Evaluating New Beef Production Technologies and Their Impact on the Sustainability of a Grazing System: A Stochastic Dynamic Model

By

A.R. Alford, O. J. Cacho and G. R. Griffith

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Key words: farm level evaluation, genetic trait, stochastic dynamic model

Net feed efficiency (NFE) technology is expected to improve the productivity of grazing systems in Australia's southern beef producing regions. The extended time path required for implementation of this genetic technology into commercial herds and the influence of climatic variability on the pasture base are important issues to address in estimating the benefits of this technology at the farm level. NFE also has the potential to impact on the sustainability of the grazing systems in terms of maintaining adequate pasture cover. These issues are investigated by developing a stochastic dynamic simulation model. The bioeconomic model includes pasture, animal production, herd dynamics and economic sub-models. In this paper the model is presented and the implications of the results for adoption of the technology are discussed.

1. INTRODUCTION

Economic evaluation of new technologies at the farm level is important for providing information to farmers, extension and research personnel about a technology's application at the farm level. As well these results represent input data for the broader objective of measuring the economic gains, both *ex ante* and *ex post* from agricultural research. Additionally, there is increasing interest in undertaking more holistic evaluations of technologies at the farm level to also include the impact of a new technology on the 'sustainability'† of the agricultural resource base or the farming system.

The use of a bioeconomic framework can incorporate not only the critical biological relationships, but also the dynamic and stochastic characteristics of an agricultural system. Such an approach is applied to Net Feed Efficiency (NFE) in beef cattle, a major research initiative of the Cooperative Research Centre for Cattle and Beef Quality (CRC).

The paper proceeds by presenting a background discussion of the reasoning for selecting a bioeconomic modelling approach, an outline of the model and a description of the NFE technology. This technology is then applied to the bioeconomic model using both deterministic and stochastic frameworks and the results compared to the without technology case. This analysis is undertaken within the constraint of maintaining a minimum pasture mass reflecting an important management practice for sustainable grazing. The paper concludes by highlighting

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*Beef CRC PhD student, University of New England, Armidale; Associate Professor, University of New England, Armidale; and Principal Research Scientist, NSW Agriculture, Armidale, and Adjunct Professor, University of New England, Armidale. The financial assistance of the Cooperative Research Centre for Cattle and Beef Quality is gratefully acknowledged. Contact address: andrew.alford@agric.nsw.gov.au

† 'Sustainability' here refers to the sustainability at the individual production system level and is consistent with the definition of sustainability as "*an improvement in the productive performance of a system without depleting the natural resource base upon which future performance depends*" (Pandey and Hardaker, 1995).

findings of the research and their implications for adoption of the technology for both extension and research personnel.

2. BACKGROUND

In general, the economic evaluation of new technologies as a result of agricultural research and development is based upon the notion of economic surplus. A new agricultural technology leads to an improvement in productivity in the industry and a consequent shift in the supply curve for the relevant commodity brought about by the adoption of the new technology by the target group. This shift in supply is known as the K-factor (Alston, Norton and Pardey, 1995).

However, the information required to undertake a farm-level evaluation of a technology to estimate K, is not always immediately obvious. In discussing the evaluation of agricultural research, Pannell (1999) identifies categories of information that are applicable to the evaluation of technologies at the farm level. Any method utilised to undertake farm-level evaluations of new technologies should address as many of these information categories as possible. These include:

- the biological, technical and/or management changes from the new technology;
- the costs to the farm in implementing the new technology;
- the economic benefits accruing on a per hectare or per farm basis;
- the extent of adoption on the individual farm, for example, the number of hectares on the farm affected; and
- the impact of side effects from implementation of the new technology, which could be internal or external to the farm, including environmental impacts or price changes as a result of supply shifts of a farm output.

Economic tools used to evaluate new technologies include technical ratios and partial budgets, gross margins and budgeting, mathematical programming including linear programming and dynamic programming and econometric methods. Each of these various modelling approaches may capture to lesser or greater extents some or all of the abovementioned categories of information. For example, linear programming (LP) is well suited to measuring the impact of a new technology at the whole-farm level, as well as providing additional information such as shadow prices and costs (Pannell, 1999).

Two factors that contribute to the complexity of evaluations at the farm level are the dynamic characteristics of some technologies, and the impact of risk.

The production risk that occurs in grazing systems as a result of climate variability may have a significant impact on the level of adoption of a technology on a individual farm and consequently on the benefits of a new technology. Incorporation of a stochastic framework in the bioeconomic model will enable the effect of risk on the value of a new technology at the farm level to be examined compared to a deterministic analysis. However, the potential importance of risk in farm level modelling has been considered by Pannell, Malcolm and Kingwell (2000) who suggest that depending upon the purpose of the results, inclusion of risk aversion at least, may be of secondary importance.

In the case of technologies that have dynamic attributes, measuring the cashflow over time becomes important. Genetic traits in ruminants that have long biological lags are such technologies. Typically, a commercial beef or sheep producer is constrained to purchasing the enhanced genetic trait through buying in superior sires to infuse the desired trait into their commercial breeding herd over time. Consequently, planning periods of 20 or more years may be relevant. This means that a single-year equilibrium model will be unable to effectively measure the costs of introducing the new technology over time. In the case of the NFE technology in beef cattle, any herd expansion that is possible as a result of introducing the trait is based on retaining NFE-improved heifers rather than selling them. Thus, the change in herd dynamics has to be properly incorporated as do the opportunity costs of forgone heifer sales. These herd dynamics can be represented explicitly within the bioeconomic model.

The method followed in this research project was to develop a model that could incorporate the important characteristics of the production system and the technology in question, being stochastic and dynamic attributes respectively. The bioeconomic model described in the following section provides a method by which to assess the benefits of a technology by comparing with and without technology scenarios.

A multi-period LP has previously been applied to the NFE technology by the authors (Alford, Griffith and Cacho, 2004), results from which are compared with results obtained in this study. This whole-farm model enabled the estimation of the NFE technology in the context of a mixed grazing system allowing for the potential for output substitution to occur between various sheep and beef enterprises as a consequence of the availability of the NFE trait. However the resulting size of this model precluded the addition of stochastic elements.

Therefore a dynamic simulation modelling approach which can capture non-linear biological relationships was developed that may more readily be able to incorporate dynamic and stochastic attributes of a production system. Such a modelling framework would also lend itself to the examination of the impact of a new technology on the sustainability of a production system.

3. METHODOLOGY AND OUTLINE OF THE BIOECONOMIC MODEL

The model is based upon a beef enterprise typical for the Northern Tablelands region of New South Wales. The Northern Tablelands farming system has been previously described by Alford, Griffith and Davies (2003) and broadly consists of various beef and sheep grazing enterprises. In this case, a self-replacing beef herd that produces heavy feeder steers is modelled. Typically cows are joined to calve in August/September, and heifers are joined to calve at 2 years of age. Heifers are sold as weaners at nine months of age, while steers are sold at 18 months of age at 440-450 kg (l.w.) suitable for entry into feedlots.

Comparisons between the without-NFE case (base) and the with-NFE case, were done using optimal enterprise plans generated by conducting several modelling experiments including both deterministic and stochastic pasture growth assumptions. The model is also able to be constrained by setting minimum pasture mass requirements as a proxy for sustainable grazing management.

Cacho (1997*a*, 1998) developed a theoretical bioeconomic model for a grazing system incorporating economic and biophysical models. This model has been used as a base for the development of the current beef cattle model.

Annual profit is obtained from cattle sales less herd and sale costs and pasture and supplementary feed costs. An area of 320 hectares is assumed. Further details of the beef enterprise and associated resources are given in Alford *et al.* (2004).

The biophysical model is linked to the economic sub-model through an equation determining cattle sales and herd, pasture and supplementary feeding costs for each year over the simulation period. The biophysical model is implemented and solved using Simulink 4® (The MathWorks Inc, 2001a) and Matlab 6® (The MathWorks Inc, 2001b). The model has a daily time step, and captures two main components:

- Pasture – pasture growth and pasture mass, and
- Animal production – pasture consumption, stocking rate, supplementary feed and cattle sales.

Figure 1 shows an outline of the bioeconomic model including the linkages between the various sub-models and their main data inputs and outputs.

