have greatest utility in NE Australia because of its reliance on the ENSO mechanism.

The Bureau of Meteorology also runs a global circulation model (GCM) consisting of ocean, atmosphere and data assimilation components coupled together into a predictive model (Alves et al. 2003). Called POAMA (Predictive Ocean Atmosphere Model for Australia), this model makes ensemble predictions of Pacific Ocean SST up to 12 months ahead. However, the current version does not predict rainfall over Australia; it is left to the farmer to convert predictions of SST to something more relevant to decision making.

Approaches to forecasting based on GCMs are almost certainly going to lead to the most skilful forecasts in the long run. This is because these large complicated models are able to take into account all the important physical processes that affect our climate. However, they have not yet reached the point where GCM forecasts are more useful than the simpler statistical techniques. There is a great deal of work still to be done on how these models are initialized, and on how they represent important physical processes such as mid-latitude synoptic systems, clouds and rainfall. In the meantime, careful analysis of observations to elicit the key physical processes controlling seasonal climate variations seems like the most promising approach.

The question of what to forecast is an important one. Farmers invariably ask for rainfall forecasts, perhaps thinking that they will get daily rainfall amounts for the next season. This is simply not possible. What might be possible is to forecast the rainfall total for the season, but this is not necessarily desirable for a couple of reasons. First, rainfall distribution is just as important as rainfall amount. A monthly rainfall total of 30 mm could fall as 1 mm per day, or as two 15 mm events. The former is all lost to evaporation, while the latter will soak into the soil and be available to plants for some time. Second, rainfall is one of the hardest quantities for a model to get right. The physics of clouds and rainfall is very complicated and not well understood; nor is it modelled particularly well because the fine spatial scale on which convection occurs is not explicitly resolved by seasonal GCMs.

Recent work by McIntosh et al. (2005) showed that for northeast Queensland, forecasts of plant growth days were more valuable to a grazier than forecasts of rainfall. As we will see, this study highlights the importance of developing forecasts with knowledge of the region, time of year and management decision options for a particular agricultural industry. By forecasting an appropriate quantity other than rainfall, not only is forecast skill improved, but forecast value is increased also.

This paper, then, has two parts. The first looks at ways in which the basic understanding of seasonal variability might be increased by understanding the key physical processes controlling seasonal climate. The second explores the way in which forecasts might be used to best value for particular industries, focusing on northern Queensland grazing, and grains in the southeast of Australia.

Physical understanding

Synoptic decomposition

Seasonal climate is made up of a sequence of weather events. One way of understanding why seasonal climate varies from year to year is to explore the factors controlling the building blocks of seasonal climate; synoptic weather systems. It is this philosophy that motivated Pook et al. (2006) to explore the synoptic systems that make the dominant contribution to rainfall in southeast Australia. The intention is that if one, or at most a few, types of synoptic weather systems can be isolated as causing most of the rainfall, then a careful study of the factors controlling the rain generated by these systems might shed some light on the causes of seasonal variability.

The method used by Pook et al. (2006) involves classifying the dominant synoptic weather system every day it rained in NW Victoria, from 1970 to 2005. Clearly the results will vary from region to region, and so the major grain growing area surrounding Birchip in Victoria was chosen for this first study. The classification is performed manually by an expert synoptic meteorologist, and is therefore somewhat subjective. However, the process is a necessary first step in developing rules that might guide a computer-based expert system that could then be used in other regions. It was found to be important to look at not only the surface pressure chart, but also upper air charts, particularly the 500 hPa height. This was particularly important in classifying what turned out to be the dominant synoptic system: the cutoff low.

A cutoff low is an isolated low pressure system that has broken away from the low-pressure belt to the south. Such a system extends vertically through much of the atmosphere, and is sometimes not apparent on the surface chart. Cutoff lows are responsible for 51% of growing season rainfall in NW Victoria, with fronts of all types being responsible for 32%. The growing season is defined as Apr-Oct. The percentage of growing season rainfall due to the various synoptic types over the 36 years 1970 to 2005 is shown in Figure 1.

