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From rainfall to farm incomes—transforming advice for Australian drought policy. I. Development and testing of a bioeconomic modelling system

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Abstract. In this paper we report the development of a bioeconomic modelling system, AgFIRM, designed to help close a relevance gap between climate science and policy in Australia. We do this by making a simple econometric farm income model responsive to seasonal forecasts of crop and pasture growth for the coming season. The key quantitative innovation was the use of multiple and *M*-quantile regression to calibrate the farm income model, using simulated crop and pasture growth from 2 agroecological models. The results of model testing demonstrated a capability to reliably forecast the direction of movement in Australian farm incomes in July at the beginning of the financial year (July–June). The structure of the model, and the seasonal climate forecasting system used, meant that its predictive accuracy was greatest across Australia's cropping regions. In a second paper, Nelson *et al*. (2007, this issue), we have demonstrated how the bioeconomic modelling system developed here could be used to enhance the value of climate science to Australian drought policy.

Introduction

The economic impacts of climate variability and change are of significant concern to governments and rural communities. Changing seasonal patterns of rainfall and temperature affect the incomes of rural businesses directly through changes in production, and indirectly through the variability of international commodity prices (Chapman *et al*. 2000; White 2000; Hill *et al*. 2001). In the longer term, climate change has potential to influence the productivity and profitability of agricultural systems, altering patterns of land use and regional economic outcomes (Kokic *et al*. 2005; Heyhoe *et al*. 2007). The concern that governments and communities share in terms of the social and economic impacts of drought arises from the welfare implications for rural households and others in the community faced with a risk of catastrophic loss (Hardaker *et al*. 1997; Anderson 2003).

The impacts of climate variability and change on human systems are ultimately social and economic in nature. Drought, for example, is largely a social construct representing the risk of agricultural activity being substantially disrupted by spatial and temporal variation in rainfall and temperature (Botterill 2003; Meinke *et al*. 2006). In Australia, a drought in 2002–03 reduced farm incomes by 60–80%, albeit from the relatively high income levels in 2001–02 (Martin *et al*. 2007). Economic effects of this kind have been linked to dramatic social impacts on rural communities, such as divorce, illness, and suicide (Hayman and Cox 2005; Perry 2006). Reduced farm incomes can have significant flow-on effects on the national economy and society more generally. Estimates of the impact of the 2002–03 drought on the Australian economy range between 0.75 and 1.6% of GDP, with significant effects on employment (Penm and Fisher 2003; Horridge *et al*. 2005).

In contrast, the information systems used to support climate-related policy in Australian agriculture focus almost exclusively on biophysical measures of climate variability and its impacts on agricultural production. Traditional drought science, for example, has been heavily dominated by reductionist measures of variability in rainfall, temperature, soil moisture, and plant growth (Laughlin and Clark 2000). At the beginning of 2007, this narrow biophysical emphasis remained in the newly developed National Agricultural Monitoring System (www.nams.gov.au), nearly 10 years after this divergence between drought science and policy in Australia was first pointed out (Thompson and Powell 1998). Meinke *et al*. (2006) refer to this misalignment of drought science and policy in Australia as a *policy relevance gap*, highlighting a range of potential disciplinary and institutional causes that need to be addressed.

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In this paper and its sequel we explore the potential of bioeconomic modelling to address a dimension of this policy relevance gap: the ability of multi-disciplinary science to inform policy makers of the likely impact of climate variability on farm incomes in the coming season. The key quantitative innovation described in this paper is the use of *M*-quantile regression to calibrate a simple econometric model of farm incomes to agroecological models providing probabilistic forecasts of crop and pasture growth for the coming season. We then test the predictive capability of the model by using it to hindcast farm incomes across Australia from 1990–91 to 2002–03. Potential policy applications of this bioeconomic modelling system, the Agricultural Farm Income Risk Model (AgFIRM), are explored in a second paper (Nelson *et al*. 2007, this issue).

Background

Past approaches

Most policy-related analyses of income variability in Australian agriculture have been based on information provided by farmers through the Australian Agricultural and Grazing Industries Survey (AAGIS) (ABARE 2003). AAGIS is a large-scale, stratified sample survey conducted annually since 1978–79 for 770–1654 farms in Australia's broadacre cropping, beef, and sheep industries. A range of information has been collected from each sample farm including its production and physical characteristics as well as its financial performance. Information for individual farms is aggregated to provide national, regional, and industry statistics.

Previous attempts to empirically relate the seasonal variability of farm incomes reported in AAGIS to the seasonal variability of rainfall have been hindered by other sources of income variability (Kokic *et al*. 1993; Scoccimarro *et al*. 1994). In addition to climate, the variability of farm incomes is influenced by seasonal and longer term trends in commodity prices, and multiple influences on productivity such as differences in soils, past land management, and enterprise mix. Attempts to regress farm incomes against seasonal rainfall inevitably also need to contend with a high degree of intrinsic heterogeneity between farms in similar locations and with apparently similar physical characteristics. These include differences in management, aversion to risk, family composition, and lifestyle goals. This has been exacerbated by a rotating panel of sample farms in AAGIS representing each industry and region, with around 80% of farms remaining in the sample from one year to the next (Kokic *et al*. 1993).

With multiple sources of variability, the 27 years (1978–79 to 2004–05) of data provided by farmers via AAGIS are a relatively short period when it comes to isolating the effects of climate on farm income variability. This is because extreme climate events such as droughts and floods may only be represented once or twice during this period, and because the effect of a drought depends on the profitability and wealth of farm businesses in preceding years.

The potential of bioeconomic modelling

Bioeconomic modelling has potential to improve our understanding of the impacts of climate variability on farm incomes. Policy-relevant bioeconomic modelling of agricultural systems has been comprehensively reviewed by Kruseman (2000). According to Kruseman (p. 15): 'An important role of bio-economic modelling is to make complex interactions between agro-ecological and socio-economic phenomena transparent in policy debates'. From this perspective, bioeconomic modelling is a quantitive way of integrating alternative disciplinary approaches to provide consistent and intuitively meaningful decision support for policy advisers.