The bioeconomic model has the potential to examine issues regarding the sustainability of the grazing systems as far as it relates to maintaining minimum pasture levels, since these can be set in the model. Scott *et al.* (2000) identified the maintenance of a minimum pasture cover (of which pasture mass is a proxy) to be of primary importance for the sustainability of Northern Tablelands grazing systems. As a consequence of various research into sustainable grazing practices in the Northern Tablelands a best management practice of maintaining a minimum pasture mass at 1000 kg DM has been recommended (McDonald, 2000). This model is applied initially to the NFE trait in beef cattle to examine the value of the technology within this minimum pasture constraint.

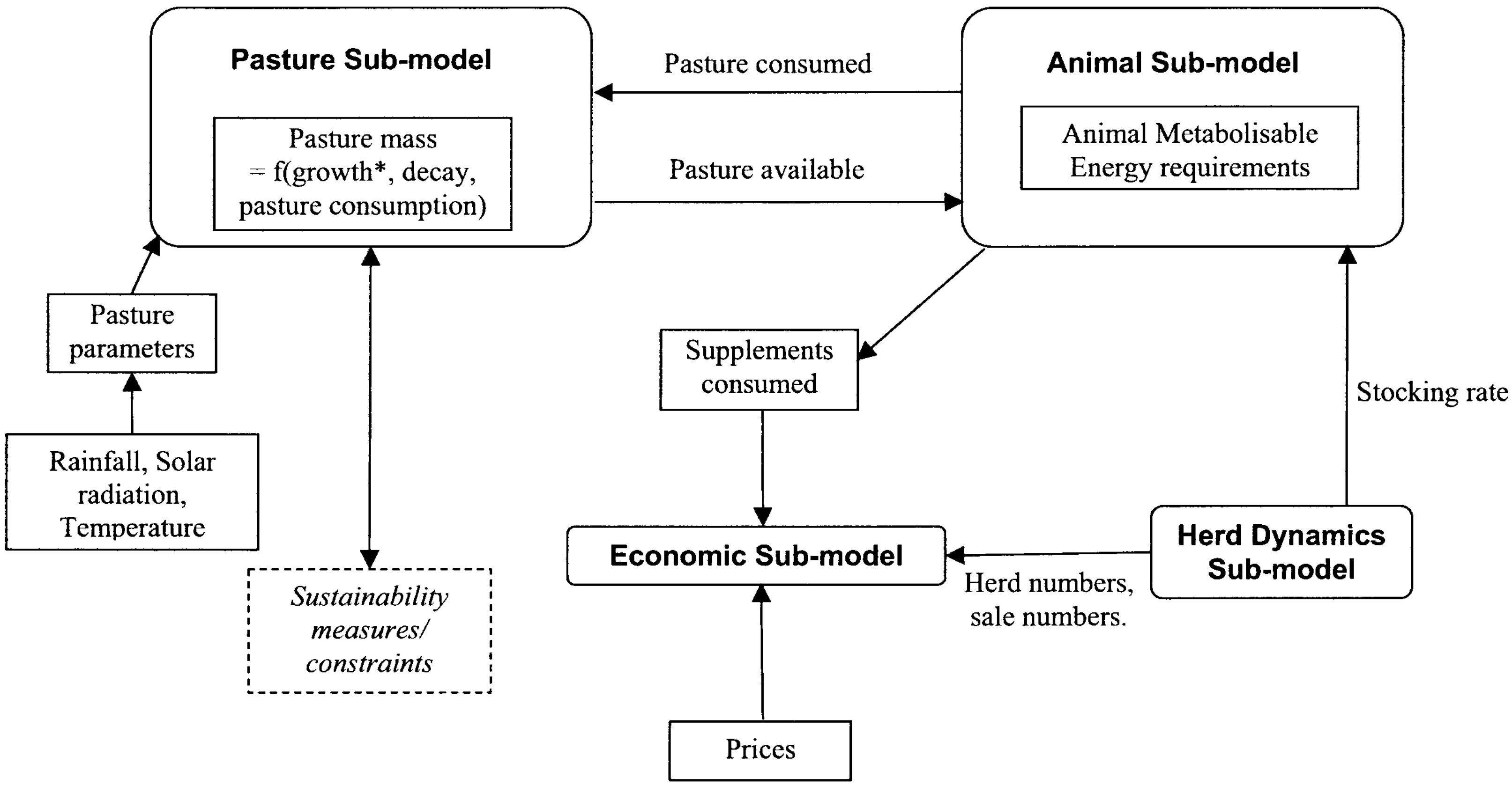
3.1 Pasture Sub-model

Pasture growth and the impact of grazing upon the potential growth of pasture is fundamental to grazing models. In the agronomic literature pasture growth has been represented by various types of equations from relatively simple single equations for empirical modeling or complex mechanistic simulation models that include a series of equations describing photosynthesis, respiration and phenology. Examples of the latter type include **GrassGro** (Moore, Donnelly and Freer, 1997; CSIRO, 2003) and Johnson and Parsons (1985).

The growth of individual pasture plants or pasture swards is directly influenced by defoliation (or grazing), while factors such as light, temperature and moisture availability and nutrients also impact upon potential pasture growth.

Bioeconomic models can be organised to describe the biological processes of a system of interest with relatively few equations which relate current state and control variables to future states of the system (King, Lybecker, Regmi, and Swinton, 1993; Oriade and Dillon, 1997). In contrast biological simulation models are generally highly mechanistic involving a large number of equations detailing various biological

Figure 1. Diagrammatic representation of the Beef Grazing Bioeconomic Model



subsystems. An advantage of mechanistic models is their greater applicability to various conditions (Cacho, 1997*b*). The generality of highly mechanistic models was exploited in this study by using the **GrassGro** (CSIRO, 2003) model to derive pasture growth data for the Northern Tablelands since long term pasture growth trials with sufficient sampling points are not available.

In the region of interest, the authors identified many trials that typically were undertaken for 3 years or less; for example, Lazenby and Lovett (1975), and Curll, (1987). Other longer term trials undertook few readings within each year since their primary objectives were other than examining pasture growth rates *per se* over the whole period; for example, Robinson and Lazenby (1976), and Hutchinson, King and Wilkinson (1995).

Pasture Growth – Sigmoid equation

A variety of forms of equations to model pasture growth have been used in the literature including logistic, Gompertz, and Richards equations which are discussed in detail by France and Thornley (1984) and Thornley and Johnson (1990). These equations are sigmoidal in nature which assumes that growth rate continues to increase until at some point an input such as a nutrient or light becomes limiting, and/or the specific growth rate decays exponentially with time, for example due to temperature (Thornley and Johnson, 1990).

In the bioeconomic model presented here a single sigmoid equation is used to represent pasture growth under grazing described by (Cacho, 1993). The sigmoid equation can implicitly reflect the various factors that influence growth rate (moisture, light, temperature), while a scalar may be applied to reflect the impact of nutrient availability (Cacho, 1998) or general productivity of the pasture.

The equation adopted is:

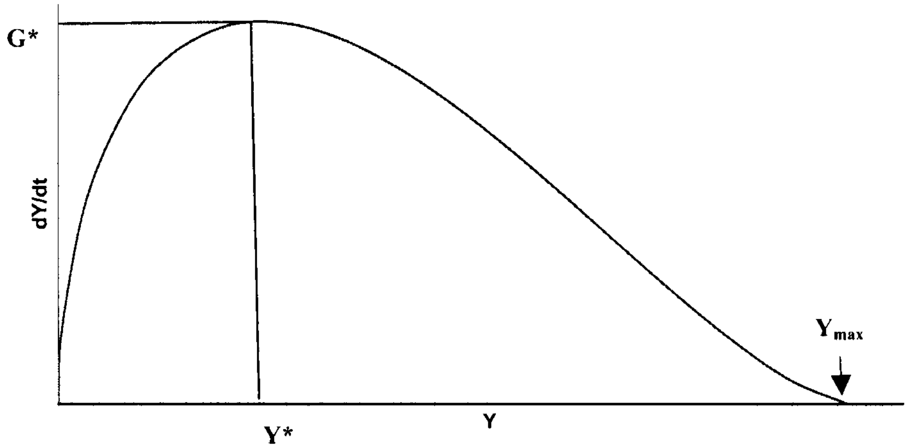
$$G = \alpha \frac{Y^2}{Y_{\max}} \left[\frac{Y_{\max} - Y}{Y} \right]^{\gamma}$$

Where: G is net growth rate (kgDM/day),
Y is pasture mass at time t (kgDM),
$Y_{\max}$ is maximum sustainable pasture mass (kgDM),
Growth parameters: α (time-1)
γ (dimensionless).

