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A study of the effect of inputs on level of production of dairy farms in Queensland — a comparative analysis of survey data

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Summary. Multiple linear regression models able to estimate total farm milk production from nutritional inputs were developed from farm survey data provided by dairy farmers in Queensland, Australia. These models were specifically developed for inclusion in a decision support system that could provide dairy farmers with an annual milk production estimate, thus enabling them to compare their production with an average farm using the same inputs in their region. Separate models were developed for each of 4 regions in Queensland and an additional model was developed for farms producing greater than 750 kL of milk per farm per year. The models were tested on dairy farms in Queensland by using the decision support system on farms that were not involved with initial model development. The partial regression coefficients for the models were biologically sensible and, apart from some minor interactions between independent variables in 2 regions, were additive. These interactions were not included in the final model in the interests of parsimony, ease of explanation and a need to provide transparent models within the decision support system. The coefficients of determination (R^2) for the models varied from 79.9 to 88.3%. Forward-feed artificial neural network models were also used to confirm the relative accuracy of the multiple linear regression models and to allow for any interactions or non-linear functions in the data and to show that the simple equations are more appropriate for a farmer-orientated decision support system.

Addition keywords: regression models, decision support systems.

Introduction

Regression analyses of industry survey data can provide a method of estimating response rates of milk to nutritional inputs (Rees *et al.* 1972; Kerr *et al.* 1995*a*) and these response rates can be compared with real farm production. Several surveys have been conducted on the dairy industry in northern Australia over the past 40 years, including Mawson (1953), Rayner and Young (1962), Rees *et al.* (1972), Anon. (1988), and Kerr *et al.* (1995*a*). The primary objectives of these surveys varied from gathering baseline statistics (Mawson 1953; Anon. 1988) to the interpretation of relationships and the development of whole farm explanatory models (Rees *et al.* 1972; Kerr *et al.* 1995*a*).

In 1990–91, a survey was initiated in Queensland with the object of defining relationships between farm inputs and outputs. Equations were developed from these relationships with the aim of providing realistic estimates of the response rate to inputs for farms in Queensland and for inclusion in a decision support system (DSS) called DAIRYPRO (Kerr 1996). This DSS was designed to provide a benchmark for dairy farmers that would allow them to compare their farm milk production performance with other farms using the same inputs in their region. In addition, the farmer could enter hypothetical changes to his or her farm and the DSS would provide a series of 'what-if' scenarios indicating the profit or loss associated with each proposed change.

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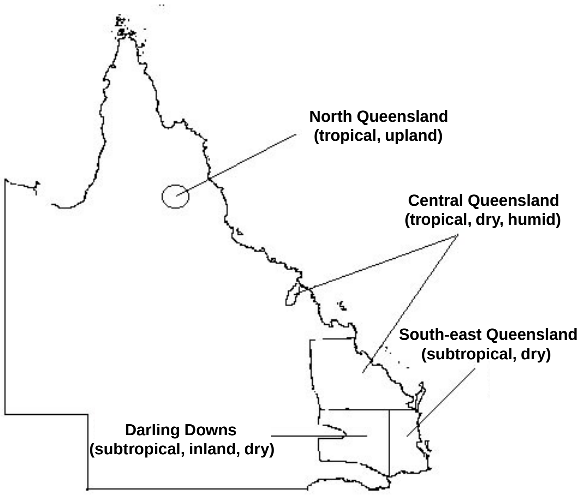

Figure 1. Map of Queensland showing the location of the 4 regions identified in the 1990–91 survey.

Materials and methods

The survey was designed to encourage farmers to record inputs and outputs for their farm on a daily basis. Selected farmers were asked to complete 4 separate forms, which were designed to record annual, monthly and daily inputs and outputs. Data collection was continued for 1 year and collated routinely in a central office.