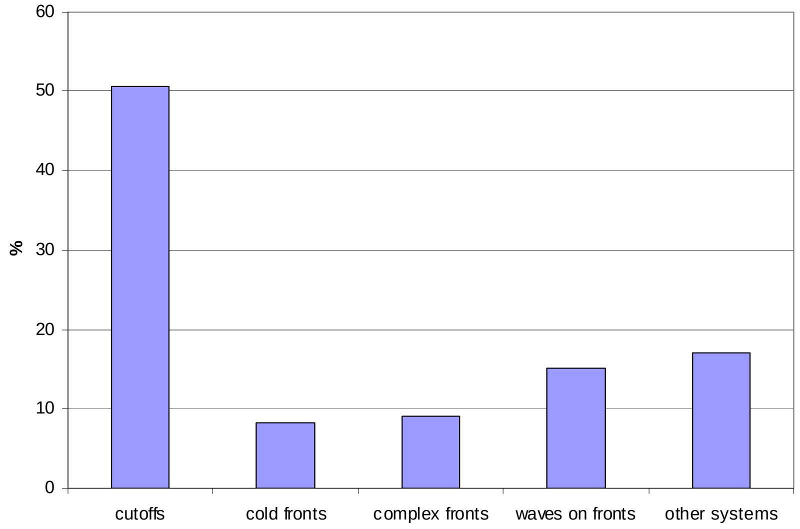

Figure 1. Growing season rainfall (Apr-Oct) in NW Victoria (%) by synoptic type for the period 1970-2005.

If only significant rainfall events are considered, then some 70% of rainfall events over 10 mm/day in the growing season are attributable to cutoff lows, and this percentage increases further for higher rainfall amounts (see Figure 2). It is these significant rainfall events that are of real importance to farmers, as the benefit of low rainfall events is mostly lost to evaporation. One other striking feature of the synoptic decomposition is that the rainfall decrease experienced in NW Victoria since about 1995 is mainly due to a decrease in the rainfall due to cutoff lows (see Figure 3). The rainfall due to fronts of all types has remained reasonably constant.

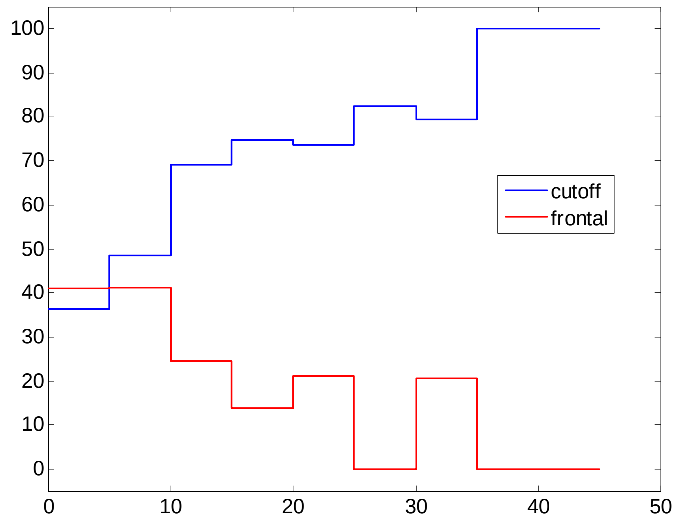

Figure 2. Percentage of rain in 5mm bands due to cutoff lows and fronts of all types.

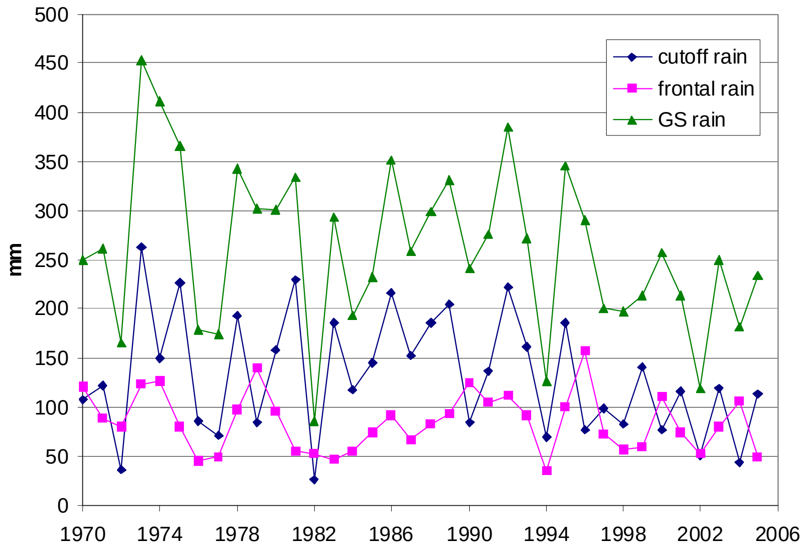

Figure 3. Rainfall amount by year due to cutoff lows (blue), fronts (magenta) and total growing season rainfall (green).

