Can linking a climate model to a crop model, provide useful predictions of yield potential?

Jaclyn N. Brown[1], Zvi Hochman[2] Dean Holzworth[3] and Heidi Horan[2]

[1] CSIRO, Hobart, TAS 7001, Jaci.Brown@csiro.au
[2] CSIRO, Brisbane, QLD 4001
[3] CSIRO, Toowoomba, QLD 4350

Abstract
Skilful predictions of upcoming yield potential allow producers to mitigate risk and implement effective management decisions, thereby increasing productivity and profitability. The season-ahead climate forecast is a key parameter in determining upcoming yield potential yet it is difficult to incorporate into crop models. Seasonal climate models are at lower spatial resolution than the paddock scale needed for yield predictions in crop models and often contain many biases particularly in crucial factors such as rainfall. The science of climate modelling is progressing rapidly and we have explored whether the models now have adequate skill to provide direct daily weather input into crop models, after only a simple downscaling and calibration. We find that in some locations, the daily climate input is very effective for predicting yield. In other locations the biases are still large and the forecasts unreliable. The reasons for this poor predictive skill appears to come from numerous sources including a tendency to always under predict yield, errors in the rainfall amount and distribution, radiation and temperature. A new climate model is being implemented in Australia this year and we expect to soon see improvements from this baseline level.

Keywords
APSIM, POAMA, nitrogen risk, SILO.

Introduction
A probability guide of the yield potential expected on a farm can help make valuable cropping decisions - how much fertiliser can be applied, which crop to plant, whether low risk strategies should be applied in a poor year and the higher risk strategies in the good years. For example, in 2016 the high probability of a better than average yield potential in many areas gave growers the confidence to plant crops such as canola and invest in higher levels of nitrogen application.

As the cropping season progresses, crop models such as the Agricultural Production Systems Simulator (APSIM; Holzworth et al. 2014) can be run with historical weather information to give a range of potential yields for the year ahead. Alternatively, statistical methods can be used to narrow the range of historical weather scenarios to consider. A more direct method is to put the daily climate forecast directly into the crop model. Output from climate models however is generated on a coarser grid than what is required for farm-scale crop forecasts and contains inherent biases. To overcome this ‘connectivity problem’ (Stone and Meinke 2005) a two-tiered approach is often applied - for example a climate model predicts the Southern Oscillation Index and then this is used to pick historical analogues from local weather data as input to the crop model. These methods have been successful, but are limited.

The scientific understanding and skill of dynamical climate models continues to improve. Studies, such as Charles et al. (2015), suggest that forecasts of seasonal rainfall from dynamical climate models now supersede the previously used statistical techniques. Such an approach would allow for forecasts that incorporate the effects of a number of climate modes, rather than just the Southern Oscillation Index which is not the only driver of climate variability (Brown et al. 2009). It is therefore timely to explore whether these models can be used directly to force crop models. That is, can gridded daily output from seasonal climate models be used to drive crop models with adequate skill to provide yield potential predictions beyond our current capabilities?

To assess this, we derived a probabilistic forecast of potential yield across the Australian wheat belt. The coarser grid climate forecast data is downscaled with a simple linear interpolation to the locations of observed weather stations where the climate model data is then calibrated to have similar statistical weather properties (McIntosh and Brown 2017).

Method

The Agricultural Production Systems sIMulator (APSIM; Holzworth et al. 2014) is a farming systems modelling framework that contains interconnected models to simulate systems comprising soil, crop, tree, pasture and livestock biophysical processes. In this project it was used to assess on-farm management practices under future climate scenarios.

APSIM is driven with the daily weather output from the Bureau of Meteorology seasonal climate model POAMA (Hudson et al. 2013) that has first been downscaled and calibrated. The forecast skill is assessed at 57 stations across the Australian wheat belt over the years 1981 to 2015. We assess the performance of the climate forecast by its ability to simulate water limited yield potential compared to the water limited yield potential of the corresponding observed weather data recorded in SILO (Jeffrey et al. 2001).