The equation has been demonstrated to be applicable to modelling the accumulation of green pasture dry matter (growth minus senescence) or growth that is defined as the accumulation of live and dead biomass and so accounts for senescence and decay (Cacho, 1993). Woodward (1998) noted that the majority of pasture biomass models have followed the approach of modelling net pasture production and so avoided the need to explicitly describe senescence and decay.

Figure 2 illustrates a generalised sigmoid growth curve showing the point of maximum growth (Y*,G*); where Y represents pasture mass which may be green pasture mass or total pasture mass and is normally measured in kilograms or tonnes of dry matter per hectare, and dY/dt is growth rate such as kilograms (or tonnes) of dry matter per day. The peak of the curve represents maximum growth rate (G*) which occurs at the optimum herbage mass (Y*). Y_{max} is the maximum sustainable herbage and is related to the relatively stable state where new growth equal senescence of older leaves.

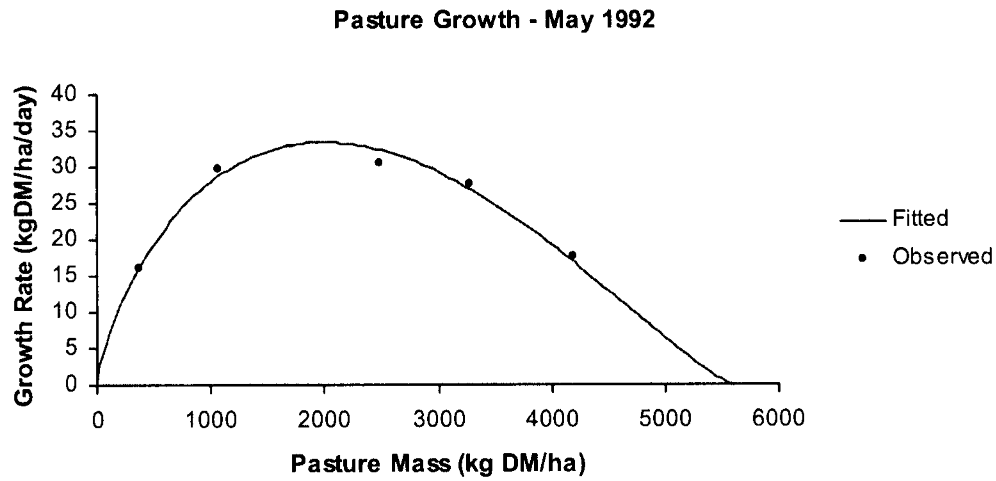
Figure 2. Sigmoid growth curve



The sigmoid growth curve requires three parameters α, γ and Y_{max}. Simulated data from which to estimate the three parameters were obtained by undertaking a series of **GrassGro** simulation experiments using data for Armidale over the period 1985 to 1999. The pasture modelled is for a mixed pasture sward including early annual grass species, phalaris and white clover, derived from a Northern Tablelands pasture detailed by CSIRO (2003). Each of these three pasture components have different phenology resulting in differing stages of reproductive and vegetative growth.

Daily pasture growth simulation experiments were undertaken for a representative day of each month over the 15 years. The simulations undertaken in **GrassGro** were run from the start year of the simulation period 1st January 1985 to the representative day of interest; the representative day being that day of each month which most closely matched the median daily growth rate for that month. Simulated cutting trials were undertaken using the "spinning up" function in the **GrassGro** model which allows the model to be stopped during a simulation run (in this case three days prior to the selected representative day to allow for some adjustment) and the predicted above ground biomass reduced and the run recommenced to the day after the selected representative day to mimic a pasture cut experiment. This enabled simulated daily growth rates and corresponding total above ground pasture biomass to be determined. Pasture mass was reduced by 0, 25, 50, 70 and 90 % respectively for each representative day to provide 5 observations. Y_{max} was estimated visually by plotting the observed **GrassGro** simulation data and estimating where the trajectory might reasonably intersect the horizontal axis. This method was deemed to be adequate given that under continuously or frequently grazed pastures the portion of the curve close to Y_{max} would rarely be reached (Cacho, 1993). Figure 3 shows an example of data obtained from the **GrassGro** simulations and the resulting fitted sigmoid growth curve. The model replicates a continuous grazing or set-stocking management strategy.

Figure 3. Example of simulated "pasture cutting trial" using repeated GrassGro simulations on a representative day in May 1992 and the fitted sigmoid curve



To estimate the coefficients for the pasture growth equations the simulated "cutting trial" pasture growth and mass data were fitted using a non-linear least-squares procedure with the statistical package TSP® (TSP International, 1997). These resulted in generally good fits with high R-squares while the two estimates for α and γ were always significantly different from zero with P values for the *t*-statistic of less than 0.001. This demonstrates that the sigmoid equation is a good approximation of the mechanistic multi-equation **GrassGro** simulation model. To ensure that there were no consistent biases plots of observed simulations and fitted data were plotted. A summary of the coefficient estimates and related statistics and plots for the representative year 1992 are provided in Table 1.

These estimated pasture growth parameter coefficients were used to derive a deterministic pasture growth year taken as the 12 monthly averages across the 15 years for α and γ and Y_{max} respectively. The stochastic pasture growth parameters were taken as the 15 sets of 12 monthly parameter coefficients.

A pasture decay rate is applied separately to the cumulative pasture mass as it is passed through the various months of the year in the biophysical model. This was determined from monthly averages from the **GrassGro** output and these rates ranged 0.3% to 2.0%. This compares with Bowman, White, Cayley and Bird (1982) who found decay rates in southern Australian pastures of up to 1.8% of dry matter per day; this rate being correlated to lagged cumulative rainfall.

The resulting daily growth rate from the biophysical model for the deterministic year at a stocking rate of 15 dse/ha is shown in Figure 4. As part of the validation process of the biophysical model, simulated results may be compared with published pasture growth estimates. Two such studies are compared in Table 2.

While the experiments detailed in Table 2 are not directly comparable to the biophysical model since they included a variety of pasture species and were undertaken using monocultures or binary mixtures they serve as a broad guide of typical growth rates that might be encountered in Northern Tablelands environments.

Table 1. Estimated values of pasture growth parameters for the representative day for each month over the 15 years (1985-1999)

Pasture parameter	α mean	CV(%)	minimum	maximum		γ mean	CV(%)	minimum	maximum		Y_{max} mean	CV(%)	minimum	maximum
Jan	0.012	98	0	0.036	Jan	1.333	14	1.050	1.695	Jan	4105	55	750	7700
Feb	0.010	99	0	0.025	Feb	1.221	13	0.914	1.440	Feb	4700	40	1500	8000
Mar	0.016	76	0	0.044	Mar	1.172	17	0.820	1.435	Mar	4323	55	750	8000
Apr	0.014	82	0	0.036	Apr	1.259	18	0.654	1.532	Apr	4000	55	850	7200
May	0.017	38	0.002	0.023	May	1.326	18	0.864	1.943	May	5157	34	900	7500
Jun	0.014	59	0	0.026	Jun	1.299	13	0.957	1.609	Jun	4925	26	1600	7000
Jul	0.018	59	0.004	0.034	Jul	1.154	14	0.869	1.655	Jul	4340	24	2000	6000
Aug	0.016	72	0	0.036	Aug	1.128	14	0.847	1.443	Aug	5196	16	2900	6500
Sep	0.029	46	0	0.043	Sep	1.170	4	1.105	1.219	Sep	6862	14	5200	8200
Oct	0.024	74	0	0.053	Oct	1.237	6	1.064	1.345	Oct	7164	24	2350	8400
Nov	0.022	68	0	0.046	Nov	1.205	11	1.024	1.495	Nov	7117	24	2500	8500
Dec	0.018	89	0	0.045	Dec	1.246	10	1.018	1.506	Dec	5932	46	750	8300