It is easy to conclude, then, that a careful study of cutoff lows would be most advantageous in obtaining a better understanding of seasonal climate variability in NW Victoria. In particular, if it is possible to understand the dynamics of cutoff lows, the generation mechanisms and moisture sources, and ultimately the factors leading to the interannual variation observed, then it might be possible to develop a better seasonal climate prediction scheme. Certainly, any GCM must be capable of reproducing the observed characteristics of cutoff lows before it has any real chance of providing useful climate predictions.

The year-to-year variation of rainfall due to cutoff low pressure systems could be due to two main factors. Either the number of cutoff lows varies from year-to-year, or the amount of rainfall obtained out of each cutoff low fluctuates. These two factors may be linked, or they may be independent. To examine this, we performed an anomaly decomposition of rainfall due to cutoff lows. The anomaly in rainfall can be split into an anomaly due to the number of cutoffs, plus an anomaly due to the amount of rainfall from each cutoff, plus an anomaly due to both these factors occurring at the same time. The results of this decomposition are shown in Figure 4.

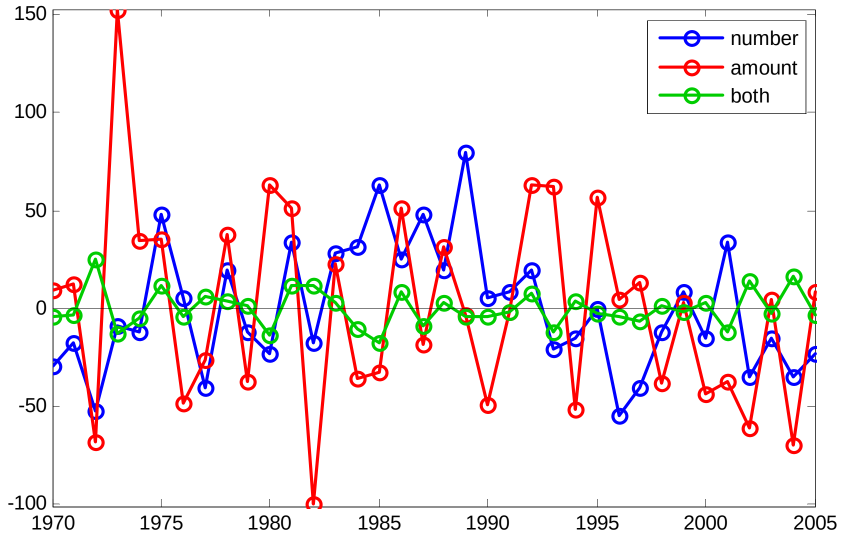

Figure 4. Anomaly decomposition of cutoff low rainfall in NW Victoria (Apr-Oct).

The first point to note is that the anomaly due to both factors occurring together (green line) is relatively small. This means that the rainfall varies independently due to the number of cutoff lows varying (blue line) and the amount of rainfall out of each cutoff low varying (red line). It can also be seen that in the major drought years of 1972, 1982 and 2002, both number and amount factors gave negative rainfall anomalies.

Relation to ocean temperatures

The next step is to explore whether this year-to-year variation is linked to large scale sea-surface temperature (SST) patterns. Ocean temperatures are very important in controlling winds and moisture in the atmosphere, and the temperature varies quite slowly compared to the atmosphere, with a timescale that can be many months. Hence it might be possible to use a knowledge of ocean temperatures as a predictor of rainfall anomalies.

Figure 5 shows the simultaneous correlation between the number and amount time series from Figure 4 and SST (averaged over April-October) over the oceans surrounding Australia. It is clear that the ocean regions associated with the number of cutoffs is quite different to the regions associated with the amount of rain per cutoff.

