Using seasonal climate forecasts to predict pasture growth rates

Matthew Harrison[1], Richard Rawnsley[1], David Phelan[2], Ross Corkrey[2] and David Henry[3]

[1] Tasmanian Institute of Agriculture, P.O. Box 3523, Burnie, TAS 7320, www.utas.edu.au, Matthew.Harrison@utas.edu.au
[2] School of Land and Food, University of Tasmania, Private Bag 78, Hobart, TAS 7001
[3] Agriculture Flagship, CSIRO, Sneydes Road, Werribee, VIC 3030

Abstract
Knowledge of forthcoming seasonal weather conditions may help end-users make complex farm decisions, such as purchasing livestock feed or pasture fertiliser. We assessed differences between seasonal pasture growth rates collected at two sites over a two year period with 30-90 day growth rate forecasts in southeastern Australia. We contrasted forecasts generated using either climate data from historical records, subsets of historical records that aligned with the current phase of the Southern Oscillation Index (SOI), or from the global circulation model POAMA. Growth rate predictions in late winter/early spring (Aug-Sep) were least reliable overall, mainly because the long-term variation in forecast growth rates was low due to consistent cool, wet climes typical of north-western Tasmania. In contrast, our nonparametric statistical analyses indicated that early summer (Dec) forecasts from all methods and for all durations were most reliable, but this result was driven by larger long-term variation in this season. Across both sites and all months, the 30-90 d POAMA forecasts and the 60-90 d forecasts from the Historical and SOI methods were the most and least reliable, respectively. However, the better performing method varied considerably across months, indicating that multiple seasonal climate forecasts produced using different means should be used to forecast growth rates, depending on time of year of the forecast. At present, seasonal climate forecasts need to improve considerably to be of value in complex farm-decision making. As GCM forecasts advance in future, we expect that seasonal growth rates forecast using dynamical climate models will provide the lowest uncertainty, and may become more useful to growers and policy-makers than statistical methods developed using historical data.

Keywords
Seasonal climate forecast, Climatic variability, Prediction, Dairy, GCM, Grazing.

Introduction
It is widely established that effective pasture management is a key determinant to dairy farm business success (Rawnsley et al. 2013). As such, there is ongoing need to find efficient approaches to monitor changes in variables related to pasture management, including pasture growth rates. While field measurements of growth rates are useful for providing information on current biomass production, they tell managers little about future growth rates. Past approaches of forecasting growth rates generally use simulation models with climate forecast data derived from historical records (Harrison et al. 2016b) or analogue years of historical data, such as the Southern Oscillation Index (SOI; Potgieter et al. 2003). Another method of producing seasonal climate forecasts is by using dynamical predictions from global circulation models (GCMs) such as the Predictive Ocean Atmosphere Model for Australia (POAMA; Hudson et al. 2013). The aim of this study was to compare pasture growth rate forecasts in southern Australia produced from historical records, SOI historical records or POAMA seasonal outlooks.

Methods
Two study sites were selected on rainfed dairy farms with perennial ryegrass pastures at Mella (40.85°S, 145.11°E) and Woolnorth (40.68°S, 144.72°E) in north-western Tasmania. Over the long-term, Mella experiences higher rainfall than Woolnorth (1052 cf. 930 mm/year respectively) and greater diurnal temperature variation (mean annual minimum and maximum temperatures of 7-17°C vs 11-16°C), respectively. The soil type at Mella is a uniform clay to 1.0 m (field capacity and wilting point = 50 and 28 v/v% respectively), whilst at Woolnorth the soils are sandy to 2.0 m (field capacity = 17 v/v%; wilting point =7% v/v). Pasture biomass was measured at each site on monthly intervals by taking four 4 m^2 quadrats to a residual of approximately 1.4 t DM/ha by cutting swards to 50 mm from ground level. Quadrat biomass was then dried at 60°C for at least 48 hr. To maintain soil N levels, urea was applied to both experimental sites at 60 kg N/ha following each defoliation. Model simulations were conducted using DairyMod (v4.9.6). Parameterisation is described in Harrison et al. (2016a). Seasonal climate forecasts were generated on a daily time-step using either the full set of historical archives from 1900 to 2013 (source:

https://www.longpaddock.qld.gov.au/silo/); a subset of historical archives using the SOI phase measured during the forecast month (SOI phase analogue years); or seasonal outlooks from POAMA (http://poama.bom.gov.au; Hudson et al. 2013). Forecasts of pasture growth rates were conducted following methods developed by Harrison et al. (2016a); only a brief summary is given here. For each approach, 30-, 60- and 90-day climate data plumes for each forecast month were created by integrating the measured climate up to the time of the forecast with each climate forecast after the time of the forecast (e.g. see Potgieter et al. 2003). Each climate plume contained 20 replicate forecasts. DairyMod was run using each climate plume as input to generate a set of growth rate trajectories. For statistical inference we used the Anderson-Darling (AD) criterion, as this test computes the integral of the squared difference between measured and predicted cumulative distribution functions, as opposed to parametric methods that compare only a single value from each distribution (e.g. the mean or median is compared using t-test and Wilcox-test, respectively).

Results

No forecasting method consistently had better performance in all months and forecasting durations at both sites (Mella data shown in Figure 1; Woolnorth forecasts not shown). Nevertheless, there were some months in which POAMA appeared to have better predictability than other methods. For example, in the winter and spring of 2013 (Jul-Oct) and early spring of 2014 (Sep), the mean of the measured values lay closer to the median of the distribution from POAMA than from the other methods (Figure 1a). Further, in seasons that deviated significantly from the long-term distribution (i.e. the Historical approach), POAMA had a tendency towards greater forecasting ability, as evidenced in September 2014 at both sites. Variability of forecasts generally increased for longer duration forecasts, though more so between the 30- and 60-day forecasts than between 60- and 90-days forecasts. Anderson-Darling statistics associated with each monthly forecast pooled across locations are shown in Table 1. Forecasts from POAMA generally provided better forecasting accuracy (smaller AD statistics indicate less difference between observed and simulated data), but there was high variability in the method providing the most reliable forecast across months. Forecasting ability of all methods and durations was poorest in late winter/early spring (Aug-Sept); in all cases growth rate predictions were above measured values. Predictive ability in winter was likely lowest because the margin for error was lowest, as shown by the small range in distributions of each forecast in Figure 1. POAMA was clearly more reliable than other methods in these months.

Discussion and Conclusions

In months that typically experience low long-term variation in growth rates such as winter, all forecasting methods were significantly different to observations, mainly because the margin of error to deviate from the observations was low (Figure 1). In such months, pasture growth forecasts are unlikely to be of value to farmers, since long-term growth rates are relatively stable (evidenced by the reliability of 90-day forecasts in June). Conversely, in seasons that experience larger long-term variation in growth rates such as spring, many of the forecasting methods were often very different to the observed data. As with winter forecasts, this result was not borne out in the statistics in Table 1 however, since the range of forecasts was much higher. This indicates that additional statistical analyses should be performed, allowing data assessment using different metrics. For example, Harrison et al. (2016a) used empirical cumulative distribution functions of monthly average growth rates to compare hindcast growth rates (simulated using observed weather in DairyMod) with historical and POAMA forecasting approaches. They found that all forecasting approaches systematically differed to hindcast values between 30 and 55 kg/ha/day, and that POAMA approaches were generally more reliable over the entire range of growth rate values. Harrison et al. (2016a) also used R^2, slopes and intercepts of linear regressions fitted to the association between hindcast growth rates and the median of each monthly forecast growth rate as another form of statistical analyses. Similar approaches could be adopted here to compare the forecasts to the measured data.

Differences between observations and forecasts in individual months may have been caused by error in either modelled or measured values. In the latter case, measured growth rates in a given season or location may have been influenced by spatial variation. In the former case, the reliability of model parameterisation against measured data could be tested by simulating climate data realised *a posteriori*, as conducted by Harrison et al. (2016a) using hindcast growth rates. To increase replication of pasture measurements, we pooled data across all sites and years and detrended each growth rate by the monthly median (data not shown). Using this method we found that all forecasts differed significantly from the observed data.