Table 2. Biophysical simulated pasture growth rates compared with experimental pasture growth rates

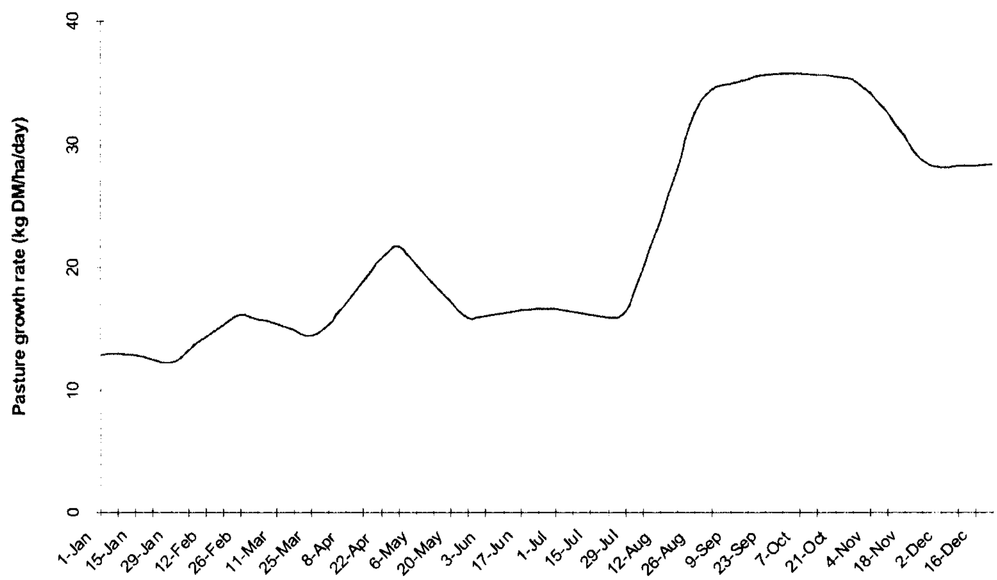
	Bioeconomic model monthly average ranges kgDM/ha.day*	Begg (1959) kgDM/ha.day	McPhee *et al.* (1997) kgDM/ha.day*
Spring	32-36	42-52	25
Summer	13-28	19-48	15-20
Autumn	15-19	-	15-20
Winter	16-23	12-20	7-12

* Pasture grazed at 15 sheep/ha.

The pasture type described by CSIRO (2003) and used for pasture growth parameters in the bioeconomic model includes three major components annual grasses, phalaris and white clover. The characteristics of these three components affect the overall growth rate pattern seen in Figure 4. In particular, the relatively high winter activity of the predominant Phalaris cultivar (Watson, McDonald and Bourke, 2000) would contribute to the greater level of winter production in the model pasture. Also while the large proportion of early annual grass species which are relatively active in spring and early summer are senescent by January and while providing biomass do not contribute to pasture growth in summer.

The average metabolizable energy per kilogram of pasture dry matter for the different months of the year are taken from **GrassGro** simulation estimates.

Figure 4. Daily pasture growth rate for the deterministic year



3.2 Animal Sub-model

Feed related components of the model are based upon metabolizable energy, as such it is a compromise, as it in effect assumes that other necessary nutritional requirements such as protein, fibre, vitamins, minerals and water are not limiting to the ruminant. Typically for ruminants grazing pasture energy and then protein are the primary limiting nutritional requirements and hence ruminant simulation models typically use energy or energy and protein requirements to derive feed requirements, for example **GRAZFEED** (Freer, Moore and Donnelly, 1997).

The animal sub-model is based upon the daily metabolizable energy (ME) requirements (MAFF, 1984; SCA, 1990) required to reach market specified age and weight targets (NSW Agriculture, 2003) and matched with the ME provided by the pasture including pasture carried over from the previous month and any supplementary feeding. As well, the maximum dry matter intakes of various livestock are also accounted for. ME equations used in the bioeconomic model are provided in Alford *et al.* (2004).

Net Feed Efficiency in Beef Cattle
Selection of beef cattle for increased feed efficiency is a relatively new research area. Feed-related costs represent the single largest cost category for a beef enterprise, typically greater than 60 per cent (Arthur, Archer and Herd, 2000). Previous selection objectives in beef cattle focused on the output side in terms of liveweight gain and fertility gains, as well as improved carcass traits (Archer, Richardson, Herd and Arthur, 1999). In contrast, selection for improved feed conversion efficiency is an attempt to reduce input costs. This approach has been especially successful within the monogastric poultry and pig industries.

NFE "refers to the variation in feed intake which remains after the requirements for maintenance and growth are accounted for. It is calculated as an individual animal's actual feed intake minus the expected feed intake based on its size and growth rate. Because an efficient animal is one which eats less feed compared to its weight and growth rate, efficient animals have a negative [NFE] while inefficient animals have a positive [NFE]" (Exton, Archer, Arthur and Herd, 2001, p.20).

Heritability of the NFE trait is moderate and of similar magnitude to the heritability of growth (Arthur *et al.*, 2000). Archer, Arthur, Herd and Richardson (1998) estimated a heritability for the trait of 0.43. The physiological basis for feed-efficient cattle is uncertain, with various hypotheses proposed (Archer *et al.,* 1999). Further, there is some uncertainty as to whether selection for efficient growing (young) cattle will result in greater feed efficiency for the overall breeding herd (Archer *et al.,* 1999). Major investigations have centred on feed efficiency of growing stock including the validation of a test to measure NFE during the 70-day post-weaning period (Archer, Arthur, Herd, Parnell and Pitchford, 1997), while examination of cow lines has found heifer weaners selected for NFE also display improved NFE as mature cows (Arthur, Archer, Herd, Richardson, Exton, Oswin, Dibley and Burton, 1999).

In a study of beef industry breeding schemes for the NFE trait, Archer and Barwick (1999) assumed genetic correlations between the NFE criterion and the improvement in NFE expressed by young animals to be 0.75 and for mature cows to be 0.50. In this present study these estimates were taken to be the correlations between the estimated breeding value for NFE and the actual improvements in growth efficiency and maintenance efficiency respectively.

Other assumptions regarding the NFE trait included that initially bulls with an EBV for NFE that is 4 per cent superior for NFE could be purchased by a commercial beef producer (Exton *et al.*, 2000). Further, an annual improvement in the NFE of the seedstock herd of 0.76 per cent was assumed to be feasible. This was derived from Arthur, Archer, Johnston, Herd, Richardson and Parnell (2001) who found an annual response to selection for an improvement NFE of 0.16 kg/day; however given multiple-breeding objectives, the annual potential rate of progress in the NFE EBV might reasonably be assumed to be only half, or 0.08 kg/day. In the study by Arthur *et al.* (2001), daily feed intake averaged 10.5 kg of dry matter per day therefore a reduction in NFE of 0.08 kg/day is equivalent to a 0.76 per cent improvement in the NFE trait per year.

The rate of improvement in NFE was determined by developing a simple cumulative model based upon fixed proportions of the age cohorts within the commercial cow herd. That is, 19.8 per cent of the cows were in the 2 year old cow cohort, and 17.1 per cent, 14.7 per cent, 12.7 per cent, 11.0 per cent, 9.5 per cent, 8.2 per cent and 7.0 per cent were in the 3 to 9 year old age cohorts, respectively. Additionally, since the herd was a commercial herd it was assumed that the farm manager does not impose additional selection pressure for NFE and that replacement heifers selected for the cow herd are selected on visual type and growth performance. The result is that by year 25 there is a 5.9 per cent reduction in the herd's ME requirement over the base herd.

3.3 Economic Sub-model

Annual profit is obtained from cattle sales less herd, pasture, supplementary feed and cattle sales costs. The net present value of a series of 25 years of gross margins is used as a basis of comparison between without and with-technology scenarios for the representative cattle enterprise. Salvage values for the base and NFE cow herds are assumed to be $979 per breeding unit (bu) and $1,068/bu respectively. (Refer to Alford *et al.* (2004) for details.)

