A calibrated model for predicting pasture yield response to nitrogenous fertiliser

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Abstract

The increasing use of nitrogen (N) fertiliser in pasture-based dairy systems is commensurate with a decline in N use efficiency and increase in N surplus. An improved ability to predict pasture yield response to applied N is a crucial first step in determining the production and economic benefits of N fertiliser inputs. Data and meta data on pasture yield response to N fertiliser were utilised from a database repository of Australian fertiliser trials. Despite the extent of the data, there was patchy availability of meta data, only two nitrogen rates applied in the majority of trials, skewed representation of states, regions and seasons, and likely selection biases arising from trial protocol. These data were analysed and a quantitative non-linear mixed effects model based upon the Mitscherlich function was developed. The model included fixed effects for state by season, phosphorus status and harvest type (initial or residual), and nested random effects for location and trial/sub-trial. The model may be useful in predicting pasture yield response to applied N fertiliser as a proportion of obtainable yield and can be scaled to absolute response using the fitted model estimates of maximal yield, classified by location and season and by P status and harvest type, or by specification of a target harvest yield.

Key Words

Pasture, nitrogen fertiliser, urea, response, Mitscherlich.

Introduction

Strategic applications of N fertiliser on pastures are now used by most dairy farmers in Australia as an effective way of increasing pasture production (Dharma et al. 2012). As pasture-based dairy farms have continued to intensify over the past 2 decades, there has been an ongoing increase in N fertiliser usage per hectare and a concurrent decrease in use efficiency and increase in whole-farm nitrogen surplus (Stott and Gourley 2016). While considerable field research has been undertaken to assess pasture growth responses to N fertiliser applications for southern Australia (for example Eckard 1998, McGowan 1987, Mundy 1999), these outcomes are largely relevant to specific soil and climate conditions, with pasture growth responses to increasing N fertiliser applications varying substantially.

In order to simplify N fertiliser recommendations, broadly based and linear predictions of pasture yield responses to N inputs have been developed, for example 10 - 30 kg pasture DM/kg N applied (McGowan 1987, Eckard 1998). While some existing experimental pasture responses to N applications may appear to be well described by linear models, a common problem is the limited range of N fertiliser rates. Responses to applied N therefore need to be standardised to curvilinear response functions, so that marginal responses can be determined.

The aim of this work was to derive an evidence-based mathematical relationship between pasture yield and applied N using data collated from historical fertiliser trials in Australia, and which is capable of supporting a realistic economic analysis. These imply that the model should account for any dependence of the response relationship on geographic and temporal environmental variables.

Methods

Data

The raw data were drawn from the Better Fertiliser Decisions database, a compilation of fertilizer trials carried out in Australia from 1955 to 2012. The N fertiliser trial data extracted from the database consisted of 19,915 rows, related to 920 individual response trials derived from 55 named experiments. Each row consisted of a measured pasture yield (kg DM/ha), a corresponding amount of N applied (kg N/ha) and 62 fields of meta-data. The meta-data included experiment and trial ID, location, region and Australian state, soil analyses, fertiliser type, rates of P, K and S applied, season, rainfall, soil temperature and moisture, harvest number, dominant pasture species, and dates for: soil sample, pasture yield measurement, fertiliser application. The meta-data had significant gaps, with examples of meta-data fields and number of experiments contributing provided in Table 1.

Table 1. The number of experiments that reported certain environmental and soil meta-data, out of 55 pasture nitrogen fertiliser experiments included in the database.

Meta-data	Number of experiments
Growth days between N fertiliser application and pasture DM yield	49
Soil temperature	2
Soil moisture	1
Rainfall	25
Soil pH (in H_2O or CaCl)	17
Soil N (by Total N, Nitrate N, or Ammonium N)	26
Soil P (by Olsen P, Colwell P, acid extractable P, PBI, or P buffering capacity)	17
Soil K (K index, Colwell K, Skene K, or Exchangeable K)	11
Soil S (by CPC S, KCl40 S, or MCP S)	10
Organic C	1
Water holding capacity	2

Data were included for at most two harvests (a primary harvest and, if present, a residual harvest) following an application of fertiliser for any trial. Data from re-applications of N fertiliser over existing applications were excluded. Following these, and exclusions of recording errors, duplicate data and data representing aggregate harvests, the working dataset consisted of 14,048 rows. Most of the data came from the 1960's and 1970's, with 83% of the data from autumn yield measures in Victoria (Table 2). In contrast, there were only 6 rows of data for summer in Queensland, and there were no data for several season by state combinations. Victorian autumn, that accounted for 83% of the data, comprised extensive 2^3 factorial P×K×N experiments, each having just 2 levels of N applied (Table 3). Relatively few trials had large applications of N fertiliser. Out of 920 trials, 117 included an application of at least 80 kg N/ha, better informing a curvilinear response.