Kruseman classifies bioeconomic models for agricultural systems research according to their temporal scale and spatial aggregation, and the extent to which they are descriptive, explanatory, or predictive. Descriptive models are by definition qualitative, explaining interactions within a system using a consistent set of terms and definitions. Explanatory models provide interpretative insight into past relationships between measurable indicators. Predictive models take this explanatory power one step further, providing interpretive insights into the likely future relationships between measurable indicators. Models of all 3 kinds can provide intuitively meaningful policy-relevant insights by enhancing the mental models used by policy advisers to design and implement policy.

The model developed by Kokic *et al*. (1993, 2000) is an econometric farm-scale supply-response model that is calibrated and applied at a regional scale. The model (described below) is explanatory by design, because it is used to abstract from farm to farm variability in the way that management decisions are made. It is not a farm household model in the classic sense described by Singh *et al*. (1986) because consumption is not incorporated. Most farm household models have been designed to model the delicate balance of household supply and demand for food in subsistence agriculture (Kruseman 2000). Omitting consumption is consistent with the commercial nature of Australian farm businesses in which household consumption is largely separate from supply-response decisions.

As the model is explanatory by design, we concentrated our evaluative testing on its ability to provide explanatory insight into the likely direction of farm income variability in the coming season. For completeness, we also tested the model's predictive performance. In previous forecast applications, the model accurately predicted the direction of change in production and farm incomes in response to changes in commodity prices (Kokic *et al*. 1993, 2000). However, Kokic *et al*. (1993) showed that not modelling the dynamic aspects of decision making and supply response reduced the precision with which the model could predict the magnitude of these changes. In this paper, we enhance the dynamic response of the model to seasonal climate variability by incorporating forecasts of crop yield and pasture growth from previously published and long-operational agroecological modelling systems.

Methods

Overview: linking the models

Two methodological steps are reported in this paper. The first is the use of ordinary least-squares and *M*-quantile regression to calibrate the farm income model (FIM) to agroecological models providing probabilistic forecasts of crop and pasture growth for the coming season. In the second step, the calibrated model is used to hindcast farm incomes for 13 years from 1990–91 to 2002–03. A sequel to this paper explores a third step: potential policy applications of this bioeconomic modelling system.

The first step is to describe and then calibrate the econometric model. The problems encountered in past attempts to develop empirical relationships between farm income survey data and rainfall suggest an opportunity for a more structural bioeconomic modelling approach. In particular, a model is required that abstracts from farm to farm variability in decision making, and that is capable of disaggregating and separately modelling the multiple sources of variability in farm incomes (π), especially the price (**P**) and yield (**y**) components:

$$\pi = \text{function}(\mathbf{P},\ \mathbf{y}) \tag{1}$$

The FIM developed by Kokic *et al.* (1993) is a farm-scale, econometric supply-response model that estimates production and farm incomes based on changes in commodity prices and yields. The version of the model applied in this paper estimates supply elasticities for 6 major broadacre commodities: beef, wool, lamb, wheat, winter crops, and summer crops. Supply elasticities are estimated from the detailed financial, physical, and economic information provided by Australian farmers each year via the AAGIS survey (ABARE 2003). A full description of how AAGIS survey data are used to estimate the various parameters of the model has been provided by Kokic *et al.* (2000), with a brief overview provided in Appendix 1. In forecast application, the model has 2 basic inputs: (*1*) the expected yield of the 6 broadacre commodities (per hectare); and (*2*) their expected prices. In this application, we use the crop and pasture models (CPMs) to improve the yield forecasts used in the FIM, which would otherwise be solely derived from price changes.

In this application of the FIM we use 2 agroecological models to simulate the effect of climate variability on crop and pasture growth to forecast the direction of change in farm incomes. The shire-scale crop forecasting system of Potgieter *et al.* (2002, 2005, 2006) is used to predict the seasonal variability of crop yields. The shire-scale wheat model integrates a biophysical model for predicting wheat moisture stress (Potgieter *et al.* 2006) with a regression model to calibrate moisture stress to wheat yields from the Australian Bureau of Statistic's agricultural census across the 284 shires in the Australian wheatbelt (Potgieter *et al.* 2002). For summer crops, sorghum yields have been simulated using a simple shire-scale sorghum moisture-stress model described by Potgieter *et al.* (2005).

The Aussie GRASS model described by Carter *et al.* (2000) is used to predict the seasonal variability of pasture growth. Aussie GRASS is a national pasture forecasting system based on the GRASP model of Rickert *et al.* (2000). Models that predict more direct measures of livestock productivity such as liveweight gain are under development (McKeon *et al.* 2000) but were not available for this application. Aussie GRASS was therefore used to simulate an overall index of pasture growth (PGI), and an indication of extreme pasture growth conditions in terms of the number of days in a month that PGI is less than 0.05.

The CPMs simulate wheat yield (w), sorghum yield (s), and pasture growth (r) using a large number of biophysical variables (**R**) that include rainfall, plant phenology, evaporation, soil type, and farm management. That is:

$$(w, s, r) = \text{function}(\mathbf{R}) \tag{2}$$

The critical innovation is the statistical linkage between the CPMs and the FIM. The first step in our approach is therefore to develop and test statistical models capable of predicting the yields (**y**) reported by farmers in the AAGIS survey using wheat yield (w), sorghum yield (s), and pasture growth (r) simulated by the CPMs:

$$\mathbf{y} = \text{function}(w,\ s,\ r) \tag{3}$$

Nesting equations (1) to (3) together enables farm incomes to then be predicted from commodity prices and the climate variables:

$$\pi = \text{function}(\mathbf{P},\ \mathbf{R}) \tag{4}$$

The development of (2) has previously been reported in the development of the component models (Kokic *et al.* 1993, 2000; Carter *et al.* 2000; Potgieter *et al.* 2002, 2005, 2006). The following sections provide more detailed description of (3) and (4) in the development of this simple bioeconomic modelling capability, including:

- the development and testing of empirical relationships between the yields (**y**) reported by farmers and those simulated by the CPMs (3); and
- testing the explanatory and predictive capability of the modelling system to predict seasonal variability of regional farm incomes (4).