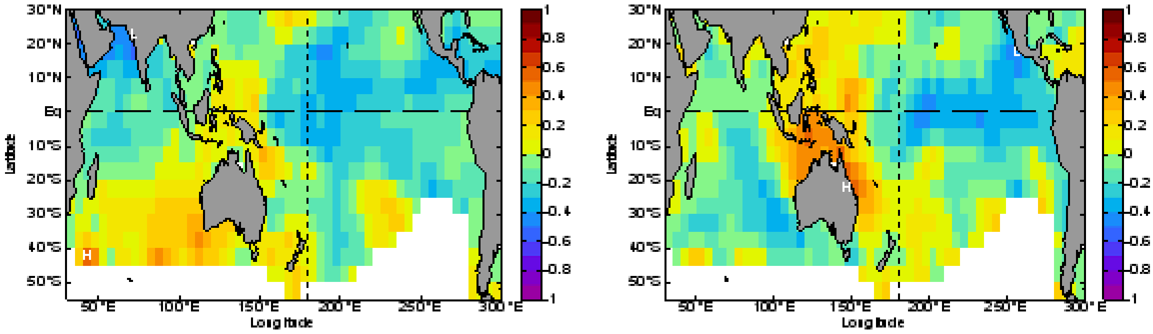

Figure 5. Simultaneous correlation (r) between Apr-Oct SST and (a) number of cutoffs, (b) amount of rain per cutoff.

There are some plausible physical arguments to explain the difference observed. Cutoff lows almost invariably travel from west to east, and are seen to develop south and west of Australia. Therefore it is not surprising that a correlation is observed in this region, although the precise details of how SST might influence the development of these systems is not yet known beyond the simplistic argument that warmer ocean temperatures supply more energy to synoptic systems. On the other hand, the warm equatorial waters are most likely the dominant source of atmospheric moisture, and clouds can often be seen in satellite images propagating from north to south, thus bringing moisture to southern regions where it is available to produce rainfall. Cutoff lows (and fronts) provide a mechanism for extracting this moisture from the atmosphere. Cutoff lows are thought to produce more rainfall because they propagate more slowly than fronts, and thus stay in a particular region for longer.

Moisture pathways

One of the key factors in understanding the rainfall produced by cutoff lows is understanding the pathway moisture takes from the ocean, which is the major source of atmospheric moisture, to the site of rainfall. One technique for exploring this is to calculate air parcel trajectories for a number of days prior to a rainfall event. This is done using the optimal model/data re-analysis produced by the National Centers for Environmental Prediction (NCEP) - National Center for Atmospheric Research (NCAR) (Kistler et al. 2001). This data set, which will be referred to here as the NCEP re-analysis, provides, amongst other variables, three-dimensional velocity, temperature and humidity on a global grid. The horizontal grid spacing is 2.5 degrees of longitude and latitude, the vertical spacing is variable but of order 100 hPa, and the temporal spacing is 6 hours.

On the day of a particular rainfall event in NW Victoria, air parcels above the rainfall stations in this region are tracked backwards in time for up to 10 days using a semi-lagrangian advection algorithm (Staniforth and Cote 1991). The parcels are assumed to start at a height equivalent to 700 hPa for simplicity, which is a good first estimate of the level from which much of the rainfall originates. Future work will start the air parcels at the level at which relative humidity is a maximum.

In order to investigate the mean air parcel trajectories associated with cutoff rainfall, the trajectories are averaged in rainfall categories, ranging from no rain up to greater than 25 mm/day. The mean trajectories are shown in Figure 6. The trajectories were all limited to a time of 5 days. Beyond that time there was considerable divergence, although there is still divergence out to 5 days. These diagrams show that as the amount of daily rainfall increases, the mean trajectory comes more from the north. A similar results holds for mean trajectories for rainfall due to fronts, although the paths are some 10-20% longer, indicating the greater speed of frontal systems.

