Can seasonal forecast minimise the threats of climate variability to achieve profitable crop-livestock productions in NSW

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Abstract
Reliable seasonal rainfall forecasts with sufficient lead time can play an important role in designing responses to rainfall variability. In this study, seasonal climate forecasts from POAMA (Predictive Ocean Atmosphere Model for Australia) are used to drive the AusFarm (agricultural systems analysis model) biophysical model at two contrasting locations of NSW. The POAMA2 was able to provide good rainfall forecasts started from 1 March at Wagga Wagga for the target months of March-August with statistically significant rainfall anomaly correlation skill (0.30 - 0.44) and 65-72% hit rate. At Narrabri for target months of July-December started from 1 July, the statistically significant rainfall anomaly correlation skill ranges from 0.15 to 0.46 with a corresponding hit rate of 57 to 73%. The good skill of POAMA2 in forecasting the station rainfall variability (even without downscaling) suggests that the forecast may provide value to strategic decision making in a mixed-farming systems. At Wagga Wagga, the forecast distribution of crop yields (wheat, barley, and canola), lamb sale weight and fleece weight for target months starting from March to August show comparable median productivity compared to the observed ones. Likewise at Narrabri, forecast distribution of sorghum, wheat and barley yield is similar to the distribution of observed ones, implying sufficient ability of the POAMA forecast during pre-planting period to make forward farming decisions. Work of this nature, particularly improvement of accuracy of seasonal forecast at a long lead time, has the potential to benefit production and financial performance in a given agricultural system.

Key words
POAMA, seasonal climate forecasts, AusFarm, Simulation, Yield, Fleece weight

Introduction
Agriculture contributes about $15 billion annually to the economy of NSW, and rainfall variability is a major determinant of risk to agricultural productivity and production. Advanced skilful knowledge of climate variability can be utilised by farmers to gear production systems to capture the benefits of high rainfall and avoid losses during drought. POAMA2 (Cottrill *et al*. 2013) is the most advanced forecasting system developed in Australia and it has proven capability to predict the main drivers of Australian climate variations, including predicting the occurrence of El Nino and La Nina 2-3 seasons in advance (Zhao *et al*. 2014) and the Indian Ocean Dipole up to one season in advance (Shi *et al*. 2012), inter-annual variations of the Southern Annular Mode (SAM) up to 2-3 seasons in advance (Lim *et al*. 2013), and the Madden-Julian Oscillation up to 3 weeks in advance (Marshall *et al*. 2011). The forecast model also faithfully reproduces the impact of these climate drivers on regional climate in Australia (e.g., Langford and Hendon 2013), although local level skill varies markedly between regions (Asseng *et al*. 2012). The main objective of this paper is to take some initial steps to develop a seasonal forecasting capability at the localised farm scale, prior to pre-planting crops and making stocking rate decisions at two sites, at a winter and a summer rainfall dominant region of NSW. Initially an assessment of the farm level skill of rainfall forecasts from the POAMA2 is carried out. The rainfall forecasts are then used to simulate crop and livestock productivity at a site in the wheat-sheep belt of Southern and Northern NSW.

Methods
Site: The study focused on two sites in NSW:(1) Wagga Wagga (35°1311' S, 147°3091' E), characterised by austral winter dominant rainfall averaging 571 mm/year and annual mean temperature of 15.8°C and (2)

Narrabri (30°3401' S, 149°7552' E), a summer dominant rainfall region averaging 662 mm/year and annual mean temperature of 19.1°C respectively.