Table 2. The number of rows in the database of N fertiliser pasture experiments by Australian state and season of origin, and by decade of origin..

State	**NSW**	**Qld**	**SA**	**Tas**	**Vic**	**WA**
Spring	83	0	0	128	42	0
Summer	0	6	0	0	0	0
Autumn	40	0	352	120	11735	396
Winter	40	0	0	427	655	24
			Decade beginning			
1950	**1960**	**1970**	**1980**	**1990**	**2000**	**2010**
12	3391	8412	2	1622	603	6

The data were partitioned such that each partition supplied a response curve from an experiment and site, with the same N fertiliser application date, pasture yield measurement date, harvest number, applied P and applied K. There were 5,959 partitions in the dataset. Data on soil P and P fertiliser application were distilled into a single factor, "P.check", indicating limiting or non-limiting phosphorus.

Table 3. The number of trials, out of 920 trials in the database of N fertiliser pasture experiments by the number of rates of N fertiliser applied

Number of distinct N fertiliser application rates per trial									
1	2	3	4	5	6	7	8	16	24
Number of trials									
19	751	7	9	84	32	1	2	1	14

Statistical methods

The pasture yield data were plotted against applied N, and initially a Mitscherlich diminishing returns model (Equation 1) was fitted separately to each partition that had at least 3 rates of applied N, using the Lattice package (Sarkar 2008), and the nls function in R software (R Core Team, 2015).

$$y = \alpha(1 - e^{-\beta - \lambda N}) + \varepsilon \qquad (1)$$

where y is pasture DM yield (kg/ha), N is nitrogen applied (kg N/ha), α, β and λ are coefficients, and ε is error. Estimated coefficients were plotted against meta-data to identify relationships. A non-linear, mixed effects model was developed using nlme software in R (Pinheiro et al 2013). The model first re-parameterised Equation 1, by replacing β and λ by e^{η} and e^{ν}, respectively. These changes constrained the

response to be non-negative and concave (diminishing returns). Secondly, the mixed model was defined by specifying linear mixed sub-models for each of the coefficients α, ν and λ. Sub-models were derived by a process of backward selection. This started by including several terms and variables (selected according to relationships identified in coefficient graphs, by theoretical consideration of probable limiting factors, and incorporating the inherent random effects nesting of measurements within partitions within locations within trials within experiments), and progressively removed terms according to goodness of fit criteria (AIC, BIC, and change in log-Likelihood). Model feasibility however, was constrained by issues of co-linearity, structural confounding, parameter identifiability, data availability, and software capability.

Results

The exploratory data analysis phase suggested no relationship between λ and other factors. This apparent independence between λ and other factors suggested that this coefficient be held constant across all partitions. As a consequence, partitions having just 2 levels of applied N could be included in the analysis, λ being estimated from the rest of the data.

Qaudratic relationships between α and month of year, and between β and month, apparent in the exploratory phase of the analysis, were not significant and were replaced by a factor for season having 4 levels. The inclusion of a factor for 'state', and its interaction with 'season', improved the model fit significantly. The factor, P.check, was statistically significant and was retained, although the size of the P.check effect was small.

The final sub-models, embedded in Equation 1, were as follows:

$$\alpha = \mu_\alpha + \tau_\alpha + \varphi_{P.check} + L_\alpha / Pa_\alpha,\ \beta = \exp(\mu_\beta + \tau_\beta + \theta_{\text{state.season}} + L_\beta / Pa_\beta), \text{ and } \lambda = \exp(\nu).$$

The μ were constants representing the mean, or reference level, of their respective coefficients. τ_α and τ_β were adjustments made for a residual harvest. $\varphi_{\text{P.check}}$ was the adjustment made to α when P was adequate. $\theta_{\text{state.season}}$ was the adjustment made for a particular state and season combination. These parameters represented fixed effects. The random effects terms L / Pa described nested variation between partitions (Pa) within locations (L) for parameters α and β.

The parameter α represents the mean maximum attainable yield when N is non-limiting. This was estimated as 1,881 (SE=170) kg DM/ha for primary harvest when P was limiting, and 2,182 (176) kg DM/ha when P was not limiting. The additive effect τ_α for residual harvests was 2,774 (74) kg DM/ha giving α as 4,655 kg DM/ha when P was limiting and 4,956 kg DM/ha when P was not limiting. No detectable relationship was found between α and harvest interval (days between fertiliser application and harvest). The estimated effects of state and season on β and the estimate of λ are expressed graphically in Figure 1. For residual harvests, proportionately less, by 20-60%, of the maximum yield was attributable to the application of N fertiliser, compared with the primary harvests. The random effects of partition and location were summarised by their standard deviations (SD). For maximum attainable yield (α), the estimated SD for location was 1,418 kg DM/ha, and 1,048 kg DM/ha for partition within location. Considering most of the data fall within ±2 SD of the mean, these reflect a large spread of α between locations and between partitions. For β, the estimated SD for location was 0.40, and 0.32 for partition within location. These were also large relative to the mean, 1.08. The residual error SD was 383 kg DM/ha.