Prices used in the budgets are expressed using 2001 dollar values. The cattle enterprise gross margin ($419 per breeding unit for a steady state herd) and pasture costs ($67/ha.year^{-1}) are detailed in Alford, Griffith and Davies (2003) while supplementary feeding costs are assumed to be $0.15 /kg DM with a metabolizable energy of 10 MJ/kg DM to account for wastage at feeding out. The cost of the NFE technology is reflected in an increase in purchase price of NFE bulls being $160 (adjusted to 2001 dollar values) above the standard bull price of $3750 per head (Exton *et al.*, 2000; Alford *et al.*, 2003).

Labour costs are not included in this analysis. Since the results from the modelling experiments resulted in only modest increases in herd size (less than 10%) it was decided that the costing of additional labour was not warranted given the practical difficulties in defining various thresholds for the extra labour for each additional cow added to the herd above the base case.

A real discount rate of 5% is used.

4. RESULTS AND DISCUSSION

4.1 The Base Herd in a Deterministic Environment

In the first experiment the model was run using pasture growth data from the deterministic year and the unimproved (or base) cow herd. The model was tested to determine the stocking rate that maximised the net present value (NPV) of a 25 year series of annual enterprise gross margins. The model was constrained to maintain a minimum 1000 kg DM/ha of pasture (McDonald, 2000). Supplementary feed is introduced to maintain this minimum pasture mass and achieve weight targets for stock, as well as to overcome livestock dry matter intake constraints as a consequence of low pasture feed quality.

A NPV maximising stocking rate of 18.2 dse/ha or 1.04 breeding units (bu) per hectare, was identified which equates to a 333 cow herd for the Heavy Feeder Steer enterprise modelled. This resulted in a NPV of gross margins of $1,651,900 plus a present value of livestock of $96,270, summing to $1,748,170.

This stocking rate of 18.2 dse/ha results in the pasture biomass approaching the minimum 1000 kg DM/ha in the late winter and early spring period when pasture growth has been constrained by low winter pasture growth rates (refer to Figure 5). This period coincides with the increased energy requirements for the cow herd pre and post calving. The stocking rate identified compares favourably with published stocking rate estimates for similar pastures as that modelled here for the Northern Tablelands. Lowien, Duncan, Collet and McDonald (1997) suggest that pastures which include an introduced perennial grass and legume on basalt derived soils range in stocking rates of 15 to 25 dse per hectare.

Figure 5. Daily pasture mass over a year using the deterministic pasture growth parameters

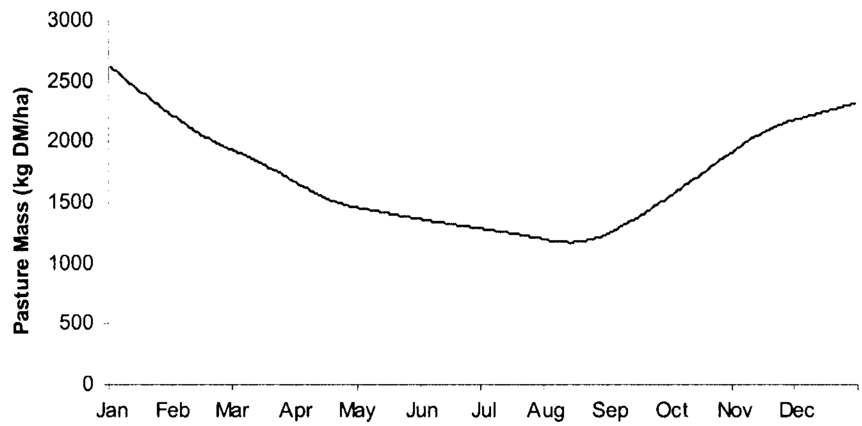
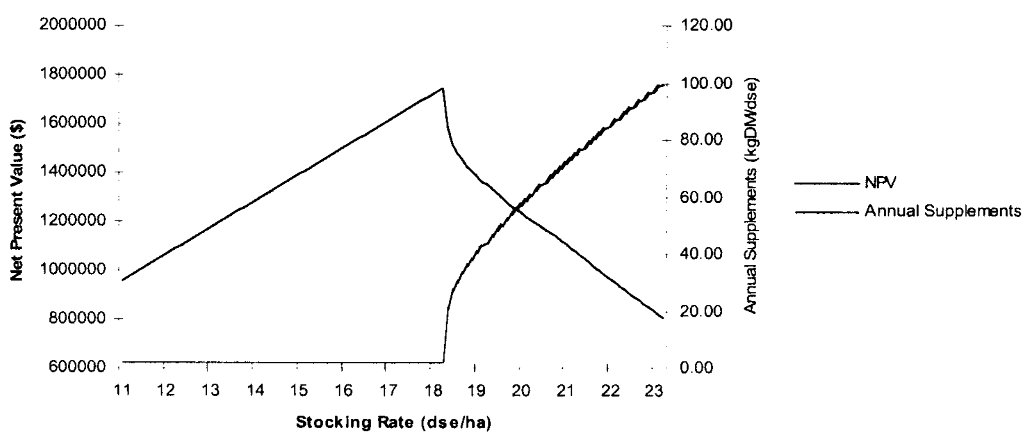


Figure 6 shows the change in NPV as the stocking rate is increased on the model farm. It can be seen here that the NPV has a direct negative correlation with the level of supplementary feeding required.

Figure 6. Change in NPV for the Heavy Feeder Steer Enterprise as stocking rate changes



4.2 The Base Herd in a Stochastic Environment

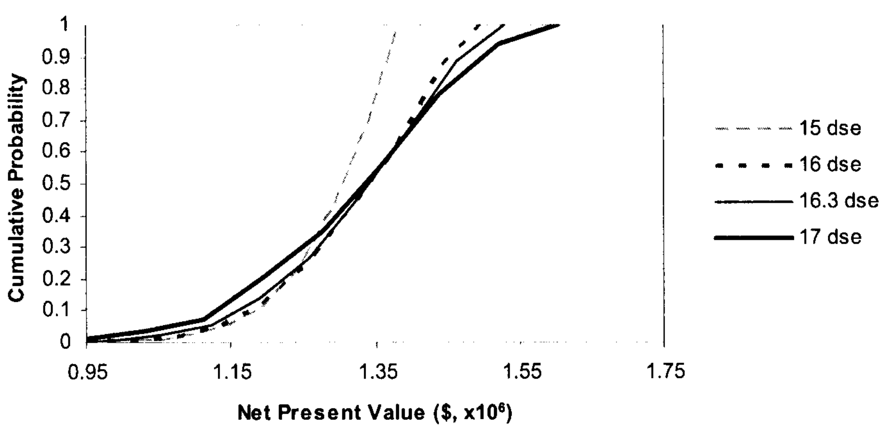
To examine the effect of production risk on the optimal stocking rate, the model was run using a Monte Carlo simulation procedure using the 15 years of derived pasture parameters. The stochastic simulation experiment was undertaken to determine the stocking level that maximised the net present value of a series of 25 year annual gross margins. 500 iterations were used. A stocking rate of 16.3 dse/ha (or 0.93 bu/ha) was identified as the optimal choice for a risk indifferent producer with a NPV including livestock salvage values of $1,327,900, while a risk averse producer would consider a lower stocking rate again (refer to Table 3).

Table 3. Estimated expected NPV and risk (in terms of NPV standard deviation) at different stocking rates for the base herd

Stocking Rate (dse/ha)	mean NPV ($ x10^6)	SD ($ x10^6)
11	0.9314	0.0077
12	1.0389	0.0164
13	1.1387	0.0299
14	1.2242	0.0498
15	1.2904	0.0755
16	1.3258	0.1078
16.3	1.3279	0.1184
17	1.3230	0.1439
18	1.2941	0.1747

Examination of the resultant cumulative distribution functions shows that the plan to adopt a stocking rate of 15 dse/ha is dominated by the three higher stocking rates shown in Figure 7, using second degree stochastic dominance. Similarly the optimal stocking rate dominates the 17 dse stocking rate scenario. However, discrimination between the stocking rates of 16 and 16.3 dse/ha is less evident without using more demanding risk aversion criteria.