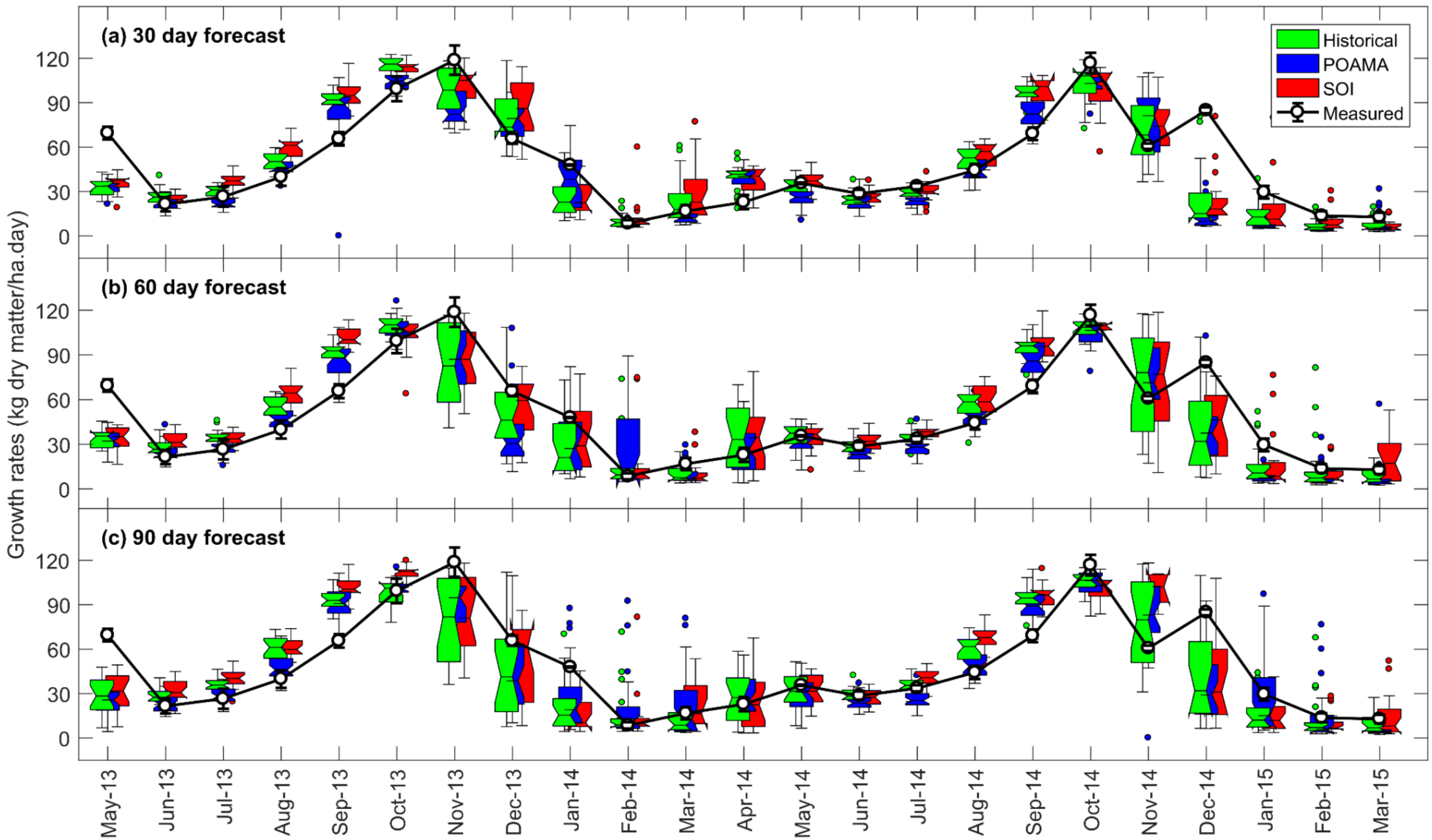

Figure 1. Forecast and measured pasture growth rates at Mella. Boxplots represent modelled values using data from historical archives, POAMA or historical analogue years with the same SOI phase as measured during the forecast month. Boxplot notches that do not overlap indicate that median values of each forecast within that month differ at the 5% probability level. Measured values are means ± one standard deviation. Dots show boxplot outliers greater than two standard deviations of the mean; colour corresponds to forecasting method and boxplot.

Table 1. Anderson-Darling statistics for each method and forecast duration sorted in ascending order of column averages. Lower values indicate closer association between measured and forecast data, where green represents low difference, yellow represents the midpoint and red indicates large difference. Analyses were computed using all sites and years. HIST = Historical.