The northern Australian dairy industry in 1990–91 was assumed to consist of 2 separate populations. The first was dairy farms producing less than 750 kL of milk per year and the second consisted of farms producing greater than 750 kL of milk per year. This assumption was based on the analysis of a survey conducted in Queensland in 1986–87, and overseas studies, where high producing farms appeared to be more efficient and were considered a separate population due to improved economies of scale (Kerr *et al.* 1995*a*). In addition, examination of the residuals from initial exploratory regression analysis of the 1986–87 survey indicated that there were excessive leverage points from the farms producing greater than 750 kL of milk per year. Farms producing less than 750 kL of milk per year had a random distribution of residuals about zero when the high production farms were excluded from the data set.

A stratified random sampling technique was used to select the farms required for data collection in the first population. The strata were the 4 distinct dairying regions in Queensland, namely North Queensland, Central Queensland, south-east Queensland and the Darling Downs (Fig. 1). These regions are distinct and reflect dissimilar farming practices within each region. The farming practices on the Darling Downs, for example, are based predominately on cropping compared with the coastal systems that are pasture based. There are also obvious climatic differences between regions in coastal areas as one moves north (Kerr *et al.* 1996).

Thirty farms were selected at random from each stratum and extension officers from the Queensland Department of Primary Industries were responsible for informing farmers of the data to be collected. The total sample size of the first population was 128 or 7% of all dairy farms in Queensland. Two farms from each region were selected for the second population making a total of 8 farms or 9% of the population of high production farms. Regional influences on production for the second population were thought to be minimal due to the high proportion of off-farm inputs being used to produce milk. In addition, their farming practices differed from the average dairy farm in the region; for example many high production farms feed their dairy cows in feedlots (Kerr 1993).

Four forms were developed and used by farmers for data entry. The first was designed to describe the property and consisted of a map of the farm drawn by the farmer. It was used to give a perspective on the position and size of all paddocks on the farm. The second form was designed to obtain information on the area of each paddock and the forage type used to feed the herd in each season. The year was divided into 2 growing seasons based on the pasture or forage types found in winter and summer. As the study was conducted over 1 financial year (June 1990–July 1991), 3 copies of the second form were completed, one for each of the 3 periods of winter, summer and part of the next winter (April–June). The third form was used to record the total inputs associated with dairy cows not milking and young stock. It was filled in every 3 months and only changes from the daily routine were recorded. The fourth form was filled in on a daily basis and used to record inputs of fertiliser, irrigation, concentrates and conserved fodder. The paddock numbers grazed by the milking herd during the day were also recorded and these inputs were matched with forage type and the paddock areas from the second form. This fourth form was also used to record total daily milk production for the farm.

The data collection process was successful, with 111 of 128 farms completing all the forms. Of these 111 data sets, 103 were from farms from the first population producing less than 750 kL of milk per year and 8 from the second population producing greater than 750 kL of milk per year.

It was anticipated that the models developed would be able to relate nutritional inputs to milk output. To this end the following 3 dependent variables were considered: (i) milk production per hectare; (ii) milk production per cow; and (iii) milk production per farm.

The dependent variable selected for this study was milk production per farm and the reasons for this selection are discussed later.

The most important variables affecting total farm milk production were identified from Kerr *et al.* (1995*a*) and the experience and knowledge of 3 dairy farming systems experts (Kerr and Chaseling 1992). The 8 independent variables selected were: (i) 'cow numbers'—average number of cows milked per day throughout the year, this included both dry cows and milkers on the farm for the year under study; (ii) 'energy from concentrates'—the metabolisable energy fed as concentrates to the whole herd (MJ); this variable was then converted to a grain equivalent by dividing the calculated total megajoules of metabolisable energy from concentrates by the metabolisable energy of a typical grain (in this case barley) giving a value that farmers could easily understand as it related to the actual product found on the farm; (iii) 'nitrogen'; (iv) 'potassium'; (v)'phosphorus' (the number of kilograms of each element applied as fertiliser over the farm during the survey year); (vi) 'total hay and/or silage'—the total hay or silage fed to the herd over the survey year (expressed in kilograms on a dry matter basis); (vii) 'winter irrigation area'—the area set aside to irrigate pasture or crops in winter in hectares; (viii) 'total farm area'—total area of the farm used for dairying in hectares.

