

Using a climate-driven farm model to predict pasture mass for individual paddocks on New Zealand dairy farms

P.C. BEUKES, C.E. F. CLARK, A.J. ROMERA, G. LEVY and J.M. LEE
DairyNZ, PB 3221, Hamilton
 pierre.beukes@dairynz.co.nz

Abstract

Accurate prediction of pasture mass on dairy farms would allow for greater precision and feed allocation planning, and therefore greater utilisation and more profit. Current methods to collect these data, e.g. by rising plate meter or visual assessment, are tedious and time consuming. Daily pasture growth rate (kg DM/ha/day) can be added to a measured post-grazing residual to estimate the increase in pasture mass after a grazing or cutting event. A whole farm model (WFM) was found to predict daily pasture growth rates from climate data with an acceptable level of accuracy on a farm scale. However, growth rates can vary by up to 100% between individual paddocks, making it necessary to modify predicted farm-scale growth rates before applying them to individual paddocks. A prototype spreadsheet decision support tool was developed that applies different approaches to modifying pasture growth rates for individual paddocks. Farmers can receive daily growth rates via e-mail, and this spreadsheet enables them to combine these growth rates with observed pasture mass readings to derive daily predicted pasture mass on a paddock scale.

Keywords: decision support, grazing management, pasture growth rate

Introduction

Ryegrass-clover pasture provides the predominant feed source for New Zealand dairy cows. The most profitable farms grow and harvest large quantities of pasture, which require feed budgeting based on regular assessment of pasture mass (kg DM/ha) for individual paddocks. Rising plate meters and visual assessments are practical but time consuming methods to collect data. Modelled pasture growth rates (growth; kg DM/ha/day), if accurate enough, could be used to estimate pasture mass, and reduce the frequency with which observed readings are required. The challenge is to link the output from a grass growth model to a decision support tool with a user-friendly interface that allows for input of required parameters, a degree of manipulation of data, and provides output information (Barrett & Laidlaw 2005). This paper describes a new decision support tool that combines predicted growth on a farm scale with observed pasture mass readings to derive daily predicted pasture mass on a paddock scale.

Methods

The decision support tool was created as an Excel spreadsheet ('CovEst') that combines intermittent observed pasture mass data (from any source) with growth predictions from a whole farm model to calculate daily predicted pasture mass on an individual paddock basis.

Validating growth predictions from the whole farm model (WFM)

The WFM (Beukes *et al.* 2008) consists of sub-models (pasture, cow, crop) in different programming languages linked to a central framework in Smalltalk (VisualAge, IBM). The pasture sub-model (McCall & Bishop-Hurley 2003) predicts daily growth using climate input (temperature, rainfall, wind speed, solar radiation, and potential evapotranspiration) and information about management (i.e. dates and residuals from grazing and cutting, dates and amounts of nitrogen fertiliser and irrigation). The accuracy of the model was tested using observed data for the period September 2004 to 2005 from a plot experiment at DairyNZ's Scott farm near Hamilton (Lee *et al.* 2008). In this experiment, pasture growth was measured on nine unfertilised plots grouped into three blocks, with each block being cut between the two and three-leaf stages of regrowth to a standard post-cutting residual height of 35 mm. The WFM was simulated with the observed cutting regime for each block. Climate data for the simulation runs were obtained from NIWA (Ruakura Meteorological Station, 4 km from the experimental site) for the period 1 August 2004 to 30 September 2005. Observed growth with standard deviation was plotted against model prediction, and prediction error was expressed as relative prediction error (RPE):

$$RPE = \frac{\text{Mean}(|\text{Predicted} - \text{Observed}|)}{\text{Mean}(\text{Observed})}$$