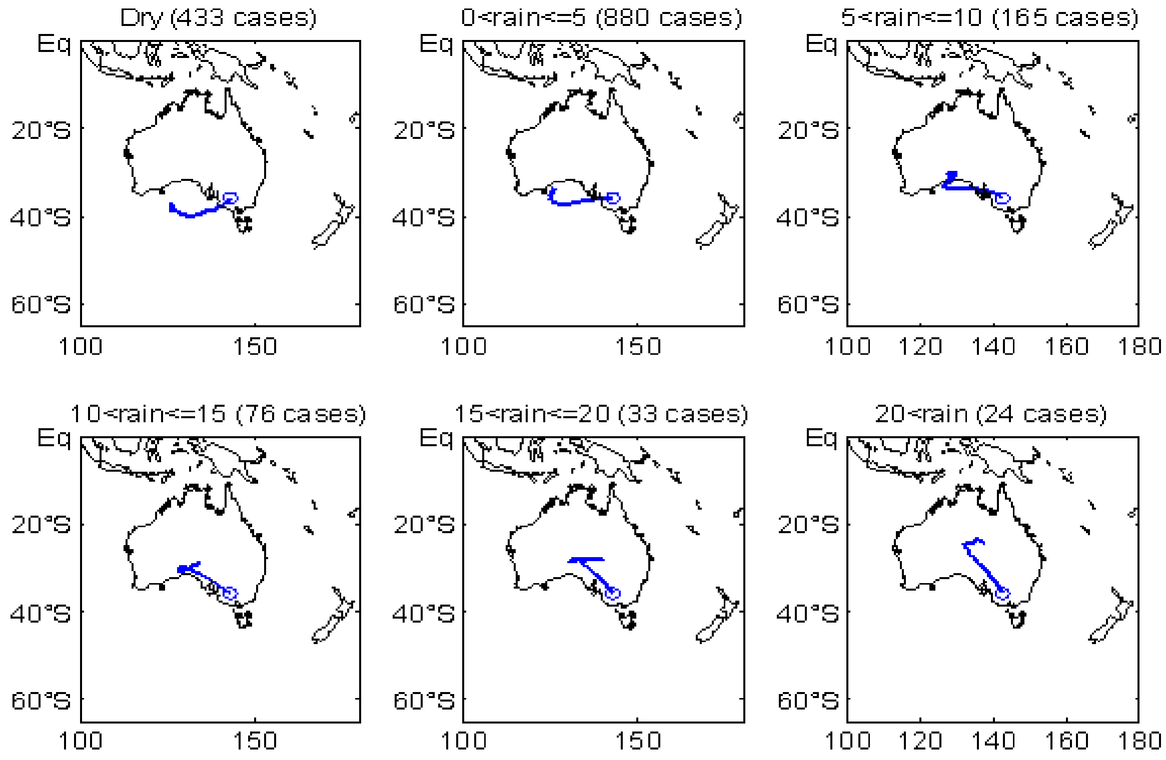

Figure 6. Mean 5-day air parcel trajectories, ending at the open circle in NW Victoria, for cutoff low rainfall events in various rainfall categories (given in mm).

The mean trajectories indicate that air parcels carry moisture from the tropics down to the mid-latitudes, particularly for the higher rainfall events. This goes some way to explaining the correlation between SST and rainfall amount observed earlier. Note, however, that trajectories on individual days can differ considerably from these mean trajectories. The atmosphere is quite variable and chaotic, and trajectories are observed from the Coral and Tasman Seas as well as the Southern and Indian Oceans. When relative humidity is plotted along the trajectories, it is often observed that a lot of moisture is picked up as air parcels cross the east coast from the Tasman Sea. There is a great deal more work that needs to be done in order to really understand the moisture pathways for rainfall that ends up in NW Victoria.

Rainfall trigger mechanism

Once there is enough moisture in the air to produce rainfall, there needs to be a “trigger mechanism” to actually extract the moisture and turn it into rain. The cutoff low is such a trigger mechanism, as is a frontal system. Both these systems act to cause air parcels to rise. When the three-dimensional structure of air parcel trajectories prior to rainfall events are examined, one striking feature is that almost all trajectories have an upwards direction in the day or two prior to rain falling.

This observation suggests that perhaps a third factor is needed in studying year-to-year variations of cutoff rainfall: vertical intensity. It may be that interannual rainfall variability is as much related to the vertical motion needed to extract moisture from damp air as it is to the amount of moisture or the number of cutoff lows. Further work will explore this additional factor. In the meantime, the generation mechanism of cutoff lows is being sought to gain an understanding of what might control the number of cutoff lows seen in any year.

Using forecasts

What to forecast?

The most common quantity that farmers want to know is rainfall. It is also the most obvious starting point when developing a forecast system. However, it is essential to put some effort into understanding the agricultural system before doing this. For example, the time of year in which a forecast is most useful will vary depending on the crop and the region. There will be times and places where a forecast would be most valuable but there is little or no forecast skill. For example, in regions where ENSO is the dominant physical mechanism, farmers might want to know about the coming season early in the calendar year. The so-called "predictability barrier" means that forecasts of ENSO-related climate quantities made in the period Mar-May have little or no skill beyond that time (Torrence and Webster 1998). There will also be times and places where a forecast is skilful but it is not possible to base a management decision on the forecast.