In testing the model, we draw insights into forecast quality and usefulness using the approaches outlined by Potgieter *et al.* (2003) and Meinke and Stone (2005). Because the FIM is theoretically derived, we used hindcasting to test the ability of the model to forecast the direction of movement in farm incomes for the coming season.

Calibrating to the crop model

In forecast application, the FIM uses probabilistic forecasts of crop and pasture growth from the CPMs to forecast farm incomes for the coming season. The simulated crop yields are similar in spatial and temporal scale to the crop yields reported by farmers in the AAGIS survey. This meant that crop yields from AAGIS could be regressed directly against yield simulated by the crop models using multiple linear regression.

The FIM incorporates 3 crop yield variables that need to be predicted: wheat yield (wh), other winter crop yield (wc), and summer crop yield (sc), all measured in tonnes per hectare. These 3 measures of crop yield were regressed against the appropriate combinations of wheat (w) and sorghum (s) yields simulated by the crop models. Simulated wheat yield (w) was used to predict wheat and other winter crop yields, while simulated sorghum yield (s) was used to predict summer crop yield.

The regression model used to explain the variability of wheat yields, $wh_t^{(g)}$, reported by farmers in the AAGIS survey was:

$$wh_t^{(g)} = \alpha_{g0} + \alpha_{g1} f_t^{(g)} + \alpha_{g2} w_t^{(g)} + \varepsilon_{gt} \tag{5}$$

where $f_t^{(g)}$ is fertiliser costs in year t, $w_t^{(g)}$ is simulated wheat yield, and ε_{gt} is a residual random error term with mean zero and variance σ_{gt}^2, while α_{g0}, α_{g1}, and α_{g2} are unknown regression coefficients. Here and throughout the paper the variable g is used to signal the level of aggregation used. This is discussed in more detail below. At an early stage of model development, it was found that incorporating fertiliser costs in (5) significantly improved the ability of the regression model to explain the variability of wheat yields reported by farmers in the AAGIS survey.

The corresponding regression models for winter, $wc_t^{(g)}$, and summer crop yields, $sc_t^{(g)}$, were, respectively:

$$wc_t^{(g)} = \beta_{g0} + \beta_{g1} f_t^{(g)} + \beta_{g2} w_t^{(g)} + \delta_{gt} \tag{6}$$

and

$$sc_t^{(g)} = \gamma_{g0} + \gamma_{g1} f_t^{(g)} + \gamma_{g2} s_t^{(g)} + \zeta_{gt} \tag{7}$$

where $s_t^{(g)}$ is simulated sorghum yield, and δ_{gt} and ζ_{gt} are residual random error terms with zero means and constant, but different, variances.

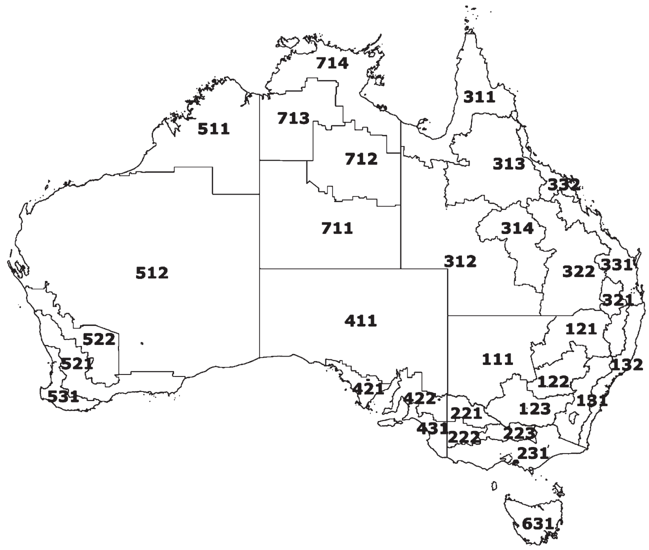

Fig. 1. Australian broadacre regions: first digit represents state; second digit represents zone (1, pastoral zone; 2, wheat–sheep zone; 3, high-rainfall zone); third digit represents region within state and zone.

Calibrating to the pasture growth model

A statistical relationship between the livestock yields in the FIM (beef, wool, and lamb) was estimated from the pasture growth indices produced by the Aussie GRASS model using *M*-quantile regression (Breckling and Chambers 1988, Appendix 2). It results in a single livestock yield index, q, which is predicted from the pasture growth index using the logistic-linear regression model (8):

$$\log\left(\frac{1-q_t^{(g)}}{q_t^{(g)}}\right) = \lambda_{g0} + \sum_{j=1}^{4} \lambda_{gj} r_{jt}^{(g)} + \sum_{j=5}^{8} \lambda_{gj} p_{jt}^{(g)} + \eta_{gt} \tag{8}$$

where $r_{jt}^{(g)}$ is the average of the pasture growth index in quarter j of the current financial year t, $p_{jt}^{(g)}$ is the average proportion of days in quarter j that the pasture growth index is less than 0.05, and η_{gt} is a residual error term with mean zero and constant variance. As described in Appendix 2, *M*-quantile regression produces non-parametric functions that relate q to each of the livestock yields, which together with (8), provides a method of constructing the yield function (3).

The dependent and independent variables in the regression Eqns 5–8 correspond to a particular level of aggregation, or geographic stratification, denoted by g. Two regional scales were tested in the course of model development: local government areas, also known as shires, and ABARE farm survey regions, which are considerably larger than shires (ABARE 2003, Fig. 1).