Growth predictions for a test-case farm

A commercial Waikato dairy farm currently participate in evaluating 'CovEst' and is assessed weekly with a rising plate meter. This farm was described in WFM using observed stocking rate and best-practice management policies for pastures and cows (Macdonald & Penno 1998). In WFM, paddocks are modelled individually and can behave differently depending on

soil water holding capacity and inherent soil fertility. However, the objective of this part of the exercise was to derive a farm-scale predicted growth, and all paddocks were therefore assumed to be similar regarding soil water holding capacity and fertility. The scenario was set up as a daily automated run on DairyNZ computers. On a daily basis, NIWA sent interpolated climate data (available from ‘virtual’ climate stations available on a 5 km grid across NZ) for the farm. These data were appended to the existing climate file and the automated run was executed, starting on 1 June and finishing on the last day of available climate data. Three levels of potential soil water holding capacity (poor, average and high) were modelled. The three growths for the last day of climate data were subsequently extracted from the model output and automatically e-mailed to the farmer.

The ‘CovEst’ spreadsheet

The output worksheet of ‘CovEst’ consists of a matrix with paddock identifications, last date with observed pasture mass (which could be from any source), and current date and predicted pasture mass. The current predicted pasture mass is based on the last observed pasture mass and sum of the daily predicted growth since the last observation date. The farmer pastes into a worksheet from e-mail the three predicted growths for the three levels of soil water holding capacity next to the current date. He also chooses the appropriate growth to use for each paddock depending on his evaluation of the water holding capacity of that paddock. Another worksheet provides for intermittent input of observed pasture mass per paddock either from rising plate meter readings or any other source. The nitrogen fertiliser worksheet allows input of amount of fertiliser (kg N/ha) per paddock on a specific date, and the grazing worksheet allows entering of grazing/cutting events per paddock and date. The nitrogen fertiliser information is used to estimate pasture response as a result of nitrogen application following the decision tree approach described by Zhang & Tillman (2007). The information about grazing/cutting events is used to adjust pasture mass to an average post-grazing residual mass. This residual mass is specified by the farmer and can be changed according to the time of year.

Incorporating variability in paddock performance

There is large variability in individual paddock performance (Romera & Clark 2008), requiring predicted growth to be modified in ‘CovEst’ to account for differential paddock performance. The output worksheet of ‘CovEst’ returns the predicted pasture mass based on scaling of individual paddock performance. This procedure allows the system to ‘learn’ from deviations of predicted from observed pasture mass, and to develop

its own scaling of predicted growth per paddock. This ‘learning’ is best explained with an example; on a specific date the observed pasture mass for a paddock is 2000 kg DM/ha and the predicted is 2500 kg DM/ha. Let us say the previous observed reading was 1800 kg DM/ha taken 7 days earlier. This means observed growth over 7 days (200 kg DM/ha) as a proportion of predicted growth over 7 days (700 kg DM/ha) is 28.6%. Let us further assume the current scaling factor for this paddock is 1. With perfect trust in both observed and predicted results the new scaling factor should become 0.286. However, the spreadsheet is programmed to learn gradually to compensate for imperfect data and to avoid wide fluctuations in over- and under-predictions. With this system of gradual learning the adjustment is moderated (half way), and the new scaling factor becomes 0.643 to compensate for the over-prediction. The following equation is used to alter the current scaling factor:

New scaling factor = Current scaling factor * $(W_1(\text{observed growth/predicted growth}) + W_2 * 1) / (W_1 + W_2)$

If:

$W_1 = 0$ then no learning

$W_2 = 0$ then fastest and most sensitive learning

$W_1 = W_2$ then moderated learning (half way)

$W_1 < W_2$ then slower and less sensitive learning

The new scaling factor applies until the next date when both an observed and predicted pasture mass is available and ‘CovEst’ will recalculate the scaling factor. The ‘learning’ function ignores pasture mass after grazing/cutting events. This infers that the longer the period between two consecutive grazings/cuttings and the more frequent the input of observed pasture mass, the smaller the deviation of predicted from observed should be.