The coefficient α measures maximal pasture yield at non-limiting nitrogen. Its value could be affected by any environmental factor or harvest protocol, in particular a choice of time or DM yield at which to harvest, imposed at the site. It is therefore unsurprising that α varied widely in this large data set compiled from a diverse range of seasons, locations and experimental protocols. It was unexpected, however, for maximum yields of residual harvests to be larger than for primary harvests. This could be explained in terms of data selection; for example, if residual harvests were opportunistically taken only at times when substantial residual regrowth was evident. By contrast, primary harvests were necessarily present in every trial.

The coefficient α is of course important for economic analysis, as it determines the absolute dry matter yield attainable in a given situation. It is therefore unfortunate that several important environmental and management causes of variation in α remain un-modelled, due to paucity of relevant meta-data. The yield response to a non-limiting application of N fertiliser, expressed as a *proportion* of maximal yield, is given by $e^{-\beta}$. Like α, β may have been subject to selection biases. Plausibly, however, proportional response (controlled by β), and response curvature (controlled by λ), would be less affected by management protocol

factors. While it was observed, for example, that DM yield was higher in residual harvests, a lesser proportion of the residual yield was attributed to applied N. This is understandable as the efficacy of the added N fertiliser would be expected to diminish with subsequent harvests.

The economic rate of response is affected by the curvature determined by the λ coefficient, as well as by the magnitude and proportion of response determined by the other coefficients. The model specified λ as invariant, which may be an oversimplification, but in the absence of further evidence, this also provided a practical solution that allowed a large amount of trial data having just 2 rates of applied N fertiliser to be included in the model selection and calibration.

Conclusion

A mixed effects non-linear model was used to describe pasture DM yield responses to N fertiliser applications, using a database of Australian fertiliser trials. By using random effects to describe variation among parameters it provided a good fit to a large body of data, using just a handful of readily interpretable coefficients. The fixed-effect coefficients were used to obtain N response curves as a *proportion* of maximal DM yield. To convert these to an absolute yield, it is necessary to specify this maximal yield, α. In pasture-based systems, with or without N fertiliser application, specifying maximal yield is a normal part of determining grazing rotations. In the end this is largely a management decision. For purposes of response prediction and economic analysis, a value for α could simply be specified as the maximum amount of pasture DM chosen to be present before grazing or harvesting. Alternatively, it could be calculated from a subjective estimate of y_0, the expected yield under zero N fertiliser, as $\alpha = y_0 / (1 - e^{-\beta})$. The proportional response functions identified here therefore may be scaled to provide a suitable starting point for economic analysis of the value of N fertiliser decisions (Stott et al. 2016).

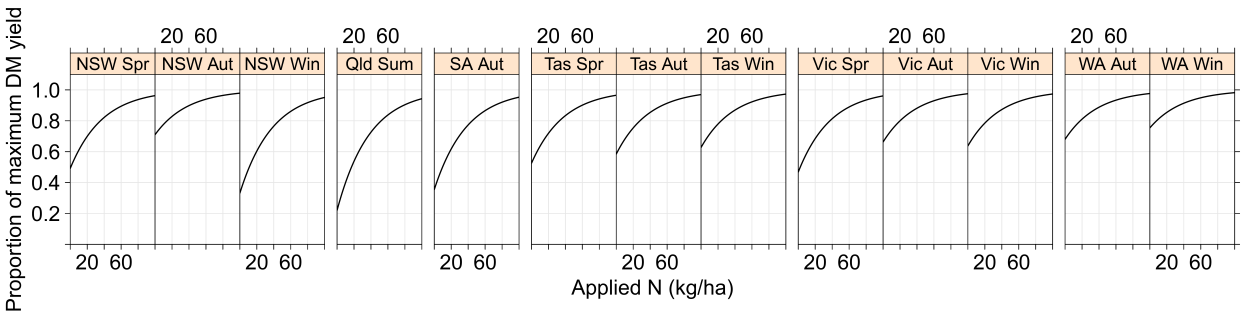

Figure 1. Dry matter yield, as a proportion of its maximum, versus applied N fertiliser by state and season for the primary harvest.

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