Early results of fitting models 5–8 to shire-scale data can only be described as moderately acceptable, at best. For wheat (Eqn 5), for example, the average R^2 value across all regions was 47% and, in several of the wheat-growing regions, substantially smaller values than this were obtained. Consequently it was decided to only consider linking the models at a regional scale (Fig. 1).

Forecasting farm incomes

In forecast application, the FIM was recalibrated each year to the areas of land allocated by farmers to each commodity, and then used to forecast farm incomes 1 year into the future. This accounts for trends and dynamic responses, particularly in livestock herds, which are not incorporated into the simple econometric model. For example, supply elasticities tend be lower in years when prices are relatively high, yield is high, or when relatively few commodities contribute to farm income. For this application, the FIM was recalibrated each year from 1989–90 to 2001–02, and used to forecast income in the years 1990–91 to 2002–03. Kokic *et al.* (1993) found that hindcasting farm incomes in years before 1990–91 was difficult because of the significant structural changes in Australian agriculture brought about by the end of a wool floor-price scheme in 1987. The actual prices realised in each year were used for hindcasting in order to isolate the explanatory power of the crop and pasture growth simulations for forecasting farm incomes. In forecast mode, anticipated commodity prices for the coming season would be used, introducing an additional source of variability into the forecasts.

For each of the 32 agricultural regions, crop and pasture yields were simulated 103 times using historical climate data from 1900–01 to 2002–03. A unique set of 103 simulations of crop and pasture growth was generated with the antecedent soil moisture conditions that prevailed across Australia for each of the 13 years between 1990–91 and 2002–03. An assumption of current technology means that these simulations show what crop and pasture growth would have been across each region if the climate for each year between 1900–01 and 2002–03 had been experienced. These simulations of crop and pasture growth were then used to simulate climate-responsive, regional farm income distributions for each of the 13 years over the hindcast period.

Forecasts of annual seasonal conditions are not yet routinely available in Australia (Meinke and Stone 2005). In lieu of a reliable, annual forecasting system, annual farm incomes were assumed to be closely related to seasonal conditions in autumn and winter. Australia's rainfall variability is strongly influenced by the dynamics of the El Niño/Southern Oscillation (ENSO) phenomena, and the Southern Oscillation Index (SOI) is a convenient method of indexing the state of the ENSO system. Prolonged periods of negative (positive) SOI values are often indicative of El Niño (La Niña) type climatic conditions that generally result in decreased (increased) rainfall probabilities over much of Australia (McBride and Nicholls 1983; Stone *et al*. 1996).

The SOI phase forecasting system was used to develop a leading indicator of winter seasonal conditions, which is available at the end of June. To forecast farm incomes, each of the distributions of farm income was subdivided into 3 groups of historical analogue years, using the SOI phase forecasting system of Stone *et al*. (1996). Each year of simulated farm income was classified as positive/rising (negative/falling) if the SOI phases were consistently positive or rapidly rising (consistently negative or rapidly falling) at the end of both May and June. All other years were defined as SOI neutral. This results in a stricter classification of year types than the use of an SOI phase at the end of a single month, with 26 years classified as positive/rising, 14 years negative/falling, and 63 years considered SOI neutral.

The result is a probabilistic forecast of annual farm incomes conditional on the SOI for each of the 13 years from 1990–91 to 2002–03 across Australia's 32 agricultural regions. These probabilistic forecasts can then be validated against the realised farm incomes that occurred in each region for these years.

Testing the bioeconomic model

The model was tested in 2 steps. First, calibration of the econometric model using simulated crop and pasture growth was tested using standard regression statistics. Second, the ability of the bioeconomic modelling system to forecast farm incomes was tested using explanatory and predictive measures of forecast quality.

Calibrating to the CPMs

The crop and livestock regression models (Eqns 5–8) were fitted using 24 years of farm survey data from 1978–79 to 2001–02. The predictive accuracy of each regression model was assessed using estimates of R^2 and mean absolute error (MAE) of fit. The proportion of variability in yield explained by the simulated crop and pasture yields was reported separately as the R^2 *difference*. This statistic was calculated as the difference in R^2 achieved by models 5–8 compared with the corresponding models excluding the simulated crop and pasture growth variables. Note that because we are interested in the predictive accuracy of the regression models, the statistical significance of the coefficients was of less concern than measures of the actual fit of the model (see Chambers 2001).

Forecasting farm incomes

The bioeconomic modelling system was tested by hindcasting farm incomes across Australia's broadacre agricultural zones for 13 years between 1990–91 and 2002–03. Separate forecasts were made for each of the 32 farm survey regions across Australia (Fig. 1). Figure 2 shows how the reliability of the probabilistic forecasts of farm incomes was assessed for each region, drawing on the pragmatic approaches of Potgieter *et al*. (2003) and Meinke and Stone (2005) for assessing the quality of probabilistic forecasts of agricultural production.

A Brier score was used as one measure of forecast quality. The Brier score measures whether the realised outcome is consistent with the forecast probability of exceeding the median:

$$BS = n^{-1} \sum_{t=1}^{n} (f_t - o_t)^2$$

where n is the number of years, f_t is the forecast probability of exceeding the median income, and o_t is an indicator of whether the realised farm income exceeded the median in year t or not. For example, in Fig. 2, the forecast probability of exceeding the median is 80% ($f_t = 0.8$) and the realised farm income exceeded the median ($o_t = 1$). The statistical significance of the Brier score can be computed by Monte-Carlo simulation by comparing it with a reference (or null) distribution for the realised farm incomes, i.e. one in which no climate or price information had been used in making the forecast. In this case the reference distribution is the same in all years and has 50% chance of being above or below the median. The null distribution of the Brier score and hence statistical significance was computed by repeatedly simulating the set of o_t values from the reference distribution while holding the f_t values fixed.

