Near-term pasture growth rate forecasts: which method works best?

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Abstract
Knowledge of near-term pasture growth rates helps livestock farmers with important management decisions, particularly feed budgeting. Here we contrast three approaches for generating three-month pasture growth rate forecasts using a biophysical plant model. Two methods were based on statistical growth rates simulated using either historical climate data or historical data having Southern Oscillation Indices (SOI) matching those of the current month. The third method accounted for current earth and ocean measurements using dynamic climate outlooks from the global circulation model POAMA. We used twelve months of measured pasture growth rates to calibrate the model, and then contrast each forecasting method over several three-month periods using empirical cumulative distribution functions. In general, dynamic forecasts from POAMA had the greatest skill and reliability in forecasting the near term (30 day) pasture growth rates, indicating that the use of current climate outlooks and recent weather measurements are more reliable than using methods based on historically measured data. This work is being developed into a graphical-user interface that will allow farmers to view a near -term pasture growth rates forecast using an online tool.

Key Words
Pasture growth forecasting, growth rates, DairyMod, Seasonal climate forecasts

Introduction
Effective pasture management and pasture consumption are key determinants of dairy farm business success. There is an ongoing need to establish approaches to monitoring changes in variables relating to effective pasture management such as pasture growth rate, pasture biomass and leaf appearance rate. Such approaches often rely on direct measurement. While historical regional pasture growth rate data provides some knowledge about likely growth rates for a given location, both inter- and intra- annual variation lead to a higher degree of uncertainty in these predictions. Biophysical models are an effective means of generating such information. Several biophysical models have been developed for the Australian and New Zealand grazing industries, including DairyMod (Johnson et al. 2008) and APSIM (Keating et al. 2003). The performance of DairyMod has been extensively evaluated (Cullen et al. 2008; Rawnsley et al. 2009) and the model can realistically simulate monthly pasture growth and seasonal yields of ryegrass based pastures across a range of soil types and pasture management options. Whilst such models have been used to generate regional information, little effort has been devoted to using biophysical models to produce short-term forecasts of pasture growth rates. The successful application of models such as DairyMod depends on both the ability of the model to accurately simulate the edaphic and biotic factors influencing pasture/crop growth as well as the accuracy of the forecast weather used within the biophysical model.

The aim of this study was to compare and assess the accuracy of simulated pasture growth forecasts produced using historical weather records, Southern Oscillation Index (SOI) phases in concert with historical records and the Bureau of Meteorology global circulation model POAMA (Predictive Ocean Atmospheric Model for Australia, see http://poama.bom.gov.au/).

Methods
A study site was selected on a commercial rain-fed dairy farm at Woolnorth (40.68^{o}S, 144.72^{o}E), north-western Tasmania. The site was an established perennial ryegrass (*Lolium perenne*) pasture. The soil was fine loamy sand and soil tests to a depth of 75mm were undertaken in March 2013 and a basal dressing of fertiliser applied to correct any nutrient limitations. The experimental site was sprayed with Agritone® (a.i. MCPA, present as dimethylamine salt, 750 g/L) at an equivalent rate of 1.5 L/ha to remove existing broad-leaf weeds in February 2013. Fences were constructed around the experimental site, prior to which pastures were grazed by dairy cows. On monthly intervals, four 4 m^2 quadrats were defoliated to a residual of ~1.4 t

DM/ha, consistent with prior grazing by cattle. Nitrogen fertiliser was applied to the experimental site as urea (46% N) at 60 kg N/ha following each defoliation event to maintain soil N at levels optimal for ryegrass growth. Quadrat biomass was freshly weighed and a subsample of approximately 500g dried in a forced-draught oven at 60°C for at least 48 hr, allowing determination of pasture dry matter (DM) and monthly growth rates.

Simulations were conducted using DairyMod (version 4.9.6). Simulations were designed to mimic experimental management and site characteristics as closely as possible, including harvest residuals, cutting and fertilisation dates, as well as soil properties. The climate data used in model parameterisation was Patched Point Data obtained from the SILO database (http://www.longpaddock.qld.gov.au/silo/, Jeffrey et al 2001). Pasture forecasts were simulated using DairyMod with climate data from three sources; historical (HIST, derived from the SILO data described above), the Southern Oscillation Index, (SOI-historical), which was derived from a subset of SILO data, and POAMA (derived from GCM seasonal outlooks and calibrated using hindcasts and climatologies of historical weather). Pasture forecasts from the three climate data sources were derived for a period of one, two, and three months from the beginning of the forecast date. The SOI-Historical simulations were produced using a subset of historical climate data using analogue years in accord with the current SOI phase. In contrast to the HIST data set (which used recent climate data from 1994-2013), SOI years were sourced from climate data between 1901 and 2013 due to the need to select compatible SOI phases for the month starting the forecast. The POAMA climate data was simulated and the ranges of one to three months from forecast date were used to produce the forecasts.