A forward selection, stepwise regression technique (SAS 1987; Sen and Srivastava 1990) was applied to the population of lower production farms to select the most important factors affecting production.

Artificial neural network (ANN) methods were also used as an alternative method of analysis. Nelson and Illingworth (1991) describe ANN as models of the human mental process. They state that an ANN has the ability to simulate parallel processing and can learn a pattern from examples and results. The terminology used to describe the processes used by ANN are the same as those used in biology, with neurons or nerve cells described as the basic units for the building blocks of an ANN. In biology, each neuron has a network of nerve fibres called dendrites connected to the cell body. This nerve cell is also characterised by the axon, which is a long fibre extending from the neuron. Synapses are at the end of each axon and they form the connecting link to other nerve cells or neurons (Hertz *et al.* 1991). A signal is transmitted from one neuron to another through substances released from the transmitting side of the junction. This has the effect of lowering or raising the electrical potential inside the receiving cell. If this reaches a threshold, a pulse is sent down the axon and the nerve cell is said to have fired (Hertz *et al.* 1991). Nelson and Illingworth (1991) extend this biological model to neural networks, equating the neuron with the simplest element in an ANN. This artificial neuron is also referred to as a 'processing element'.

A processing element must determine the strength of each input, calculate a total for the combined input signals, compare that to some threshold value, and finally determine what the output should be. It is usual for a processing element to have many inputs and will produce an output if the threshold level is exceeded. This threshold level is determined by a weighting factor. Various possibilities exist for connecting the processing elements throughout the network and Nelson and Illingworth (1991) describe the following 3 network designs: (i) feed forward—the output only is sent to the next layer; (ii) feed back—the output is allowed to go back and become input to the preceding layer; and (iii) feed lateral—lateral connections are able to send inputs to the processing elements in the same layer.

The form of ANN used in this study was a feed-forward artificial neural network (FFANN) (Sanzogni 1995). The object was to compare the goodness of fit of a FFANN model against that of the multiple regression model (MLR). It was recognised that the FFANN technique would not be able to attach a coefficient to each variable as it would provide a prediction only, with all weighting calculations being done in the internal processing elements of the FFANN. The FFANN method provides a means of confirming the relative accuracy of the more straightforward multiple regression models, as it can allow for any interaction terms or non-linear functions in the data (Sanzogni 1995).

Three types of FFANN were used. The first was a standard FFANN with one hidden layer consisting of 50 neurons; the second a standard FFANN with one hidden layer consisting of 8 neurons; and the third a product FFANN with 8 Pi-Sigma units containing 2 neurons each. The product FFANN was used for comparison with MLR as it provided the best fitting model of all the FFANN.

The data used for all the FFANN types were the same as those used for the MLR. A modified version of the feed-forward back-propagation algorithm was used to train the product FFANN with the 8 Pi-Sigma product units (Sanzogni 1995). The root mean square error (RMSE) was used as a measure of the reliability of each method, with a low RMSE indicating a model with a smaller unexplained component.

The models that were selected for use in the DSS were tested on 13 dairy farms in Queensland by using DAIRYPRO on farms that were not involved with the initial development of the models.

Results

The mean and standard deviation for all variables from the 1990–91 survey are shown in Table 1.

Multiple linear regression models

Variables were considered to exert a significant effect on total annual milk production if the partial regression coefficient was significant at the 5% level of

Table 1. Mean and standard deviation (± s.d.) for variables included in the 1990–91 survey

NQ, North Queensland; CQ, Central Queensland; SEQ, south-east Queensland; DD, Darling Downs