The expected value of the forecast distribution was used as a point prediction of farm income to compare with realised income values (Fig. 2). The predictive accuracy of the model was tested by comparing the relative mean absolute error (RMAE) of predicted and realised farm incomes over the 13 years of the hindcast period. Predictive accuracy in this sense is higher the

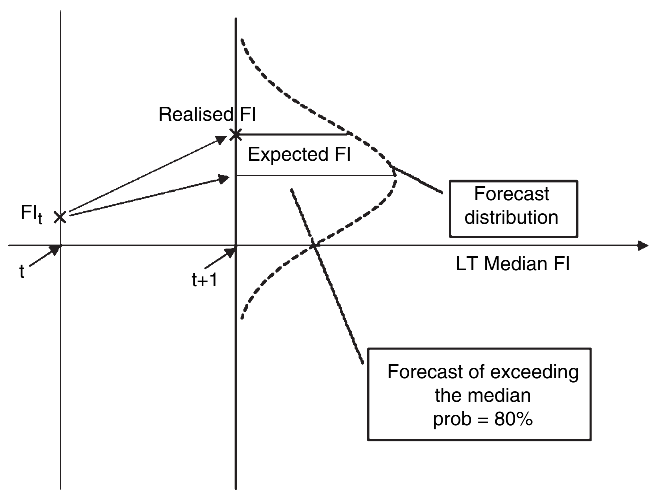

Fig. 2. Measures of forecast quality were derived to compare probabilistic forecasts of farm incomes with the realised values (FI, farm income; LT, long term).

closer this statistic is to zero. RMAE is one of the measures of distributional shift described by Potgieter *et al.* (2003). RMAE needs to be interpreted alongside the Pearson correlation coefficient, with skill improving towards 1.0, in order to include the potential effects of mean reverting processes.

Predictive accuracy is a demanding criterion to satisfy, particularly for a simple descriptive model such as this one, and a forecast can still carry valuable information even when the ability to predict point outcomes with precision is poor (Potgieter *et al.* 2003; Meinke and Stone 2005). For this reason, the following 2 simpler tests of forecast quality were used to assess how often the direction of the forecast was accurate.

- Direction: the proportion of years in which both the predicted and realised values of farm income were on the same side of the long-term median. In Fig. 2, for example, they are both above the median at time $t+1$.
- Change: the proportion of years in which the predicted change in farm income from the previous year was in the same direction as the realised change. In Fig. 2, both arrows are pointing upwards and so, in this case, the change is in the same direction.

Skill in either of these statistics is indicated by a value significantly greater than 0.50. The statistical significance of both these statistics was assessed relative to the same reference distribution used for the Brier score.

Results

Calibrating to the crop model

Table 1 shows summary fit statistics for the 3 crop yield regression models (Eqns 5–7) by farm survey region. As can be seen from Table 1, the fit of the wheat yield model as measured by R^2 exceeded 71% across most of Australia's main crop-producing regions (zone 2; second digit of region). The proportion of variation explained by simulated wheat yield was very high across zone 2. While simulated wheat yield explained only 26–27% of the variation of wheat yields from AAGIS in Western Australian, the overall R^2 exceeded 77%. The performance of the model was poor in the coastal regions (zone 1) where there is less crop production.

The fit of the *other winter crops* model at the survey region level was, as expected, not as good as for the wheat model, with the average R^2 value across all regions of 56% compared with 75% for wheat. Given the fact that wheat makes up 64% of total winter crop production, the performance of the *other winter crops* model was considered adequate to proceed with testing the ability of the model to predict the direction of change in farm incomes. The fit for summer crops to simulated sorghum yields was also considered adequate.

Table 1. Fit of winter and summer crop yield models (Eqns 5–7) to survey region level data

Region	Obs.	Wheat (wh)		Other winter crops (wc)		Summer crops (sc)	
		R^2	R^2 diff.	R^2	R^2 diff.	R^2	R^2 diff.
121	24	0.76	0.51	0.65	0.22	0.60	0.01
122	24	0.79	0.60	0.72	0.11		
123	24	0.73	0.43	0.61	0.29		
221	24	0.82	0.76	0.64	0.42		
222	24	0.75	0.65	0.65	0.62		
223	24	0.72	0.46	0.49	0.38		
321	24	0.76	0.62	0.51	0.09	0.55	0.27
322	24	0.56	0.56	0.34	0.01	0.48	0.42
421	24	0.85	0.66	0.78	0.30		
422	24	0.74	0.30	0.71	0.25		
521	24	0.77	0.27	0.14	0.09		
522	24	0.80	0.26	0.58	0.16		

Calibrating to the pasture growth model

One consequence of aggregating the data to region level was that this resulted in only 24 observations per farm survey region, one for each survey year. For the crop models, which only have 2 dependent variables, this is not an important issue, but for the livestock model (Eqn 8) there was a risk of over-fitting. Consequently, steps were taken to reduce this risk. These steps included forming higher level groupings of regions in agronomically related zones. In order to maintain the generality of the livestock model, separate pasture growth variables for each region were included. Backward step-wise regression was then used to remove statistically non-significant terms. This reduced the number of dependent variables to less than 7 in most cases.

Table 2 shows the results of fitting the livestock model as described above. Clearly the pasture growth variables explain a reasonable proportion of variation of the livestock yield index in most regions, 55% on average across all survey regions. In addition, nearly all coefficient estimates selected by the backward elimination procedure were highly significant.

Forecasting farm incomes

The results of model validation demonstrated that the model can reliably hindcast the direction of movement of farm incomes for the coming financial year at the beginning of July. The Direction and Change indicators were statistically significant across most regions of the wheat–sheep and high-rainfall zones, and in more than half of the regions of the pastoral zone (Table 3).