Following parameterisation, model performance was evaluated using a range of model evaluation statistics based on the work of Tedeschi (2006). The relationship between modelled and observed biomass was compared against a 1:1 line and statistically by calculating the mean bias, R^2, R, model efficiency, mean prediction error, variance ratio, bias correction factor and the concordance correlation coefficient. To contrast each forecasting method by forecasting period we compared the empirical median-adjusted cumulative distribution functions (CDF) with observed growth rates. In total there were ten growth rate forecasts for the start of each month: three forecasting approaches for each 30, 60 or 90-day forecast duration as well as a tenth forecasting method that used the historical (1994-2013) simulated value for each month. To contrast and assess forecast skill we subtracted the monthly median for each method and then used the Ecdf function in the Hmisc R library to obtain empirical CDFs. This procedure eliminated position differences so that possible shape and spread differences were comparable. For statistical inference a bootstrapped Kolmorogov-Smirnov test was used. All analyses were undertaken using R.version 3.0.

Results

Simulated pasture growth rates were mostly within one standard deviation of the observed mean growth rate (Fig. 1).

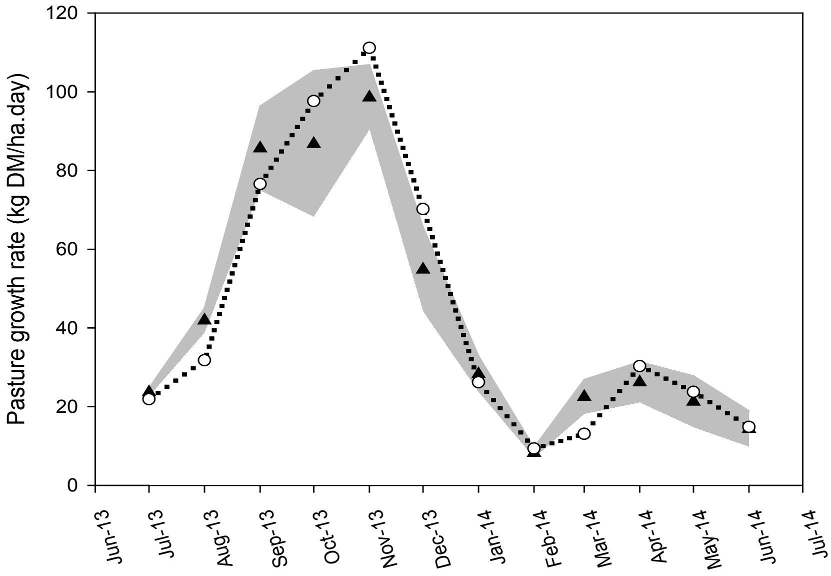

Figure 1. Observed (▲) and modelled (○) perennial ryegrass mean daily growth rates ± one standard deviation (grey shaded) at Woolnorth for the period July 2013 to June 2014.

Evaluation statistics also indicated that model calibration was acceptable. The overall observed and simulated mean pasture growth rate were both ~43 kg DM/ha.day. The coefficient of determination, mean prediction error, variance ratio and bias correction factor were 0.95, 0.19, 0.89 and 0.99, respectively. Overall, the evaluation statistics and the comparison between modeled and observed pasture growth rates indicate that the model adequately simulated pasture growth rates under rain-fed conditions with an acceptable degree of confidence.

In comparing the CDFs of the three forecasting methods for each of the forecasting periods to the observed (Figure 2a-c) only the POAMA 90 day forecast had a significantly ($P < 0.05$) different CDF to the observed. The historical (1994-2013) simulated median was also found to be consistent with observed (Figure 2d).