Seasonal Forecasting: We used the POAMA2 seasonal forecast system which consists of coupled numerical models of the ocean, atmosphere and land surface (Cottrill *et al*. 2013). A 33-member ensemble hindcast of POAMA2 starting for each month of January 1981 to December 2013 with 9 target months was available. To generate 33 ensemble predictions, the POAMA2 system uses 3 different versions of the model (Langford and Hendon 2013) to account for forecast uncertainty due to model errors. It uses an ensemble assimilation/ initialization system (Yin *et al*. 2011; Hudson et al. 2013) to obtain 10 realistic but slightly perturbed initial conditions for each model version to account for the forecast uncertainty due to initial condition errors. We assessed the skill of POAMA2 rainfall hindcast starting from 1 March for target months of March, April, May, June, July, and August at Wagga Wagga and hindcast started from 1 July for target months of July, August, September, October, November, and December at Narrabri. The capability of the POAMA2 system is limited by the relatively coarse horizontal resolution of the component models (~250 km horizontal resolution in atmosphere and land surface). This coarse resolution causes some aspects of regional to local climate in Australia to not be well resolved including topographic and coastal effects. In this study, we obtain the daily hindcasts at each site using a bi-linear interpolation of the model output at 250km x 250km to the site location.

Crop-livestock simulation: The AusFarm model (http://www.grazplan.csiro.au) comprising APSIM crop and soil models (Keating *et al*. 2003) and GRAZPLAN pasture and animal management models (Moore *et al*. 2007) was used with both observed climate (SILO patched point; http://www.longpaddock.qld.gov.au/silo/ppd/index) and POAMA2 forecast hindcasts climate data (1981 – 2013) to simulate crops-livestock productivity. Briefly, AusFarm simulates biological and physical processes in a mixed-farming system in response to climate (daily maximum and minimum temperature, rainfall and solar radiation, evaporative demand), in-crop management, livestock enterprises and animal husbandry practices. A mixed crop-livestock farming scenario representative of Wagga Wagga site was developed in AusFarm and crop rotation farming practices in APSIM for Narrabri. Parameters information available in Primefacts (http://www.dpi.nsw.gov.au/aboutus/resources/factsheets/agriculture) pertaining to crop management, sheep enterprises and animal husbandry practices were used in the simulations setup.

Results and Discussion

Despite the coarse model resolution with bi-linear interpolation, POAMA2 was able to provide good rainfall forecasts at these sites. Statistically significant rainfall anomaly correlation skill (0.30 - 0.44) and 65-72% hit rate were obtained at Wagga (Table 1). At Narrabri, the statistically significant rainfall anomaly correlation skill ranges from 0.15 to 0.46 with a corresponding hit rate of 57 to 73%. Although the skill of rainfall forecasts declined as lead time increased, the hit rate remained above 50% (Table 1) for the entire forecast period. The skill of POAMA2 in forecasting these large shifts in rainfall variability suggests there is need to evaluate the utility of these forecasts for improving strategic decision making in mixed-farming at these locations.

Table 1. Significant (P<0.001) correlation coefficients between observed (1981 - 2013) monthly rainfall anomaly and POAMA2 predicted monthly rainfall anomaly started from 1 March and 1 July for different target months in two locations of NSW.

Wagga Wagga			Narrabri		
Target months of forecast	Correlation coefficient	Hit rate	Target months of forecast	Correlation coefficient	Hit rate
March	0.444	72.21%	July	0.333	66.60%
April	0.350	67.51%	August	0.261	63.10%
May	0.319	65.93%	September	0.463	73.20%
June	0.305	65.25%	October	0.329	66.50%
July	0.334	66.72%	November	0.360	68.00%
August	0.297	64.84%	December	0.147	57.40%

A first step is to examine how well simulated crop and livestock yields driven by the climate forecasts capture those simulated using climate observations. Simulated crop and livestock production show considerable temporal variability in the performance over the historical 33 years (Figs. 2 and 3).