The predictive performance of the model was highest in the wheat–sheep zone (Fig. 3*a–c*, Table 3), where statistically

Table 2. Fit of the livestock yield index model (Eqn 8)

Region	Obs.	d.f.	R^2	MAE
111, 411	48	2	0.19	0.07
121, 122, 123	72	5	0.65	0.05
131, 132	48	3	0.30	0.06
221, 222, 223	72	6	0.75	0.06
231, 631	48	3	0.44	0.04
311, 312, 313, 314	96	6	0.76	0.07
321, 322	48	2	0.66	0.05
331, 332	48	5	0.32	0.08
421, 422, 431	72	6	0.84	0.06
511, 512	48	9	0.50	0.08
521, 522, 531	72	5	0.91	0.05
711, 712, 713, 714	63	2	0.31	0.07

Table 3. Forecast quality statistics for hindcasts of farm incomes from 1990–91 to 2002–03
$^{\dagger}P < 0.1$; $^{*}P < 0.05$

Region	*n*	Brier score	RMAE (%)	Pearson's correln. coeff. (%)	Direction	Change
			Pasture zone			
111	13	0.24†	45	10	0.85*	0.75*
311	13	0.22*	61	78*	0.85*	0.58
312	13	0.13*	41	78*	0.92*	0.42
313	13	0.23*	45	77*	0.85*	0.58
314	13	0.61	55	35	0.46	0.58
411	13	0.22*	22	30	0.85*	0.83*
511	13	0.23	97	29	0.62†	0.67†
512	13	0.36	91	39	0.54	0.58
711	13	0.16*	57	75*	0.85*	0.75*
712	12	0.33	56	57*	0.50	0.82*
713	12	0.33	71	38	0.50	0.64
714	12	0.49	85	−15	0.50	0.73*
Average:		0.30	61	44	0.69	0.66
			Wheat–sheep zone			
121	13	0.30	44	8	0.54	0.58
122	13	0.19*	20	59*	0.77*	0.75*
123	13	0.13*	25	60*	0.85*	0.83*
221	13	0.20*	40	62*	0.85*	0.75*
222	13	0.25	48	48†	0.69*	0.75*
223	13	0.25	48	51†	0.69*	0.67†
321	13	0.22†	47	53†	0.54	0.67†
322	13	0.23†	31	46†	0.77*	0.75*
421	13	0.19*	41	58*	0.77*	0.67†
422	13	0.16*	33	72*	0.92*	0.83*
521	13	0.16*	23	70*	1.00*	0.67†
522	13	0.21†	34	−4	0.69*	0.67†
Average:		0.21	36	49	0.76	0.72
			High-rainfall zone			
131	13	0.14*	44	68*	0.92*	0.83*
132	13	0.46	69	61*	0.69*	0.92*
231	13	0.32	49	69*	0.77*	0.67†
331	13	0.23	33	43	0.69*	0.67†
332	13	0.20*	63	68*	0.85*	0.75*
431	13	0.11*	37	80*	0.92*	0.67†
531	13	0.53	30	6	0.62†	0.58
631	13	0.29	29	59*	0.62†	0.75*
Average:		0.28	44	57	0.76	0.73

significant Brier Scores in 75% of regions indicated a high degree of forecast quality. As expected, however, the RMAE results indicated poorer performance in predicting the precise amount by which farm incomes were likely to vary each season. Evidence of mean reversion, particularly in the wheat–sheep and high-rainfall zones (Fig. 3*b*, *c*), suggested that smoothing during parameterisation of the model may partially explain poor performance in forecasting extreme values of farm incomes. Despite this, the Pearson correlation coefficient indicated that the model explained around half the variability in farm incomes across all 3 zones. This rose by nearly 10% in the pastoral and wheat–sheep zones if 2 outlying regions were excluded from each.

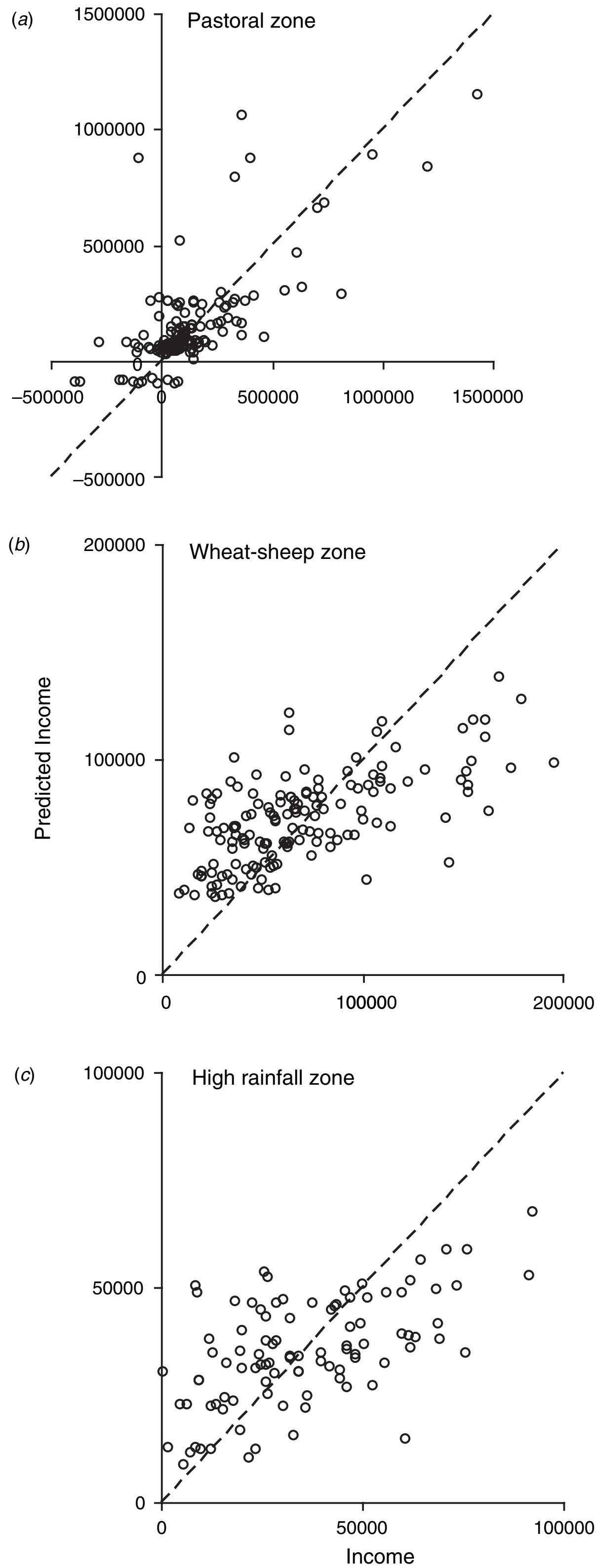

Fig. 3. Predicted *v.* realised farm incomes by agricultural zone (see Table 3, Fig. 1), in constant 2002–03 dollars, 1990–91 to 2002–03.