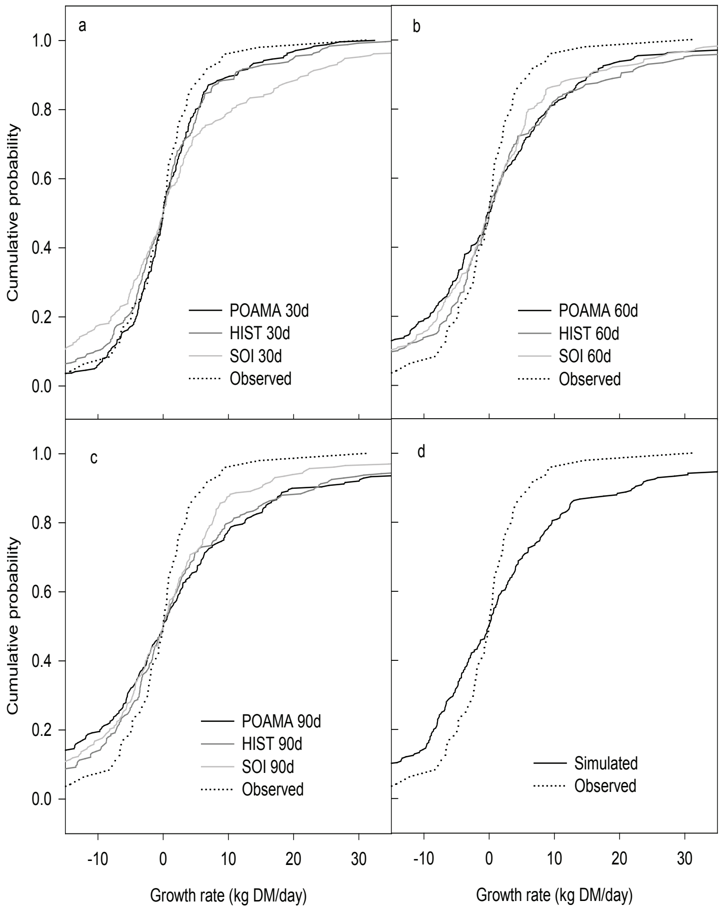

Figure 2. Empirical CDFs for monthly median-standardised data. Measured CDFs are shown as dotted lines. The CDFs for each method (POAMA, HIST and SOI) are solid lines for the 30 day (a), 60 day (b) and 90 day (c) forecast period. The historical simulated is shown in (d). Observed represents measured values.

The lowest Kolmogorov-Smirnov (KS) statistic was found with the 30 days forecast of POAMA (KS = 0.10) followed by the 30 days forecast of HIST (KS = 0.13). All other forecast methods by forecast periods had a KS statistic greater than 0.15 (Table 2). This statistic indicates that the highest level of consistency between the observed median adjusted pasture growth occurred with the 30 day forecast period using POAMA, followed by the 30 day forecast using historical data (HIST.30).

Discussion

The strong agreement between modelled and observed indicates that DairyMod has been well designed to simulate ryegrass production in the temperate region, provided calibration is appropriately performed. This is consistent with other reported studies using DairyMod (Cullen et al. 2008; Rawnsley et al. 2009). The application of such models has not been widely used for developing regional forecast information. This study has addressed this limitation and the forecasting approach undertaken here has produced encouraging results, particularly for short-term forecasts (e.g. one month from the forecast date). As the model is able to effectively simulate actual observed pasture growth rates, the ability to forecast pasture growth is critically

Table 1. Kolmogorov-Smirnov (KS) statistic and P value comparing the observed data to the prediction for median adjusted pasture growth value for each forecasting method, period (30, 60 or 90 days) and the historical simulated.

Method.period	KS	P values
SOI.90	0.16	0.23
SOI.60	0.18	0.15
SOI.30	0.18	0.14
HIST.90	0.19	0.12
HIST.60	0.17	0.19
HIST.30	0.13	0.48
POAMA.90	0.22	0.04
POAMA.60	0.20	0.09
POAMA.30	0.10	0.82
Simulated	0.19	0.12

dependent on an accurate seasonal weather forecast. There was an acceptable level of consistency between the forecast and the observed but generally consistency was better in the ensuing 30 day period, followed by the 60 and 90 day periods. The SOI-historical climate data appeared to have the lowest forecast skill, particularly the closer to the forecast date compared with the historical and POAMA data. In comparing each monthly forecast (data not shown) the forecasting skill was lower throughout summer and early autumn and higher from May through to October, the latter a period which experiences a higher reliability of rainfall events and lower daily variations in temperature. Overall results were encouraging, particularly for near-term forecasts of 30 days using POAMA data. At 60 and 90 days, the consistency between the forecast and observed pasture growth rate declined. Although the consistency of the 60 and 90 day forecast using POAMA was less than that of the historical and SOI approach continued improvement in the physics equations inherent to POAMA forecasts should enhance the pasture forecasting capability. We view the ability to provide reliable three month weather forecast to be highly important for extending and enhancing the approach reported here. This will ultimately lead to an autonomous framework which can deliver consistent and accurate real time forecast pasture growth information.

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