A good understanding of the agricultural system can sometimes lead to a more valuable forecast based on a quantity other than rainfall. An example is the extensive rangelands grazing industry in northeast Queensland. Stocking rate decisions are generally made in July for the following year, and the most important quantity for the farmer to know is the amount of pasture growth that is expected. McIntosh et al. (2005) showed that an imperfect forecast of plant growth (strictly plant growing days) was more valuable than a perfect rainfall forecast. This is primarily because plant growth is an integrator of rainfall, and therefore takes into account not only rainfall amount but rainfall distribution. Simply knowing the total amount of rainfall that would fall in a 9-12 month period, however accurately, is less valuable than having a modestly accurate forecast of plant growth in the same period.

The plant growth forecast of McIntosh et al. (2005) was also compared to a standard forecast based on the SOI phase system (Stone et al. 1996), and compared to a perfect forecast of plant growth. The results are summarized in Table 1. The plant growth forecast is clearly more valuable than no forecast, and has also improved considerably on the value of the SOI phase forecast. The final column indicates the value of a perfect plant growth forecast, and this is not much more than the existing plant growth forecast. This indicates that there is little room for improvement in terms of forecasting plant growth, even through the skill of the plant growth forecast is moderate (correlation r = 0.62 over 113 years).

Table 1. Forecast system benefits for a representative grazing property in northeast Queensland. Currency is $A in 2001.

	No Forecast	SOI phase	Plant growth	'Perfect' rainfall	'Perfect' plant growth
Average herd size	3523	3657	3808	3881	3885
Animals sold per year	828	878	953	960	989
Annual cash flow ($/yr)	$90,808	$103,593	$115,552	$114,780	$120,416
Soil loss index (kg/ha)	920	1010	1070	1070	1030

Another point to note from Table 1 is the soil loss index. Although using a forecast increases soil loss, the increase is negligible. Soil loss of 1000 kg/ha annually amounts to less than 1 mm of soil depth each year. Hence increases of 90-150 kg/ha are very small. The conclusion is that using a forecast allows a farmer to work the land harder without additional resource degradation.

Southeast Australian grains industry

Moving south from Queensland into the southeast grain growing regions of Victoria and South Australia poses a number of problems. First of all, moving away from the equator generally reduces the influence of ENSO on seasonal climate. ENSO is the largest seasonal climate signal on the planet, and the most studied. In mid-latitude regions there are other climate influences that may be as or more important locally than ENSO. In southeast Australia, the other possible climate influences include the Indian Ocean Dipole (IOD) (Saji et al. 1999), and the Southern Annular Mode (SAM) (Thompson and Solomon 2002). There may be additional regional influences from the Southern Ocean and Tasman Sea. Developing a forecast system here will require a careful analysis of the most important climate factors; it is most likely that even a relatively simple forecast system will need to be non-linear to take into account these multiple factors.

An additional complication is that the rainfall, and hence the grain growing season, tends to be winter dominant. Hence a forecast is needed very early in the year if it is to aid decisions made about planting time, area planted and initial fertilizer application. If the seasonal climate is influenced by ENSO to any degree, then the predictability barrier means that a forecast of this component of the seasonal climate is unlikely to have much, if any, skill. If ENSO is an important factor, then substantial forecast skill may only be possible later in the year to assist decisions about fertilizer addition in late winter/early spring.

One of the best ways to develop and test the value of a forecast system is to use a century-long simulation of wheat yields at a specific location and for a specific soil type. Such a simulation helps to isolate climate-related factors from other factors such as technology. It also allows the testing of a wide range of management decisions. This study uses the Agricultural Production Systems Simulator (APSIM) model (Keating et al. 2003) to simulate yearly wheat yields (plus many ancillary quantities) from daily climate records at Birchip in NW Victoria. This simulation runs for 116 years from 1890 to 2005, and assumes a clay soil with a relatively high water holding capacity. The soil water content is reset to the minimum plant available water content after harvest each year.