The climate input data is taken to be the observed weather up until the 'start date' when 33 POAMA weather data sets are then concatenated to the observed weather to give 33 possible futures. The start date is taken to be the first of each month over the growing season April to October, and for the years 1981 to 2015. The climate variables used are maximum and minimum temperature, radiation and rainfall. These variables are first calibrated against observed weather using the method detailed at www.agforecast.com.au (McIntosh and Brown 2017).

Results

At each station we have 35 years of hindcasts with a 33 member ensemble at each of seven start months. This is a total of 1155 APSIM simulations for each station for each start month. An example of the hindcast is shown in Figure 1 for Kellerberrin Western Australia at the 1st June. A probability bar is plotted for each year showing the predicted likelihood of the water limited potential yield lying in each of 5 categories – very low yield (decile 1), low yield (decile 2-3), average (decile 4-7), high (decile 8-9) and very high (decile 10). For example in 2011, the model predicted a 54.5% chance of a very low yield, which is what occurred using the SILO data (RHS of plot). In 1994 the model showed no chance of a low or very low yield, with 42% chance of average and 58% chance of high to very high. The SILO result was an average yield.

In 1992 the model forecast was very different to what eventuated using SILO data. The prediction was for a 70% chance of low to very low yield when the result from SILO was a high yield. Incorporating model advice into planning may have led to low risk strategies being employed which would have prevented full advantage being taken of this good year and a loss of potential profit. Predicting one end of the spectrum and having the other occur is a significant failing in the modelling system. In the Kellerberrin case this only occurred once, however in other regions it occurs quite often making the forecasting system unreliable.

Accuracy of forecasts

Before using a forecast system, we needed to understand its reliability, which varied by region (Figure 2). Here we defined a misleading forecast as predicting a low to very low yield when a high to very high occurs or vice versa. In this case we found that in April regions around central NSW and a few in WA had 'misleading forecasts' in more than 10 of the 35 years studied. As the year progresses, the predictions improve as we would expect. In June there are only a few places with high numbers of misleading forecasts.