Figure 7. Comparison of cumulative distribution functions of NPV for several stocking rates for the base herd

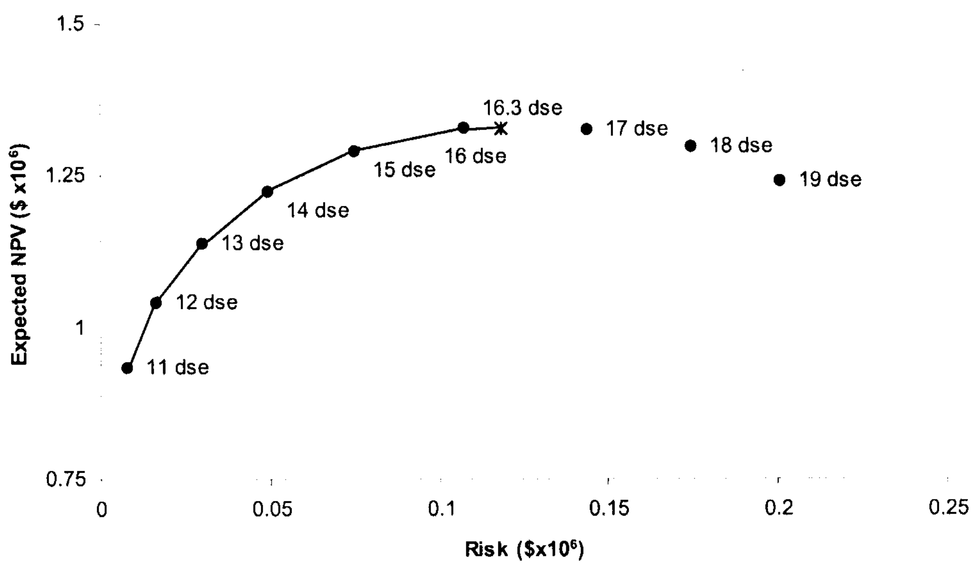


Useful information may be obtained by using risk neutral modelling approaches (Antle, 1983), and in so doing avoid assumptions regarding levels of risk aversion amongst farmers; for example, by identifying risk efficient frontiers (Cacho, Bywater and Dillon, 1999). Such an approach is supported by Pannell, Malcolm and Kingwell (2000) who provide empirical evidence that the incorporation of risk aversion, even at relatively high levels of aversion will have little impact on the farmers' optimal plan for choices which involve continuous or approximately continuous decision variables such as stocking rates.

The risk efficient frontier for stocking rates for the base herd is shown in Figure 8. Such a frontier may be used by a producer to determine their personal preference in terms of expected profit and level of risk for their individual circumstances (Cacho, Bywater and Dillon, 1999). At stocking rates above 16.3 dse/ha, risk as measured by the standard deviation of NPV increases however there is no additional increase in the expected NPV.

Taking the risk-indifferent optimal choice it is found that the stocking rate of 16.3 dse/ha is 10.4% less than the optimal stocking rate using the deterministic model (refer to Table 4). The cost of this stochastic environment compared with the deterministic state is \$420,270 or 24% in NPV over a 25 year simulation. This is equivalent to a present value cost of \$1,313/ha.

Figure 8. The risk efficient frontier with respect to stocking rate for the base herd



4.3 Net Feed Efficiency

The deterministic and stochastic bioeconomic models were then run incorporating the NFE technology. In the first case the NFE was run assuming a steady state herd, essentially this represents a before- and an after- implementation comparison of the NFE technology without accounting for the cost in herd expansion. Since comparisons between NFE cattle and base cattle on a DSE basis are not correct because the NFE trait in effect reduces energy requirements, stock numbers in terms of breeding units (bu) per hectare are used.

Table 4. Comparison of deterministic and stochastic pasture assumptions on the profit maximising stocking rate and resultant NPV for the unimproved beef enterprise

	Stocking rate (dse/ha)	Stock Numbers (breeding units/ha)	NPV ($\$x10^6$)
Deterministic – base herd	18.2	1.04	1.7481
Stochastic- base herd	16.3 (- 10.4%)*	0.93	1.3279 (- 24%)*

* Indicates percentage change compared with the respective deterministic or stochastic base herd model.

Deterministic model

The optimal herd size for NFE cows is a herd size of 337 cows on the 320 hectare enterprise. This is equivalent to 1.05 bu/ha. The resulting NPV is $1,672,600 in discounted gross margins and an additional discounted salvage value for livestock of $106,283, based upon a salvage value of $1068/bu (refer to Alford *et al.*, 2004). This represents a 1.8% increase in NPV over the 25 year simulation (refer to Table 5). The small increase in optimum carrying capacity compared with the base herd (333 cows; 1.04 bu/ha) reflects the small annual improvement in NFE in the early years of the simulation, which effectively limits the potential increased herd size. Due to the effect of discounting the cost of additional supplementary feed in the early years of the simulation necessary to enable a higher carrying capacity over the entire period is greater than the feed efficiency benefits that may be accrued in the later years of the simulation.

Table 5. Comparison of the optimal NPV and associated herd size between unimproved and NFE herds

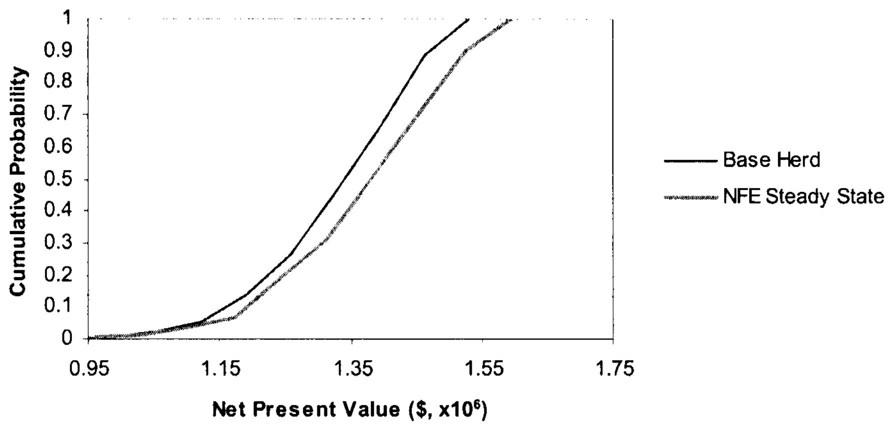
	NPV ($\$x10^6$)	Stock Numbers (breeding units/ha)
Deterministic – base herd	1.7481	1.04
Deterministic – NFE herd	1.7789 (+ 1.8%)*	1.05 (+ 0.96%)*
Stochastic- base herd	1.3279	0.93
Stochastic- NFE herd	1.3689 (+ 3.1%)*	0.96 (+ 3.2%)*

* Indicates percentage change compared with the respective deterministic or stochastic base herd model.

The optimal carrying capacity was then compared using stochastic pasture production (refer to Table 5). In this case the carrying capacity that maximised NPV of the discounted gross margins is 0.96bu/ha which resulted in a NPV, including the salvage value of livestock, of $1,368,944. As a result of the introduction of NFE to the herd there is an increase in NPV/ha of 3.1% and a 3.2% increase in beef produced per hectare over the base herd under the assumption of a stochastic pasture base. The cumulative distribution functions for the base herd and steady state NFE herd are shown in Figure 9, where the NFE technology scenario dominates the NPV cumulative distribution in terms of second degree stochastic dominance.

Examination of the NFE technology using a stochastic framework indicates a 3% improvement in NPV compared with 1.8% from the deterministic scenario, over the respective unimproved herd scenarios.

Figure 9. The cumulative distribution functions of NPV for the base herd and the NFE herd assuming the herds are in steady state.



4.4 "Optimal" expansion path

Access to a genetic technology such as NFE for commercial beef producers is predominately restricted to buying bulls and increasing herd size by retaining additional heifers above that required for maintaining a herd in steady state. Reasons for this constraint include the limited availability of commercial females with the new genetic trait in the early years of the technology, and if such females are available they may still not suit the individual producer's specific production systems and related target markets. As well, herd health management practices may restrict the number and frequency of new animal introductions to a breeding herd.

Therefore examining potential expansion strategies is warranted to account for the changes in feed requirements and cashflow as the herd expands. This was done by assuming that the initial herd size is the same as that for the optimal base herd under deterministic (333 cows; 1.04 bu/ha) and stochastic (297 cows; 0.93 bu/ha) models. Herd expansion scenario results are reported in Table 6.