Three key management decisions were identified in discussions with local farmers. These were: sowing date, starting nitrogen and topdressing nitrogen. An additional important management decision is the spatial area to plant. However, all the calculations here are done per unit area. For each of the three key management decisions, a range of reasonable values was established. APSIM was then run once for each possible combination of values, leading to a large factorial database that permits exploration of the optimum management decision over 116 years using various forecast systems. Estimates of the costs and prices associated with growing a wheat crop were also obtained from farmers, so that a gross margin could be calculated. The optimum management decision varies depending on whether wheat yield or gross margin is optimized.

For the purpose of this exercise, it is assumed that no information is available about soil moisture at planting time. It has been shown that such information is, in fact, a very valuable guide to production in the following season (Carberry et al. 2000). It is also assumed that the same crop is planted every year with no consideration given to crop rotation and fallow periods, since the calculation is per unit area.

Under these assumptions, if no climate information is available, then the optimum management strategy must be determined on the basis of the long-term climate history, and will be constant across all years. If the goal is to maximize long-term yield, then the optimum management decisions are to plant as early as possible (1 May), apply the maximum N at sowing (urea 125 kg/ha, which is about 50% N), and apply the maximum N at topdressing (urea 150 kg/ha). The long-term yearly mean yield is 2782 kg, and the gross margin is $91. However, it makes much more economic sense to optimize gross margin rather than yield. In this case, the only management decision to change is the topdressing rate, which goes from the maximum value to the minimum (none at all). The mean yield is now 2547 kg, with a gross margin of $247. Clearly it is better in a majority of years to accept a small yield penalty and reduce the input cost of the extra nitrogen in order to get a considerably better economic return. Henceforth we only consider optimizing gross margin, and the results in this case are summarized in Table 2.

Table 2. Simulated gross margin and yield in NW Victoria for various perfect forecast systems when management decisions are chosen to maximize gross margin. Currency is $A in 2005.

	No Forecast	Perfect hindsight	Perfect practical (GM–6 categories)	Perfect practical (rainfall)	SOI phase (Mar-Apr& Jul-Aug)
Gross margin ($A/yr)	$247	$455	$307	$312	$250
Yield (kg/ha)	2547	3729	2916	2996	2606

At the other end of the spectrum is the possibility that a farmer makes the best possible management decision each year in order to maximize gross margin ("perfect hindsight"). In this case, sowing takes place at the earliest date possible in about half the years, with the rest spread out between then and the end of July. Starting N is a maximum in 60 out of the 116 years, a minimum in 33 years, with few values in between. Topdressing N is nil in 55 years, near maximum in 29 years, with the rest spread in between. The mean yield is 3729 kg, and the mean gross margin is $455. This is considered to be a very good value, and shows the benefit of making the correct management decision each year. It gives a target to aim for when developing and valuing a forecast system. However, this target is artificially inflated by false skill as the next section discusses.

Assessing forecast skill
There is a very practical consideration when valuing a forecast that decreases the potential value considerably. A true forecast system cannot use knowledge of the year being valued. It is important to calculate cross-validated skill, as an estimator of true forecast skill, rather than explanatory skill. The issue is discussed at length by McIntosh et al. (2005). Consider the following thought experiment: the best possible forecast system would forecast the optimum gross margin, together with the associated management decisions to obtain this gross margin. In order to cross-validate properly, when the gross margin in a particular year is calculated, the management decisions must be determined from any years except this year. Hence when the forecast system is used to group years together into N categories, the gross margin for one of the years in a category is determined from the optimum management decision obtained from looking at all the other years in the same category. The number of categories must be chosen so that there are at least two years in each category. Hence the possibility to choose the optimum management decision in each year independently is not possible in a cross-validated sense.

The number of categories now becomes another variable. Moeller et al. (2006) considered this issue, but without the addition of cross-validation. They discovered that there was little advantage to using more than a few categories. Figure 7 shows the results of using the optimum gross margin as a surrogate "perfect" forecast as a function of the number of categories. Within each category the optimum management decision is calculated and used for years in that category. The cross-validated version withholds the year being valued from the calculation of the management decision. The diagram shows that if the calculation is properly cross-validated, the optimum number of categories is quite small; six categories gives the largest gross margin in this case, but the calculation is clearly noisy. In general 3 categories should be sufficient. If cross-validation is not used, the optimum number of categories is equal to the number of years (not shown in the figure), but this result gives a misleading indication of the possible value of a forecast system.