Variable	NQ	CQ	SEQ	DD	Whole state	High producing farm
Milk production (kL/year)	443 ± 161	340 ± 138	366 ± 130	350 ± 137	376 ± 146	1104 ± 554
Cow numbers	105 ± 30	92 ± 29	94 ± 26	83 ± 33	94 ± 30	234 ± 109
10^{-4} x Energy from concentrates (MJ/farm . year)	165 ± 72	193 ± 87	154 ± 70	160 ± 79	168 ± 78	605 ± 543
10^{-2} x Nitrogen (kg/farm . year)	70 ± 61	42 ± 53	70 ± 50	31 ± 44	53 ± 54	113 ± 68
Potassium (kg/year)	3353 ± 5063	571 ± 1194	498 ± 1116	552 ± 1172	1278 ± 3008	448 ± 885
Phosphorus (kg/year)	992 ± 1237	411 ± 723	441 ± 1022	226 ± 359	523 ± 933	729 ± 1005
Total hay and/or silage (kg DM x 10^3/year)	12 ± 54	36 ± 62	15 ± 26	90 ± 14	38 ± 89	376 ± 589
Winter irrigation area (ha)	12.2 ± 13.3	14.4 ± 18.0	23.5 ± 17.8	13.4 ± 18.2	15.7 ± 17.2	18.7 ± 23.5
Total farm area (ha)	117.7 ± 37.6	186.0 ± 76.1	117.0 ± 79.0	199.1 ± 80.9	155.3 ± 79.0	233 ± 130
No. of farms	27	26	24	26	103	8

significance. The variables selected by this technique were: (i) average number of cows milked per day throughout the year; (ii) amount of nitrogen applied (kg) per farm per year; (iii) amount of grain equivalent concentrates fed (kg) per farm per year; and (iv) area set aside to irrigate winter feed (ha).

These independent variables were used for the MLR model development, and the partial regression coefficients, R^2 values and RMSE from the developed models are shown in Table 2.

Feed-forward artificial neural network models

The product FFANN model was used on the same data set, namely the independent variables of concentrate feed (MJ), winter irrigation area (ha), cow numbers, and nitrogen (kg), with the dependent variable being total farm milk production per year. Table 3 shows the calculated RMSE for the product FFANN and the MLR.

The FFANN with product units gave a better fit to the sample data than the MLR models, producing an improvement in RMSE of between 5 and 15% (Table 3).

Multiple linear regression models for the second population

The forward selection, stepwise linear regression approach was also applied to the 8 farms sampled from the second population, namely farms that were producing greater than 750 kL of milk per year. The technique could identify only one significant explanatory variable, which was the number of cows milked. This influence was large, with 85% of the variation in total farm milk production being explained solely by the number of cows milked. The data set for the second population was too small for FFANN analysis.

The possibility of a non-linear response between farm milk production and cows milked was explored in the high production data set using a variety of non-linear functional forms. In all cases the non-linear terms were not significant at the 95% level of confidence.

Models selected for the decision support system

The product FFANN gave better milk production estimates than the MLR methods, especially when prediction estimates were considered on a regional basis. However, the total improvement in reliability and fit was not considered sufficient to change the basic parsimonious model for the DSS. The maximum 15% improvement in RMSE that was found in North Queensland was not great when considered in the

Table 2. Partial regression coefficients (± s.e.), R^2 values and RSME for the first population for the 1990–91 survey

Region	Concentrate fed (grain equivalent[A])	Winter irrigation area	Cow numbers	Nitrogen	R^2	RMSE
North Queensland	1.11 ± 0.43	2554 ± 1285	1802 ± 618	8.0 ± 3.5	79.9	78 442
Central Queensland	1.09 ± 0.35	2184 ± 838	1130 ± 824	4.3 ± 3.22	83.5	61 033
South-east Queensland	0.76 ± 0.34	n.s.	1970 ± 646	12.3 ± 3.1	86.4	52 823
Darling Downs	1.17 ± 0.24	1929 ± 688	1515 ± 393	4.0 ± 3.2	88.3	51 301
Whole state	0.82 ± 0.16	n.s.	1871 ± 301	8.8 ± 1.7	78.1	69 875

[A] Grain equivalent = (MJ/13.4)/0.9.