Method	POAMA.60	POAMA.90	POAMA.30	SOI.30	HIST.30	HIST.60	SOI.60	HIST.90	SOI.90	**Average**
Jan	2.96	2.20	2.86	4.31	4.15	2.39	2.20	3.48	5.57	**3.35**
Feb	2.11	3.06	1.03	1.26	0.79	1.97	1.49	1.92	0.93	**1.62**
Mar	2.65	1.10	3.72	1.98	0.86	1.52	1.66	1.87	0.63	**1.78**
Apr	1.18	1.38	10.74	3.60	10.67	2.07	0.92	1.89	1.68	**3.79**
May	8.25	9.52	9.61	5.83	5.30	4.81	5.51	5.04	6.05	**6.66**
Jun	4.43	1.08	0.40	0.31	6.88	10.76	4.23	10.62	3.80	**4.72**
Jul	1.19	2.16	5.02	6.66	4.94	9.26	10.36	11.66	15.17	**7.38**
Aug	8.43	8.88	11.26	24.25	15.43	22.11	27.60	24.87	29.84	**19.18**
Sep	11.44	16.77	8.35	19.61	21.16	20.89	22.53	20.95	22.57	**18.25**
Oct	1.91	3.53	4.38	-0.12	-0.57	1.26	-0.55	3.55	-0.01	**1.49**
Nov	1.95	4.15	6.18	2.38	2.23	0.63	1.48	0.65	1.04	**2.30**
Dec	6.15	1.58	1.12	0.62	-0.74	0.65	1.44	0.16	0.38	**1.26**
Average	**4.39**	**4.62**	**5.39**	**5.89**	**5.93**	**6.53**	**6.57**	**7.22**	**7.30**	**5.98**

Altogether, these results underscore the need for greater testing of these forecasting approaches, in concert with different forms of statistical inferences. This should be done both in different seasons, but also across locations, since reliability of each method may differ. To illustrate, POAMA model climatology shows that seasonal mean rainfall anomalies in northwest Tasmania are relatively high in the three-month period from September through November (r>0.65), whereas the correlation skill scores in April-June are less than -0.35 (Shi et al. 2016). On the other hand, correlation skill scores in the same three-month periods in northwestern Australia around Broome were reversed.

A popular choice of farming in northern Tasmania is dairy, wherein calving often occurs in winter so that growing livestock can utilise the pasture growth flush in spring. Given the high variability in growth rates as well as the reliance on home-grown feed in these seasons, forecasts of seasonal conditions differing significantly from the norm would be of most value to dairy farmers. Indeed, our results demonstrate that the 30-day forecasts from POAMA showed better ability than the historical method (assuming the historical method is a reliable metric for long-term average conditions). However, seasonal value of GCM forecasts will need to be of greater skill if they are to be incorporated into the complexity of the on-farm decision-making process. Since GCM forecasts will improve in future (Shi et al. 2016), we expect that dynamical forecasts from GCMs will become more valuable than statistical methods when being integrated in biophysical models to forecast pasture or grain yields.

Acknowledgements
We gratefully acknowledge funding from the SenseT program and the University of Tasmania.

References

Harrison MT, Christie KM and Rawnsley RP (2016a). Assessing the reliability of dynamical and historical climate forecasts in simulating hindcast pasture growth rates. Animal Production Science 57, 1525-1535.

Harrison MT, Cullen BR and Rawnsley RP (2016b). Modelling the sensitivity of agricultural systems to climate change and extreme climatic events. Agricultural Systems 148, 135-148.

Hudson D, Marshall AG, Yin Y, Alves O and Hendon HH (2013). Improving Intraseasonal Prediction with a New Ensemble Generation Strategy. Monthly Weather Review 141, 4429-4449.

Potgieter AB, Everingham YL and Hammer GL (2003). On measuring quality of a probabilistic commodity forecast for a system that incorporates seasonal climate forecasts. International Journal of Climatology 23, 1195-1210.

Rawnsley RP, Chapman DF, Jacobs JL, Garcia SC, Callow MN, Edwards GR and Pembleton KP (2013). Complementary forages integration at a whole-farm level. Animal Production Science 53, 976–987.

Shi L, Hudson D, Alves O, Young G and MacLachlan C (2016). Comparison of GloSea5-GC2 skill with POAMA-2 for key horticultural regions. Bureau Report 13. Bureau of Meteorology, Australia.