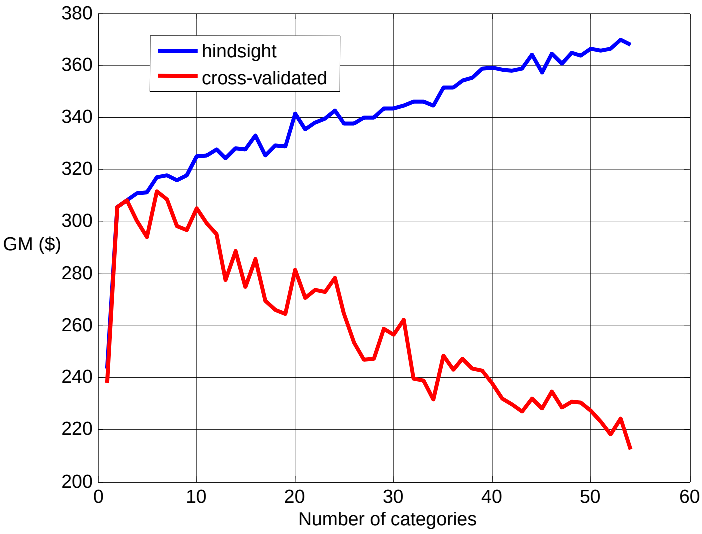

Figure 7. Gross margin (GM, in $A) as a function of the number of categories using optimized gross margin as a surrogate "perfect" forecast.

When six categories are used, the gross margin is $307, significantly more than if a constant management strategy were used ($247), but also significantly less than the apparent maximum value of $455 (see Table 2).

To explore how important it might be to be able to forecast rainfall, the sowing to harvest rainfall is calculated for each year and used as a forecast system. That is, the value of a perfect in-season rainfall forecast is assessed. Again using six categories, the cross-validated gross margin using such a forecast is $312, effectively the same as using gross margin itself. This is still a long way from the "perfect hindsight" value of $455.

The implication of this result is that a rainfall forecast system might have some value provided it is accurate enough (this issue is covered by Moeller et al. 2006). However this might not be the best way forward, as it might only capture a modest fraction of the potential benefit of a forecast. Clearly, there is a great deal of work remaining to explore the best structure for a forecast system that captures more of the relevant climate signal than just rainfall.

Potential forecast systems

One possible forecast system for NW Victoria might be based on knowing the state of ENSO and the IOD. There are good physical reasons why these two dynamical processes might influence the climate there. Meyers et al. (2006) have developed a classification scheme that assigns each year into one of three categories of ENSO (El Niño, neutral and La Niña) and one of three categories of the IOD (positive, neutral and negative). Hence each year since 1877 is assigned to one of nine possible states. The first question to ask is whether there is any value to a farmer in being able to predict this state prior to sowing time.

The short answer is that the cross-validated value of the ENSO/IOD forecast system, even assuming a perfect prediction of the state, is zero. A number of other prediction schemes have been tried, with the same disappointing result. For example, the SOI phase system (Stone et al. 1996) assigns one of five phases to the current climate state based on the SOI value this month and last month. The maximum gross margin obtained using the SOI phase in any month is $250 using the SOI from Mar-Apr (and also Jul-Aug), a very marginal gain. Note that in practice, only the first (Mar-Apr) phase is a feasible forecast scheme as it relies on data obtained prior to the sowing date.

Conclusion

The value of existing seasonal forecast systems is dependent on region, industry and time of year. While there are some examples of forecast systems that provide reasonable value, most farmers want a better forecast for their region. This is particularly so for farmers in the southern half of Australia where the climate influences are more complicated than ENSO, and existing forecast systems have marginal skill.

The development of better seasonal climate forecasts for farmers should involve more than developing a better rainfall forecast. In northern Australia, a practical forecast of plant growth with moderate skill is more valuable to a grazier than a perfect rainfall forecast. In southern Australia, a perfect rainfall forecast achieves less than half the potential value of a forecast system for the grains industry. A careful study of the structure of the optimum forecast system is needed to understand the critical quantities that need to be forecast in order to get the best value.

In any event, a better understanding of the climate system as it affects agriculture is needed. Seasonal climate is made up of a sequence of synoptic weather events. Understanding the dynamical and physical nature of these events, and the controlling factors that might lead to foreknowledge of their frequency and intensity, is essential in order to build a better seasonal forecast system. Such a system will need to contain information about moisture sources and pathways, event intensity, frequency and vertical velocity if it is to be of value.

Acknowledgements

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