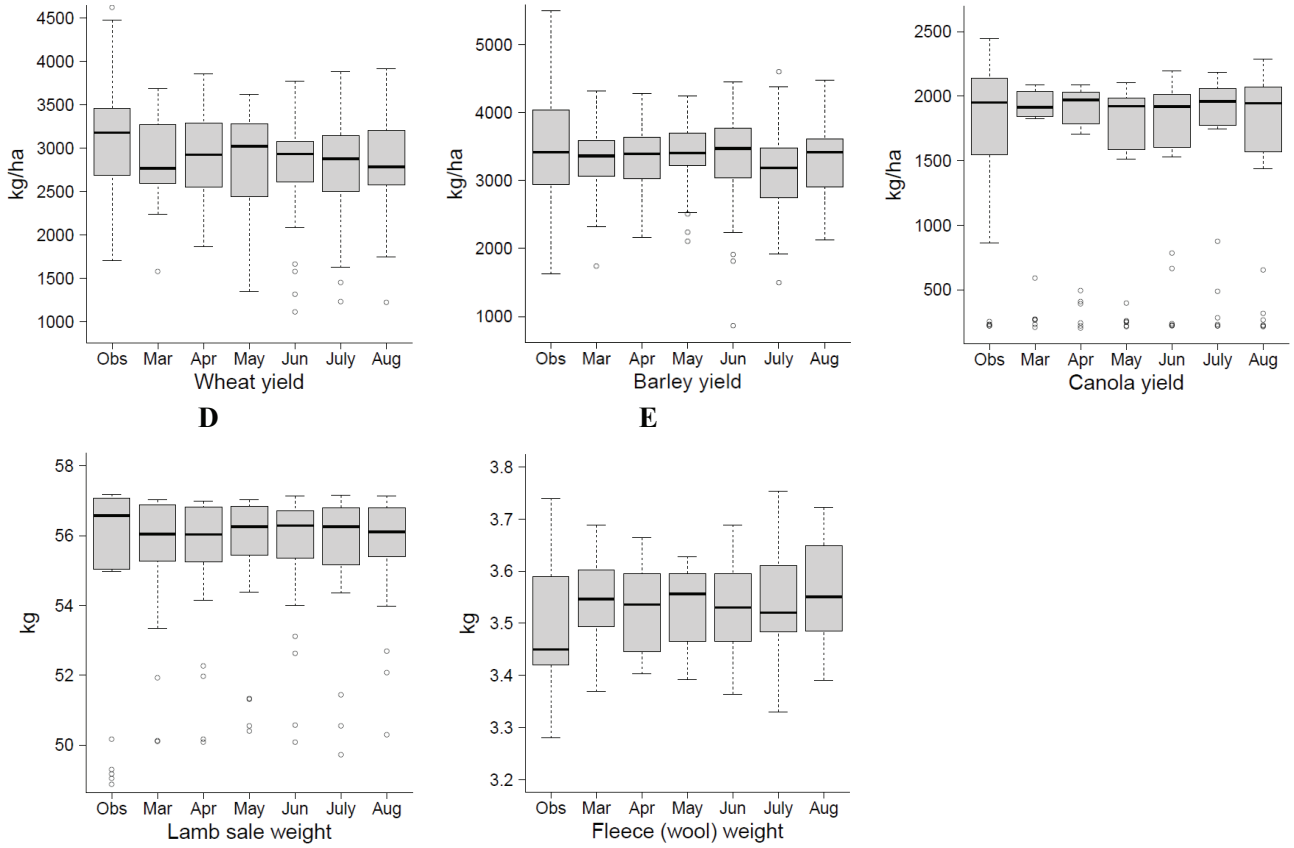

Figure 2. Relative frequency (%) distributions of simulated crop yield (A, B and C), lamb sale weight (D) and wool weight (E) in boxplots at Wagga Wagga. Obs represents yearly crops yield, lamb sale weight and wool weight simulated by observed climate (1981 - 2013). Mar, Apr, May, Jun, and Aug denote yearly crops yield, lamb sale weight and wool weight simulated by POAMA2 climate hindcasts started from the first day of March, April, May, June, July and August, respectively. The POAMA2 hindcasts comprise of ensemble mean of 1089 years (33 x 33).