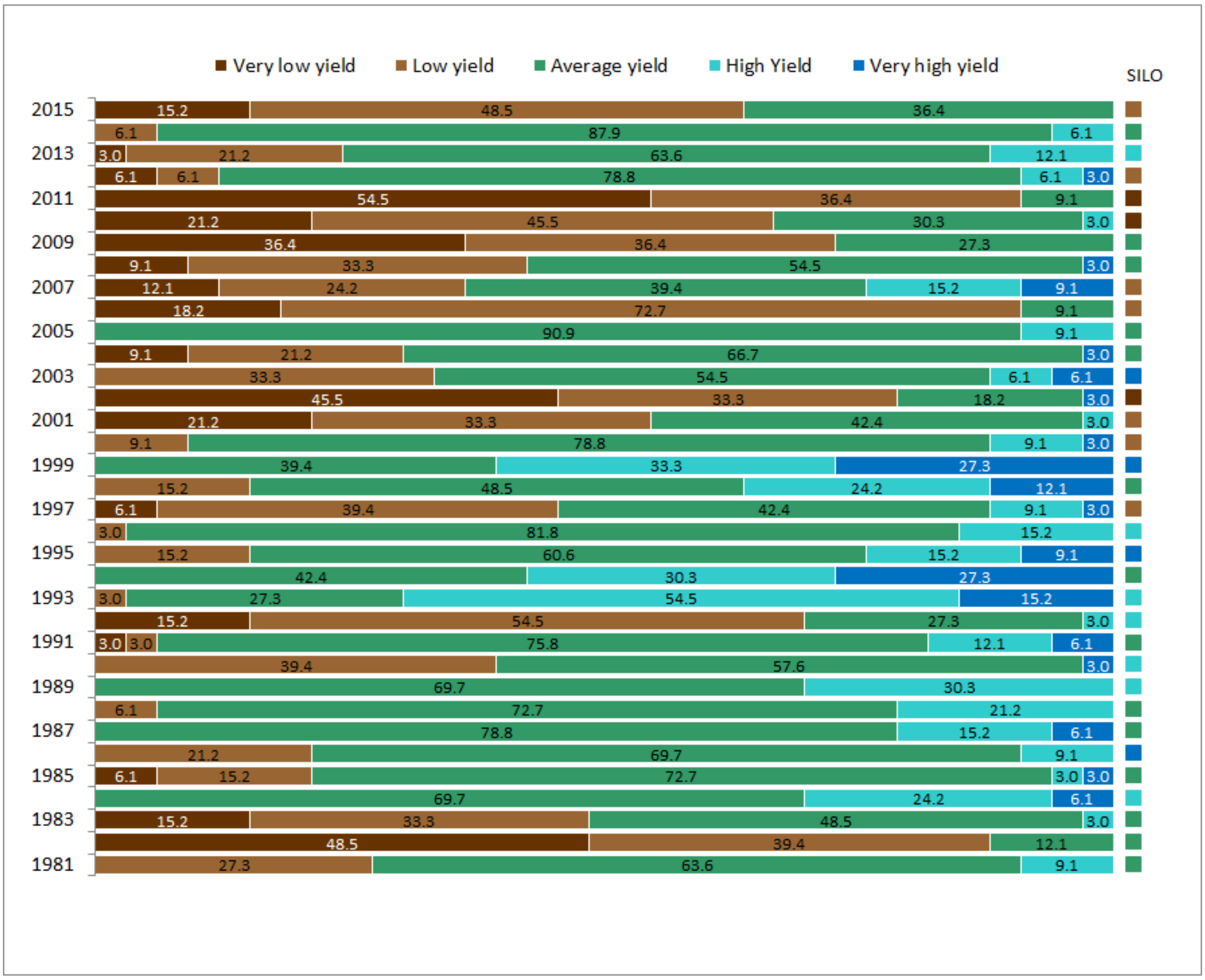

Figure 1. An example of a water limited yield potential forecast at Kellerberrin, W.A. on the 1st June for the years 1981 to 2015. Forecast categories are based on deciles: very low (decile 1), low (2-3), average (4-7), high (8-9) and very high (10). The corresponding water limited potential yield calculated using SILO weather data to run APSIM is shown in the right column.

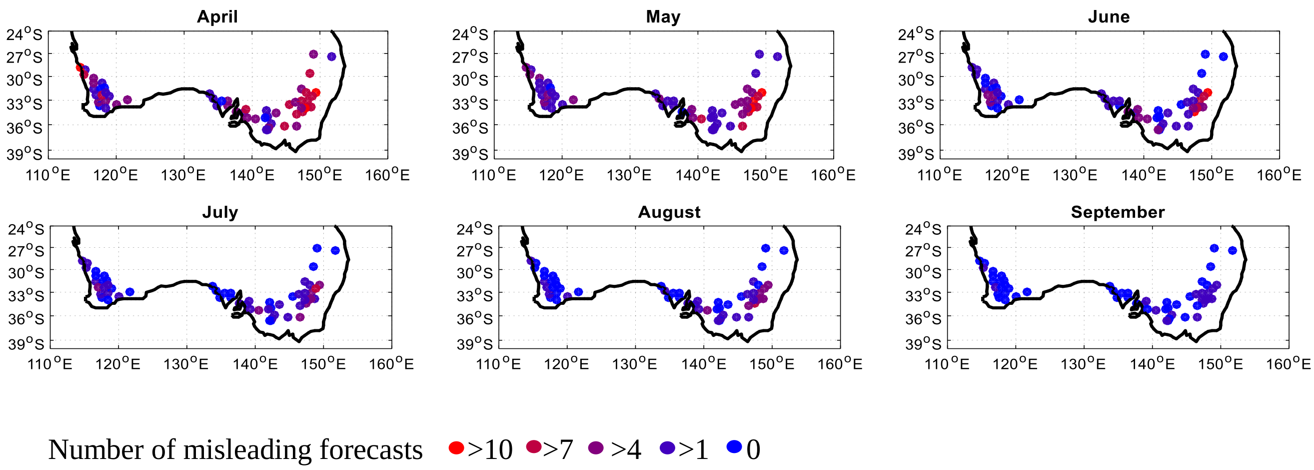

Figure 2. The number of 'misleading forecasts' at each station studied in the start months of April to September. A misleading forecast is defined as more than half the ensembles picking low to very low yield potential when SILO simulates a high to very high or vice versa.