The optimal expansion path to maximise the NPV of 25 years of gross margins in the deterministic model is to expand to a herd size of 353 cows, a 5.8% expansion in herd size over the 25 years. This provides a NPV of annual gross margins of $1,675,700. An additional amount representing the present value of NFE cattle at the end of the expansion phase is $111,348.

The extent to which herd expansion impacts upon the NPV of the cattle enterprise incorporating the NFE technology under the deterministic model assumption is illustrated in Figure 10. To maintain a steady state herd, 37% of weaner heifers are sold to allow for sufficient numbers for culling and deaths before their first calving at

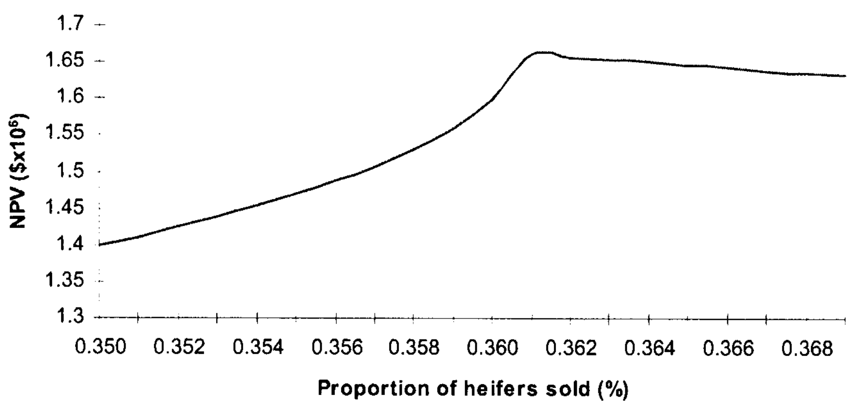
Table 6. Differences between optimal herd expansion under deterministic and stochastic pasture assumptions

	Optimal Herd Expansion	NPV ($\$x10^6$)	Final Year Breeding Units (cows/ha)
Deterministic- base herd	Steady state	1.7481	1.04
Deterministic- NFE herd expansion	+ 5.8%	1.7870 (+ 2.2%)	1.10 (+ 5.8%)
Stochastic- base herd	Steady state	1.3279	0.93
Stochastic- NFE herd expansion	1.1%	1.3663 (+ 2.9%)	0.94 (+ 1.1%)

2 years of age. Therefore, as the herd expands by selling fewer heifers to approximately 36%, NPV increases after which the NPV decreases again as the stocking rate increases and subsequently the supplementary feed requirements increase.

In contrast to the optimal farm plan that has identified a 5.8% increase in the herd size, an analysis using a multi-period linear program which included both sheep and beef enterprises, identified that the optimal farm plan would expand the herd by some 12.6% over 25 years. However, there was the capacity for output substitution in this model which resulted in resources being transferred from the sheep enterprises and invested in the NFE cattle enterprise on the representative farm (Alford *et al.*, 2004).

Figure 10. Effect of herd expansion on the NPV of the NFE cattle enterprise assuming a deterministic pasture model



Comparing the optimal herd expansion path identified within a stochastic environment to the deterministic result suggests that level of expansion of the cattle enterprise is sensitive to the opportunity cost of heifer sales and the extra contribution that retained heifers make to the annual stocking rate. The optimal expansion plan in the stochastic model is for a minor increase in herd size by 1% over the 25 year period resulting in a NPV of $1,366,250 including livestock salvage values. This is a result of the relatively low rate of improvement in NFE and the additional feed that is required by the larger number of heifers in the early part of the planning period.

5. CONCLUSIONS

From the particular issue examined here, it appears that taking account of the stochastic nature of the grazing system is important. In this case it was found that the deterministic model overestimated profit maximising stocking rates by 10% in the base herd, while accounting for this variability resulted in a 24% lower NPV for the base herd. This difference between deterministic and stochastic results was found despite applying the relatively relaxed condition of risk neutrality and so avoiding assumptions regarding farmers' levels of risk aversion. This is consistent with theory (eg., Antle, 1983) and the findings of other researchers (eg., Cacho, Bywater and Dillon, 1999).

The NFE technology appears to be of economic benefit with a 2.9% increase in net present value identified for a representative cow-calf enterprise, which is constrained by a minimum pasture mass, 'best management practice' assumption. This improvement was accompanied by a 1.1% in beef production over the 25 year planning period simulated. In contrast optimal herd expansion under a deterministic scenario was 5.8% which essentially reflects the phenotypic improvement in the net feed efficiency of the herd over the 25 years. In an environment of production risk, the potential increase in beef output as a consequence of adoption of the NFE technology may be limited by the low expected annual genetic improvement in the NFE trait in a commercial herd and the opportunity cost of heifer sales and the extra contribution that retained heifers make to the annual stocking rate in the early years of the planning period.

Future research using this bioeconomic simulation model include incorporating sensitivity analysis of various price assumptions, such as the cost of NFE bulls and beef prices; as well as assumptions regarding the rate of improvement of the genetic trait in a commercial herd. For example, research is currently being undertaken through the Beef CRC examining various markers that are genetically correlated to net feed efficiency in cattle. These markers, such as insulin-like growth factor-1 (IGF1) may decrease the cost of the NFE technology to producers.

The NFE trait may have greater benefits to producers which have not been included in this current analysis, through the addition of a premium for young stock suitable for feedlots. This assumes that a portion of the savings in feed that the feedlotter would achieve by purchasing NFE progeny is passed back to the cow-calf operator (Exton *et al.* 2000). The extent to which a producer might benefit from these savings further down the production line will depend upon the various demand and supply elasticities that exist in the supply chain. This is an area for further examination. It should be noted however, that any such premium that might be obtained by producers of young stock suitable for feedlot entry would have to account for additional costs that a producer would incur in verifying to the feedlotter the level of NFE that their stock will achieve.

The current model has the capacity to examine the economic trade-offs between short-term utilisation of pastures and the long-term sustainability of a productive pasture resource using estimates from long-term grazing management trails, for regions such as the Northern Tablelands of New South Wales. This is anticipated to be an important area for future investigation.

REFERENCES

Alford, A.R., Griffith, G.R., and Cacho, O.J. (2004), *A Northern Tablelands Whole-Farm Linear Program for Economic Evaluation of New Technologies at the Farm Level,* Economic Research Report No. 13, NSW Agriculture, Armidale.

Alford, A.R., Griffith, G.R. and Davies, B.L. (2003), *Livestock Farming Systems in the Northern Tablelands of NSW: An Economic Analysis*, Economic Research Report No. 12, NSW Agriculture, Armidale.

Alston, J.M.; Norton, G.W. and Pardey, P.G. (1995). *Science Under Scarcity. Principles and Practice for Agricultural Research and Evaluation and Priority Setting*. Cornell University Press; Ithaca.

Antle, J.M. (1983). Incorporating risk in production analysis. *American Journal of Agricultural Economics*, **65**, pp. 1099-1106.

Archer, J.A. and Barwick, S.A. (1999). Economic analysis of net feed intake in industry breeding schemes. *Proceedings of the Thirteenth Conference Association for the Advancement of Animal Breeding and Genetics*, Mandurah, Western Australia, 4-7 July; pp. 337-340.

Archer, J.A., Arthur, P.F., Herd, R.M., Parnell, P.F. and Pitchford, W.S. (1997). Optimum postweaning test for measurement of growth rate, feed intake and efficiency in British breed cattle. *Journal of Animal Science*, **75**, 2024-2032.

Archer, J.A., Arthur, P.F., Herd, R.M., and Richardson, E.C. (1998). Genetic variation in feed efficiency and its component traits. *Proceedings of the Sixth World Congress on Genetics Applied to Livestock Production*. **25**, pp. 81-84.

Archer, J.A., Richardson, E.C., Herd, R.M. and Arthur, P.F. (1999). Potential for selection to improve efficiency of feed use in beef cattle: a review. *Australian Journal of Agricultural Research*, **50**, pp. 147-161.