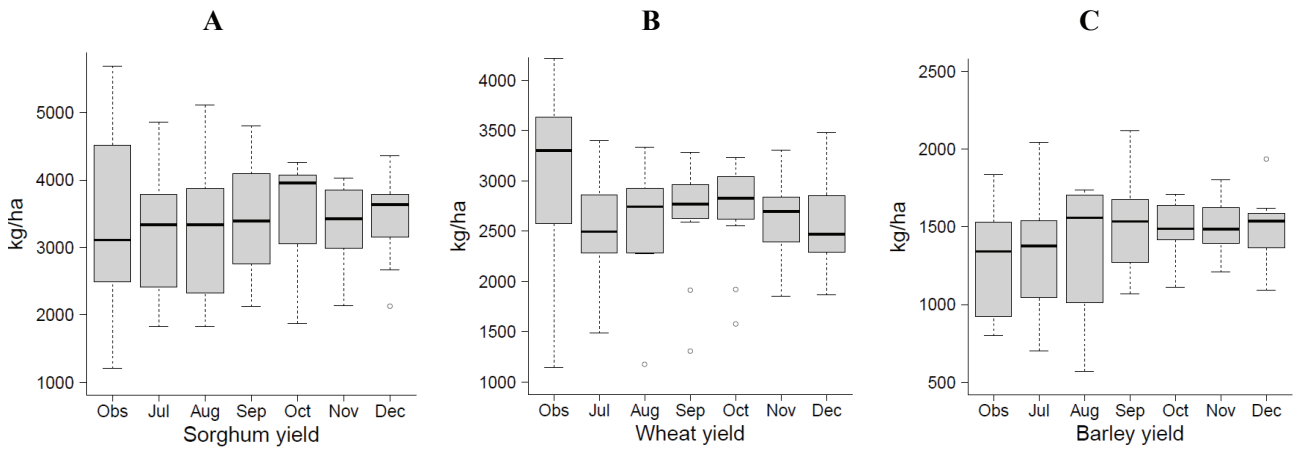

Figure 3. Relative frequency (%) distributions of simulated crop yield (A, B, and C) in boxplots at Narrabri. Obs represents yearly crop yield simulated by observed climate (1981 - 2013). Jul, Aug, Sep, Oct, Nov, and Dec denote yearly crops yield simulated by POAMA2 climate hindcasts started from the first day of July, August, September, October, November, and December, respectively. The POAMA2 hindcasts comprise of ensemble mean of 1089 years (33 x 33).

In Wagga Wagga, the forecast distribution of wheat, barley, canola, lamb sale weight and fleece weight show comparable median productivity to the observed ones for all forecasts started from March to August, respectively. In general, the inter-quartile dispersion of forecasted crops yield, animal weight and fleece

weight is smaller than the observed climate. At Narrabri, forecast distribution of sorghum, wheat and barley yield (Fig. 3) started from July to December is similar to observed climate. These results imply sufficient ability of POAMA forecast during pre-planting period to make forward farming decisions. The initial analysis results in this study confirm what has been found in more in depth broader scale evaluations of the POAMA2 forecast system at a more localised scale, that it exhibits moderate to high prediction skill in many locations around Australia. POAMA2 captures the main rainfall bearing processes at these two sites with forecasts being in the same tercile as observations between 57 to 74 percent of the time. These results are consistent with those found by Asseng *et al*. (2012) for four sites in the Western Australian wheat belt, where POAMA2 had improved skill over empirical forecasting systems. The skill level found at these sites approaches the levels reported by Crean *et al*. (2015), where farm level economic benefits for forecast use begin to accrue when prediction skill of soil moisture reaches 60-70%. This is similar to the findings of Asseng *et al*. (2012) where the level of skill available from POAMA2 started to accrue greater economic benefit to the farmer, through improved application of nitrogen fertiliser. Understanding how climate forecasts can be used to improve production and financial performance in a given agricultural system and location is complex. Broad options at these locations would include careful management of planting times, determining the area and crop variety to plant, controlling stocking rates, pre-empting health issues in livestock, managing water and fertiliser applications and optimising harvesting times.

Conclusion

POAMA2 was able to provide a hit rate of 57 to 73% rainfall forecasts at these sites. Long term averages of agricultural yields are reproduced with moderate to high accuracy, although there appears to be a tendency to both underestimate and overestimate extremes in production at these sites. As a next step the utility of using forecasts to modify one or more of these management options needs to be tested at these sites. Climate prediction skill may also be improved at the farm level by using a more sophisticated downscaling system. Work of this nature leads to the development of farm specific decision support that optimises the use of forecasting for each location and production system.

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