Testing the prototype ‘CovEst’

Weekly rising plate meter readings, nitrogen applications and grazing/cutting events from the test-case farm were available for the period 4 September to 27 November 2006. The ‘learning’ capability of the spreadsheet was tested by initially entering the weekly rising plate meter readings and predicted growths for the period 4 September to 24 October. This gave ‘CovEst’ eight sets of observed readings to ‘learn’ from before testing the validity of the ‘learning’ function as a method of scaling predicted growth for individual paddocks. The observed cover for 24 October was then used, together with daily predicted growth, to predict pasture mass per paddock for 27 November, 34 days out from the last observed reading. Predicted and observed pasture mass for 27 November (47 paddocks) were compared by calculating RPE for ‘with learning’ and ‘without learning’. Subsequently, three more sets of observed data were entered for 6, 13 and 20 November, allowing ‘CovEst’ to predict pasture

Figure 1 Model predicted versus observed pasture growth rates (kg DM/ha/day) from a plot experiment at Scott farm, Hamilton. Standard deviation error bars for the observed data are presented.

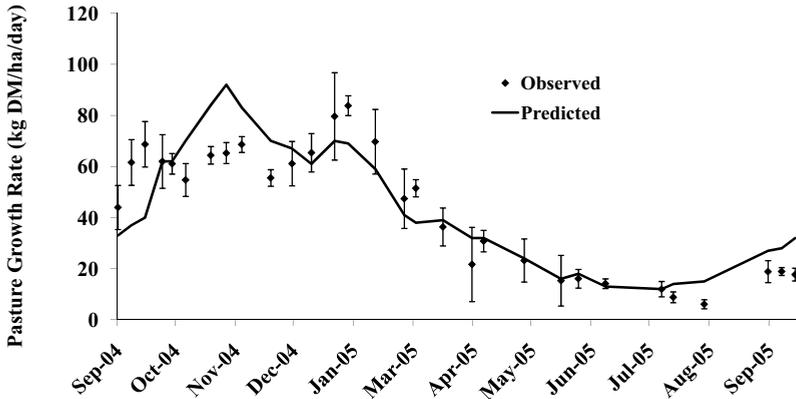


Figure 2 Predicted compared to observed pasture mass for individual paddocks on a commercial Waikato farm for 27 November 2006. Predicted pasture mass was derived from 'CovEst' using observed pasture mass on 13 November, predicted pasture growths from a whole farm model, and scaling of pasture growth rates for individual paddocks (diamonds and solid trendline, $y = 0.9256x + 162.65$, $R^2 = 0.74$) versus no scaling (open squares and broken trendline, $y = 0.7334x + 787.1$, $R^2 = 0.56$). A 1:1 line is also shown.

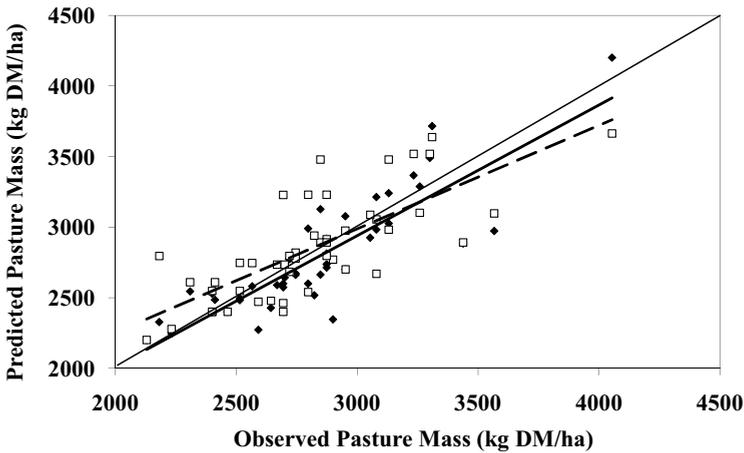
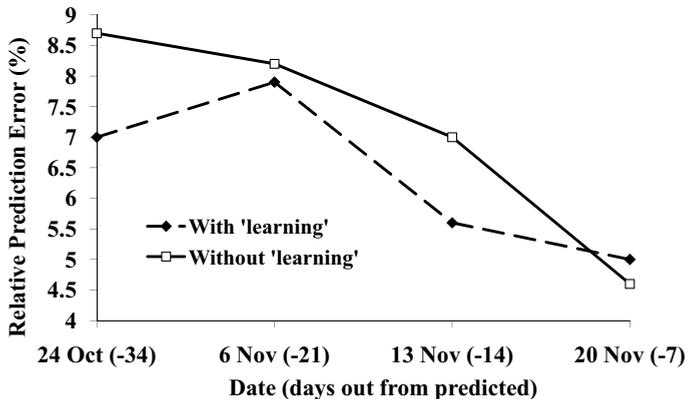