Discussion

Several factors contributed to the superior performance of the bioeconomic model AgFIRM in the wheat–sheep zone compared with the pastoral and high-rainfall zones. These factors include the structure of this version of the model, and the way it was applied.

In terms of the structure of AgFIRM, a much more direct link was able to be established between the FIM and the crop model because crop yields contribute directly to farm incomes. For livestock regions, operational forecasting systems such as Aussie GRASS currently predict pasture growth, rather than animal production on which farm incomes directly depend. Development of models such as Aussie GRASS to predict the liveweight gain for sheep and cattle across Australia continues, hampered by data limitations (McKeon *et al*. 2000). Data limitations include tracking of inter-regional transfers of animals and the influence of feed-lots, changes in herd structure, and uncertainty about birth and death rates.

The current verson of the FIM is not dynamic, with structural changes in the rural sector addressed by recalibrating the model each year and only forecasting 1 year into the future. Livestock production responds dynamically to climatic and other shocks over several years, and it was not possible to use a complete set of lagged covariates to link the FIM to the pasture model because of the risk of over-fitting. The bioeconomic model could be improved significantly in future by incorporating the dynamic adjustment of livestock herds from year to year within the econometric model. Models of this kind have already been developed for Australian agriculture, including Beef-BEM (Cao *et al*. 2003), which shares a similar heritage in being calibrated using AAGIS data.

The econometric model could also be improved by capturing the key interactions between livestock and cropping enterprises on mixed farms. Livestock can be moved around the farm, and fed in combinations of pasture grazing, grazing on-farm forage crops, and/or grain imported from off-farm. Accurately predicting the dynamic response of livestock production to factors such as climate variability may therefore require much more explicit modelling of the dynamic linkages among enterprises than the simple econometric model used in this paper (Pengelly *et al*. 2004).

A challenge for future applications of AgFIRM is to incorporate price forecasts, which are routinely available and forecast each quarter (e.g. Brown *et al*. 2007; Drum *et al*. 2007). Incorporating price forecasts would introduce an additional source of variability to farm income forecasts; one that is currently faced by decision makers without the aid of model-based income forecasts.

The performance of AgFIRM in cropping relative to pastoral regions can partly be explained by the way it was applied. The FIM at the core of AgFIRM works on an annual time step. There are currently no operational forecasting systems for forecasting annual climate conditions relevant to Australian agriculture (Meinke and Stone 2005). In lieu of an operational annual forecast system, the proven SOI-based seasonal forecasting system of Stone *et al*. (1996) was used. This choice of forecast system meant that the performance of the current version of AgFIRM depended on the extent to which winter seasonal conditions during the months of July–August influence annual farm incomes. Winter seasonal conditions contribute more to annual farm incomes in the cropping systems of southern Australia than in the pastoral systems or high-rainfall zones in which grazing depends more on autumn and spring conditions. Winter crop production dominates farm incomes in southern Australia because hot, dry summers prevent summer cropping without irrigation, and sheep numbers, formerly a major alternative source of income, have fallen dramatically since the early 1990s (Nelson 2002; Nelson and Lawrance 2004). However, given that ENSO is the major, single source of climate variability in Australia and the fact that the ENSO cycle roughly corresponds to the Australian financial year (July–June), our approach remains valid.

Many of the model's shortcomings could be addressed in future operational versions. Its design is consistent with the systems approach to applications of seasonal climate forecasting outlined by Hammer (2000), with a modular design enabling alternative models and forecasting methods to be readily applied. It can be modified to include improved combinations of CPMs in different regions for modelling crop and pasture growth. It can also be modified to include improved forecast systems as they evolve, and to use different forecast systems in different regions. Improvements to the econometric and livestock modelling outlined above would enable anticipated improvements in seasonal, annual, and inter-annual climate forecasting systems from global climate models (Hunt and Hirst 2000) to be incorporated.

Conclusions

In this paper we have reported the development of a bioeconomic modelling system, AgFIRM, capable of forecasting the direction of movement in Australian farm incomes at the beginning of the financial year (July–June). The structure of the model, and the seasonal climate forecasting system used, mean that the predictive accuracy of the current version of the model is greatest across Australia's cropping regions. Numerous opportunities exist to enhance the model using existing econometric techniques, and anticipated developments in livestock modelling and seasonal climate forecasting.

Effectively recruiting climate science to inform decision making and policy surrounding climate variability and change is becoming an increasingly topical issue. In a sequel to this paper, Nelson *et al*. (2007, this issue) demonstrate how the bioeconomic modelling system developed in this paper can be used to enhance the value of climate science to Australian drought policy. We provide 3 simple examples of how forecasts of farm financial performance can be used to enhance or replace advice to decision makers and policy processes that currently rely mostly, if not exclusively, on analyses of rainfall and temperature. By doing this we seek to close the policy-relevance gap between climate science and decision making, in order to enhance both.