Understanding the low yield bias.
We found that the primary reason for the misleading forecasts was a tendency to over predict a low yield. Statistically speaking, if the model is effective, it should predict yield as low to very low (deciles 1-3) approximately 30% of the time (347 runs out of 1155). Our results showed that this was not the case.

Some stations, particularly those in NSW, predicted over 800 out of 1155 runs to be in the lowest 3 deciles. Surprisingly the low yield bias cannot be simply explained by a low rainfall bias. In fact in many cases the seasonal rainfall totals from the model exceed the observed. A major difference however is the timing of the rainfall. Early season rainfall can lead to reduced radiation and hence low grain number. Theoretical experiments where observed radiation and temperature were used with model rainfall show significant improvement in yield prediction.

Discussion and Conclusions

Dynamical climate models are only just emerging as being as powerful as currently used statistical techniques for predicting the season ahead. Improvements in statistical techniques are limited by the length of the operational record, and will be challenged by decadal changes to our climate systems including climate change that is unprecedented in our records. Dynamical models offer a new advance on this system.

We found that the available seasonal forecast information from POAMA (Australian Bureau of Meteorology) was able to provide a probabilistic forecast of the yield potential in the upcoming year. Hindcasts were studied from 1981 to the present at 57 stations. In many locations the yield prediction, from as early as June, could give a good indication if a year was potentially going to be in the lowest or highest 30% on record. In other regions, particularly NSW, the skill of the modelling system was very low. These errors are due to many factors but primarily a tendency for under predicting the yield was found. We suspect this isn't due to one factor alone, but a combination of low skill in predicting the amount and distribution of rainfall, temperature and radiation.

This study sets the benchmark for current performance and while forecasting will always be limited by the chaotic nature of our weather systems, we do not believe seasonal climate forecasting has yet reached the ceiling of predictability. The Australian Bureau of Meteorology's new climate model ACCESS-S (released 2017), has much higher spatial resolution – and we expect skill to increase over the next few years.

References

Brown JN, et al. (2009). An Investigation of the Links between ENSO flavors and Rainfall processes in SouthEastern Australia. Monthly Weather Review 137, 3786-3795. (doi:10.1175/2009MWR3066.1).

Charles AN, et al. (2015). Seasonal Forecasting for Australia using a Dynamical Model: Improvements in Forecast Skill over the Operational Statistical Model. Australian Meteorological and Oceanographic Journal 65(3), 356-375. (doi:10.22499/2.6503.005).

Holzworth DP, et al. (2014). APSIM – Evolution towards a new generation of agricultural systems simulation. Environmental Modelling and Software 62, 327–350. (doi:10.1016/j.envsoft.2014.07.009).

Hudson D, et al. (2013). Improving Intraseasonal Prediction with a New Ensemble Generation Strategy. Monthly Weather Review 141(12), 4429-4449. (doi:10.1175/MWR-D-13-00059.1).

Jeffrey SJ, et al. (2001). Using spatial interpolation to construct a comprehensive archive of Australian climate data. Environmental Modelling and Software 16, 309–330. (doi:10.1016/s1364-8152(01)00008-1).

McIntosh PC and Brown JN (2017). Calibration and bias correction of seasonal climate forecasts for use in agricultural models. The Journal of Southern Hemisphere Earth Systems Science (submitted).

Stone RC and H Meinke (2005). Operational seasonal forecasting of crop performance. Philosophical Transactions of the Royal Society B 360, 2109-2124. (doi:10.1098/rstb.2005.1753).