Table 3. Comparison of the fit of multiple linear regression (MLR) and the product FFANN predictions

Region	Number of farms	RMSE MLR	RMSE (FFANN)
North Queensland	27	78 442	66 292
Central Queensland	26	61 033	55 462
South-east Queensland	24	52 823	46 745
Darling Downs	26	51 301	45 158
Whole state	103	69 875	66 295

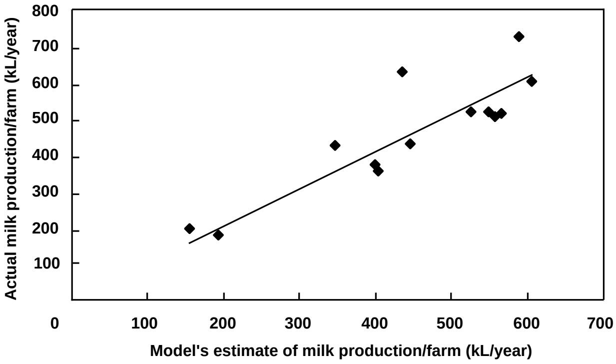

Figure 2. Actual milk production versus the model's estimate of milk production per farm. A fitted line through 0 is shown to indicate how close the gradient is to unity. The equation of the line is:

$$y = 1.0216x \ (R^2 = 0.7613)$$

context of the high coefficients of determination exhibited by all the MLR models (between 78 and 88%). In addition, the MLR models could be explained to end-users with partial regression coefficients provided by MLR being likened to marginal response rates to each component input. These coefficients were biologically sensible and were explained to farmers as the amount of milk expected from each unit of a particular input given all other inputs are also used.

Significant (P<0.05) interactions between energy and winter irrigation area, and between cow numbers and winter irrigation area in Central Queensland, and between nitrogen level and winter irrigation area in the Darling Downs region were found in this data set. The inclusion of these interactions had little effect on the overall fit of the regression equations and it was decided to omit them from the models in the interests of parsimony and providing transparent models to the proposed end users of the DSS (extension officers and farmers).

While it is recognised that there may be collinearity between independent variables, the lack of a large number of significant interactions and more importantly the fact that the partial regression coefficients were biologically sensible was further justification for using the simple model.

Verification of model

There was a correlation of 0.87 between actual total farm milk production and the model's estimate of production for 13 farms evaluated using DAIRYPRO. These farms were not involved in the initial model development and were considered by regional extension officers to be a good cross section of farms in their district. A comparison between the actual production per farm and the model's estimate of total milk production per farm from this group is shown in Figure 2. Note that a fitted line has been forced through an origin of 0 and it has a gradient of y = 1.02. A value of y = 1 indicates a perfect fit.

Discussion

The selection of the dependent variable total farm milk production involved careful consideration of the unique attributes of dairying in northern Australia. Kerr *et al.* (1995*a*) suggest that productivity measures that have been used in other studies, such as milk production per hectare (Stockdale and King 1980) or milk production per cow (King *et al.* 1980), would be largely influenced by individual farm soil types and management options. These measures are difficult to interpret in a meaningful way in northern Australia as a typical dairy farm has a variety of land types, and there is wide variation in soil types and management strategies between farms.

Experienced extension personnel have estimated an average of 80% of a typical farm in these regions consists of ridges and hills and only 20% consists of irrigable creek flats. On the Darling Downs the proportion of ridges and hills is about 45%. As the data available could not be used to distinguish between the milk obtained from these land types, an average per hectare milk production estimate would not be comparable across farms or districts.

In addition, a great deal of the milk production on the average farm is obtained from off farm inputs such as concentrates. It has been estimated that the milk obtained from sources other than paddock feed varied between 30 and 39% for irrigation farms and 44 and 61% for dryland farms in 1991–92 in south-east Queensland (G. D. Chopping and R. W. Walker pers. comm.). These off farm inputs mean that measures of milk production per hectare may not be true indicators of the productivity of the physical farm unit, and are inappropriate for comparing farms.