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Appendix 1. The Farm Income Model (FIM)

The FIM model is theoretically derived. Its design assumes that farmers have maximised net income in a base year subject to a land area constraint. The profit function for farm is:

$$\pi_i = \sum_{j=1}^{m} P_{ij} Q_{ij} - C_i(Q_{i1}, \ldots, Q_{im}), \tag{A1}$$

where m is the number of commodities produced by the population of farms of interest, P_{ij} is the price received for commodity j by farm i, Q_{ij} is the quantity of commodity sold by farm i, and C_i is the cost function.

As the size of farms increases, the costs of producing a unit of any commodity will generally also increase due to constraints on the availability of land. To capture this effect, a convex cost function of the form:

$$C_i = b_{i0} + \sum_{j=1}^{m} b_{ij} Q_{ij}^{\mu_{ij}}$$

is used, where $\mu_{ij} > 1$ and b_{ij} are unknown parameters.

The operating area A_i of the farm is assumed to be fixed over time and is written as the following functional form of the quantities of commodity sold:

$$A_i = d_{i0} + \sum_{j=1}^{m} d_{ij} Q_{ij}, \tag{A2}$$

where d_{ij} represents the inverse of the per-hectare yield, y_{ij}, for commodity j by farm i.

Subject to the constraint that the operating area on farm is fixed, Kokic *et al*. (2000) obtained optimum values of Q_{ij}, which maximise the profit function (A1) subject to (A2) given a set of expected prices $\{P^*_{ij}; j = 1, \ldots, m\}$ at the forecast time point. At this optimum the cost function reduces to:

$$C_i = c_{i0} + \sum_{j=1}^{m} c_{ij} Q_{ij}, \tag{A3}$$

where

$$c_{ij} = \frac{P^*_{ij} + \lambda_i d_{ij}}{\mu_{ij}} = \frac{P^*_{ij} + \lambda_i / y_{ij}}{\mu_{ij}} \tag{A4}$$

is the farm's unit cost of producing commodity, and λ_i is a Lagrange multiplier from constraint (A2).

Predicting income when commodity prices change

Partial derivatives of the quantity of each commodity produced (Q_{ij}) and λ_i with respect to expected prices (P^*_{ij}) are used to simulate the production of each commodity given an expected price change between the base and forecast time points. This means that the resulting change in unit costs can also be predicted (using Eqn A4). Profit is simulated by using Eqns A1 and A3 and the realised price. In other words, provided that a farm is managed so that its outputs are always adjusted to maximise its expected profit subject to Eqn A2, its micro-level supply response (change in its outputs) to price changes can be simulated.

Details of the estimation and application of the model to forecast incomes in response to changes in commodity prices have been presented by Kokic *et al*. (1993, 2000).

Predicting income when yields change

The CPMs were used to forecast the quantity of each commodity in the FIM (beef, wool, lamb, wheat, winter crops, and summer crops). The quantity of each commodity in the FIM is adjusted in proportion to yields forecast by the CPMs (y^*_{ij}) relative to the base year (y_{ij}):

$$Q^*_{ij} = \frac{y^*_{ij}}{y_{ij}} Q_{ij}.$$

Unit costs are modified using Eqn A3, and profit is simulated by using Eqns A1 and A3.

Appendix 2. *M*-quantile regression

The role of *M*-quantile regression in predicting farm incomes has been discussed in detail by Kokic *et al*. (2000). The productivity of individual farms varies with farm-specific factors such as soil moisture availability, soil fertility, management practices, and on-farm infrastructure. This means that productivity can vary dramatically among farms that share broadly similar characteristics such as location, size, and enterprise mix. The use of standard regression methods implicitly assumes that the parameters relating productivity to farm incomes are the same for all farms, resulting in *aggregation* or *averaging* bias. This can be partly overcome using *M*-quantile regression (Breckling and Chambers 1988) to estimate farm-specific productivity coefficients.

M-quantile regression is a method of modelling that implicitly allows for 'missing variables' in a regression specification, effectively replacing the conventional OLS 'average line plus noise' model by a family of lines indexed by a coefficient q (Fig. B1). Different values of q then correspond to different levels of the missing variables. The regression surface passing through the ith dependent value corresponds to a particular quantile value q_i and a set of regression coefficients d_i. The advantage of this approach over OLS regression is that the regression coefficients are disaggregated down to each data point. While this disaggregation may not be complete because of the smoothing effect of regression, *M*-quantile regression has the advantage that it is non-parametric and so the estimates of regression coefficients are dictated solely by the data.

In research reported in this paper, *M*-quantile regression was applied to the livestock components of Eqn A2. Corresponding to each value of q there are regression coefficient estimates $d_j(q)$ for $j = 1, \ldots, m$. These regression coefficients can be interpreted as a set of non-parametric functions $d_j(q)$, which map the livestock productivity index q to estimates of the yields of lamb, beef, and wool from the AAGIS survey data. The value q_i for any given farm is chosen so as to equate the livestock component of Eqn A2 to the area of the farm used for livestock production. The estimates of yield for that farm i are given by:

$$\hat{y}_{ij} = \left\{d_j\left(q_i\right)\right\}^{-1}$$

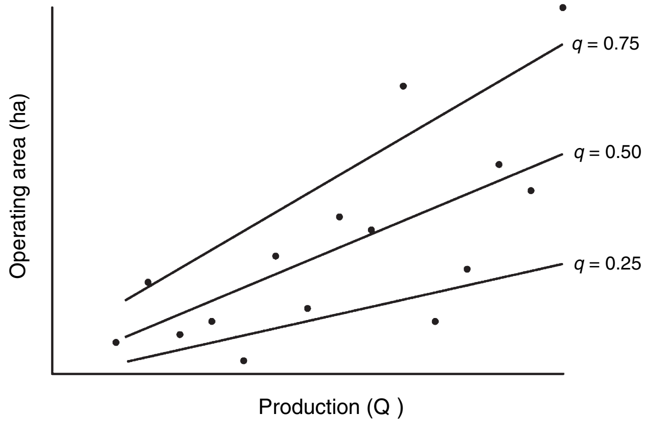

Fig. B1. Example of *M*-quantile regressions.