Figure 3 Relative prediction errors of pasture mass on 27 November 2006 for a commercial Waikato farm using 'CovEst', with last observed data at different dates and days out from predicted.



mass for 27 November. It was expected that 'learning' would improve with more observed data, and that predicted would be closer to observed for 27 November (i.e. RPE would get smaller) as the time out from the last observed was reduced to 21, 14 and 7 days, respectively.

Results

Predicted versus observed growth from the plot experiment at Scott farm, Hamilton, for the period September 2004 to September 2005 are presented in Figure 1. The model predicted growth with a RPE of 22%. Figure 2 shows predicted compared to observed pasture mass for individual paddocks on 27 November 2006 for the test-case farm. In this case the last plate meter readings used for the predictions were on 13 November. Predictions without scaling growth for individual paddocks (i.e. without 'learning') gave $R^2 = 0.56$, and predictions with scaling (i.e. with 'learning') gave $R^2 = 0.74$. Relative prediction errors decreased as the number of days since the last observed pasture mass data was reduced (Fig. 3). Figure 3 also shows a general trend that scaling of pasture growth rates for individual paddocks as a result of 'learning' improved RPE compared to no scaling.

Discussion

It is critical that pasture management allows maximum utilisation of pasture and timely decisions about conservation. Regular updating of these tactical decisions depends on information about individual paddock pasture mass. Early lactation is a busy period on most dairy farms, leaving little time for regular farm walks to collect this information. Our results indicate that a tool like 'CovEst' can be used to save time by reducing the need to collect observed pasture mass to once a fortnight or less. Predicted pasture mass for the alternate weeks can be > 95% accurate with one farm walk per fortnight. Furthermore, the value of 'CovEst' lies in its ability to scale growth for individual paddocks and thereby differentiate between high and low producing paddocks. Only one potential method of scaling was tested here. The method was based on 'learning' from over- and under-predictions over time and showed potential to improve predictions. However, there is a need to revisit the learning function, which currently may be too sensitive resulting in inconsistent performance.

Clearly the value of 'CovEst' is also dependent on the accuracy of the predicted growth entered. The McCall pasture sub-model in the Whole Farm Model is an elegant simplification of the pasture growth process, but remains only as good as the quality of the input data (e.g. climate, soil water holding capacity and inherent soil fertility). There is a need for ongoing effort to improve the pasture

model (e.g. improvements to modelling temperature responses and phenological effects in ryegrass). NIWA recently introduced interpolated climate data (from 'virtual' climate stations) available on a 5 km grid across NZ. Despite this development, the Ruakura climate data used to validate the model against Scott farm growth (4 km away) is likely to be different enough to affect the outcome of the validation.

The utility of 'CovEst' depends on daily paddock recording of grazing/cutting/fertiliser events, and accurate post-grazing residual pasture mass is important for re-setting the tool.

Conclusions

A prototype programme is being developed to allow farmers to integrate a continuous flow of estimated pasture growth data sent to them via e-mail with intermittent data from farm observations. Predicted pasture mass per paddock will be available to farmers on a daily basis to help with decision making.

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