Arthur, P.F., Archer, J.A. and Herd, R.M. (2000). Genetic selection for feed efficiency. *Proceedings of the National Beef Science Seminar, January 26-28*, Alberta.

Arthur, P.F., Archer, J.A., Herd, R.M., Richardson, E.C., Exton, S.C., Oswin, C., Dibley, K.C.P. and Burton, D.A. (1999). Relationship between postweaning growth, net feed intake and cow performance. *Proceedings of the Thirteenth Conference Association for the Advancement of Animal Breeding and Genetics*, Mandurah, Western Australia, 4-7 July; pp. 484-487.

Arthur, P.F., Archer, J.A., Johnston, D.J., Herd, R.M., Richardson, E.M. and Parnell, P.F. (2001). Genetic and phenotypic variance and covariance components for feed intake, feed efficiency and other post weaning traits in Angus cattle. *Journal of Animal Science*, **79** (11), pp. 2805-2811.

Bowman, P.J.; White, D.H.; Cayley, J.W.D. and Bird, P.R. (1982). Predicting rates of pasture growth, senescence and decomposition. *Proceedings of the Australian Society of Animal Production*, **14**, pp. 36-38.

Cacho, O.J. (1993). A practical equation for pasture growth under grazing. *Grass and Forage Science*, **48**, pp. 387-394.

Cacho, O.J. (1997*a)*. Dynamic Models, Externalities and Sustainability in Agriculture. *41st AARES Conference*, 20-25 January, Gold Coast, Australia.

Cacho, O.J. (1997*b*). Systems modelling and bioeconomic modelling in aquaculture. *Aquaculture Economics and Management*, **1** (1), pp. 45-64.

Cacho, O.J. (1998). Solving bioeconomic optimal control model numerically. J. Gooday (ed) *Proceedings of the Bioeconomic Workshop, Workshop (Post-*

Australian Agricultural and Resource Economics Society Conference), 22 January, Armidale, NSW., ABARE Canberra.

Cacho, O.J.; Bywater, A.C., and Dillon, J.L. (1999). Assessment of production risk in grazing models. *Agricultural Systems*, **60**, pp. 87-98.

CSIRO (2003). *GrassGro, Resources Kit, Version 2.4.* Plant Industries, CSIRO, Canberra.

Curll, M.L. (1987). Screening and Evaluation of pasture species mixtures for northern New South Wales. In JL. Wheeler; C.J. Pearson and G.E. Robards (*Eds.*) '*Temperate Pastures, their Production, Utilisation and Management*'. AWC/CSIRO; Melbourne.

Exton, S.C., Herd, R.M., Davies, L., Archer, J.A. and Arthur, P.F. (2000). Commercial Benefits to the Beef Industry from Genetic Improvement in Net Feed Efficiency. *Asian-Australiasian Journal of Animal Sciences*, **13** (Supplement B), 338-341.

Exton, S.C., Archer, J.A., Arthur, P.F. and Herd, R.M., (2001). Developing estimated breeding values for net feed intake. In *Proceedings of "The Beef Program – Challenges and Future Directions"*; NSW Agriculture , Dubbo; pp.20.

France, J. and Thornley, J.H.M. (1984). *Mathematical models in agriculture.* Butterworths, London.

Freer, M., Moore, A.D. and Donnelly, J.R. (1997). GRAZPLAN: Decision Support Systems for Australian Grazing Enterprises. II. The Animal Biology Model for Feed Intake, Production and Reproduction and the GrazFeed DSS. *Agricultural Systems*, **54** (1), pp. 77-126.

Goodwin, B.K. (2003). Does Risk Matter? Discussion. *American Journal of Agricultural Economics*, **85** (5); pp.1257-1258.

Hutchinson, K.J.; King, K.L. and Wilkinson, D.R. (1995). Effects of rainfall, moisture stress and stocking rate on the persistence of white clover over 30 years. *Australian Journal of Experimental Agriculture*, **35**, pp. 1039-1047.

Johnson, I.R. and Parsons, A.J. (1985). A theoretical analysis of grass growth under grazing. *Journal of Theoretical Biology*, **112**, pp. 345-367.

King, R.P.; Lybecker, D.W.; Regmi, A. and Swinton, S.M. (1993). Bioeconomic models of crop production systems: design, development and use. *Review of Agricultural Economics*, **15**, pp. 389-401.

Lazenby, A. and Lovett, J.V. (1975). Growth of Pasture Species on the Northern Tablelands of New South Wales. *Australian Journal of Agricultural Research*, **26**, pp. 269-280.

Lowien, J., Duncan, M., Collett, I. and McDonald, W. (1997). *A Guide to Better Pastures on the Northern Tablelands.* NSW Agriculture, Orange.

MAFF (1984). *Energy Allowances and Feeding Systems for Ruminants.* U.K. Ministry of Agriculture, Fisheries and Food, Technical Bulletin No. 433. HMSO: London.

McDonald, W. (2000). *Pasture sustainability and management in drought.* Agnote DAI-157. NSW Agriculture.

McPhee, M.J.; Ayres, J.F., and Curll, M.L. (1997). Growth periodicity of introduced pastures on the northern tablelands of New South Wales. *Australian Journal of Agricultural Research*, **48**, pp. 831-841.

Moore, A.D.; Donnelly, J.R. and Freer, M. (1997). GRAZPLAN: decision support systems for Australian grazing enterprises. 3: Pasture growth and soil moisture submodels, and the GRASSGRO DSS. *Agricultural Systems*, **55**, pp. 535-582.

NSW Agriculture (2003). *Livestock gross margins.* NSW Agriculture, Orange [Online] Available: http://www.agric.nsw.gov.au/reader/818/ [Accessed 11th February 2003].

Oriade, C.A. and Dillon, C.R. (1997). Developments in biophysical and bioeconomic simulation of agricultural systems: a review. *Agricultural Economics*, **17**, pp.45-58.

Pandey, S. and Hardaker, J.B. (1995). The role of modelling in the quest for sustainable farming systems. *Agricultural Systems*, **47**, pp. 439-450.

Pannell, D.J. (1999). On the estimation of on-farm benefits of agricultural research. *Agricultural Systems*, **61** (2), pp. 123-134.

Pannell, D.J., Malcolm, B. and Kingwell, R.S. (2000). Are we risking too much? Perspectives on risk in farm modelling. *Agricultural Economics*, **23** (1), pp. 69-78.

Robinson, G.G. and Lazenby, A. (1976). The effect of superphosphate, white clover and stocking rate on the productivity of natural pastures of Northern Tablelands of New South Wales. *Australian Journal of Experimental Agriculture and Animal Husbandry*, **16**, pp. 209-217.

Scott, J.M.; Hutchinson, K.J.; King, K.; Chen, W.; McLeod, M.; Blair, G.J.; White, A.; Wilkinson, D.; Lefroy, R.D.B.; Cresswell, H.; Daniel, H.; Harris, C.; MacLeod, D.A.; Blair, N. and Chamberlain, G. (2000). Quantifying the sustainability of grazed pastures on the Northern Tablelands of New South Wales. *Australian Journal of Experimental Agriculture.* **40**, pp. 257-265.

The Mathworks Inc. (2001a). *Learning Simulink 4® Release 12, International Edition.* The MathWorks Inc., Massachusetts.

The Mathworks Inc. (2001b). *Learning Matlab 6®, Release 12, International Edition.* The MathWorks Inc., Massachusetts.

Thornley, J.H.M. and Johnson, I.R. (1990). *Plant and Crop Modelling.* Clarendon Press, Oxford.

TSP International (1997). *Time Series Processor: Version 4.4, Reference Manual and Users Guide*, TSP International, Palo Alto.

SCA (1990). *Feeding standards for Australian livestock. Ruminants.* Standing Committee on Agriculture, Ruminants Subcommittee; CSIRO, Melbourne.

Watson, R.W.; McDonald, W.J. and Bourke, C.A. (2000). Phalaris Pastures. Agfact P2.5.1., Second edition; NSW Agriculture.

Woodward, S.J.R. (1998). Dynamical Systems Models and Their Application to Optimizing Grazing Management. In R.M. Peart and R.B. Curry (*Eds.*) *Agricultural Systems Modeling and Simulation*; Chapter 11, pp. 419-473. Marcel Dekker Inc., New York.