The production per cow measure of efficiency was also difficult to assess because of the wide variation in systems of production. Depending on farm location and quality and resources available in the district, the same total milk production can be obtained by milking more cows at a lower milk production per cow level or milking fewer cows at a higher per cow milk production level. Both methods of obtaining milk may be profitable depending on the circumstances. The variable total farm milk production was selected because a key variable associated with profit on dairy farms in Queensland is gross margin per farm and the largest contribution to increased gross margin per farm in recent years has been by increases in total farm production (G. D. Chopping and R. W. Walker pers. comm.). As total farm milk output was a major factor in the profitability of a farm it was used to measure the productivity of the farm.

Another factor that influenced the decision to use the dependent variable milk production per farm was that the models were developed specifically for a DSS that could allow farmers to explore different input mixes for their farm. The measures of efficiency, milk per hectare and milk per cow, assume that the farm is a self-contained unit with set amounts of land and stock. Milk per farm allows land and cows to be included in the model as part of the resource mix for a farm. Farmers using the DAIRYPRO 'what-if' module have the flexibility of adding more cows, buying more land or importing more feed to vary the resource mix on their farm. This enables them to hypothetically change their mix of inputs for each 'what-if' scenario they may wish to explore. The milk per farm model is then able to estimate the expected milk production for each of these 'what-if' scenarios.

The models used in DAIRYPRO confirm the response rates obtained from research results in Queensland. They add to the knowledge of dairy farmers in Queensland as they are used in an extension tool that is able to provide estimates of total farm production for a hypothetical farm in the farmer's own region. Thus, the farmer can determine how his or her farm compares with another similar farm in the same region. The partial regression coefficients shown in this paper are similar to those from other data sets where total farm milk production was the dependent variable (Kerr *et al*. 1995*a*, 1995*b*).

Though complex, the use of intensive sampling did provide accurate data for analysis with the elimination of a major problem in past surveys, namely farmers having to remember purchases made throughout the year (Kerr *et al.* 1995*a*). The study did, however, encounter problems with data management with large computer files being generated. One file (the daily diary) was 7 megabytes in size and a great deal of time was spent ensuring that the data were accurate. Many of the errors were only obvious to people with a great deal of experience in dairy farm operations. For example, concentrate feeding rates outside typical industry ranges were always questioned before entry into the database. These intensive checks and the apparent consistency of this data set enabled the inclusion of all farms that completed the necessary data entry requirements from this survey in the data analysis.

The forward selection, stepwise regression approach used in this analysis may be insensitive to farming practices used by only a small proportion of farmers and these may not appear as significant in the analysis. Despite this shortcoming, Sen and Srivastava (1990) consider the stepwise approach to be superior to other variable selection procedures. The procedure was used in this case as the object of the analysis was to develop models that were representative of the population.

The predictive models developed using this survey data may provide inaccurate forecasts when used in years where the environmental factors and management strategies are vastly different to those encountered in the year of analysis. During low rainfall conditions, for example, the pasture production component of total farm production can be affected. During times of drought, farmers usually feed more concentrates to maintain quota and the response rates to grain feeding may be altered under these circumstances (Kerr *et al.* 1995*a*).

These models have been used to provide a comparative analysis of milk production on farms with another hypothetical farm using the same inputs in the same region. The models shown in this paper have been incorporated in DAIRYPRO for use by the Queensland dairy industry. In contrast, the FFANN models provide an estimate without any explanation, as the weights are internal and cannot be displayed to the farmer. Hart and Wyatt (1990) discuss what they describe as the 'black box' problem associated with neural networks. The authors conclude that 'black box' systems present a challenge, as they cannot be as rigorously evaluated as more transparent models. These authors were referring to medical applications but there is no reason to suspect that the situation would be different in the dairy industry and this was a major reason why the FFANN model was not used in the DAIRYPRO DSS. The MLR models have the additional appeal of providing a transparent model to the end-user with only a small compromise in accuracy. The users involved with the development of DAIRYPRO were overwhelmingly in favour of using the MLR models because they provided partial regression coefficients that were biologically sensible and could be likened to response rates for each component of their dairy farm.

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