Forecasting the performance of alternative sheep production systems grazing perennial pastures

by Storer, C.E., Godfrey, S.S., Robertson, S.M., Friend, M.A. and Behrendt, K.

Storer, C.E., Godfrey, S.S., Robertson, S.M., Friend, M.A. and Behrendt, K. (2025) 'Forecasting the performance of alternative sheep production systems grazing perennial pastures' *Agricultural Systems*, 229, article number 104407.

Agricultural Systems 229 (2025) 104407

Contents lists available at ScienceDirect

Agricultural Systems

journal homepage: www.elsevier.com/locate/agsy

Research Paper

Forecasting the performance of alternative sheep production systems grazing perennial pastures

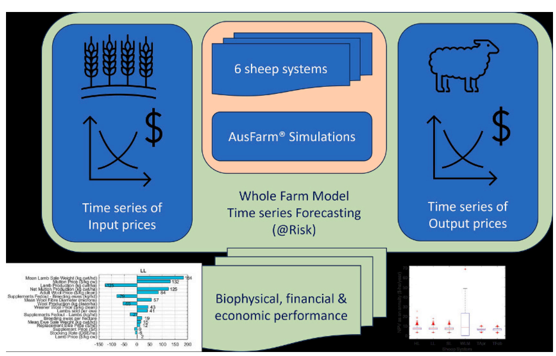
Christine E. Storer [a,*], Sosheel S. Godfrey [a], Susan M. Robertson [a,b], Michael A. Friend [b,c], Karl Behrendt [b,d]

[a] School of Agricultural, Environmental and Veterinary Sciences, Charles Sturt University, Locked Bag 588, Wagga Wagga, NSW 2678, Australia
[b] Gulbali Institute, Charles Sturt University, Locked Bag 588, Wagga Wagga, NSW 2678, Australia
[c] Office of the Pro Vice-Chancellor Research, Charles Sturt University, Locked Bag 588, Wagga Wagga, NSW 2678, Australia
[d] Harper Adams Business School, Harper Adams University, Edgmond, Shropshire TF10 8NB, United Kingdom

HIGHLIGHTS

- Six sheep production system enterprise mixes were different in dynamic modelling.
- Higher economic returns were associated with higher risks of variable returns.
- Earlier mated and terminal systems had lower economic returns but also lower risks.
- More lucerne and later mating produced greater returns that were more variable.

GRAPHICAL ABSTRACT



ARTICLE INFO

Editor name: Paul Crosson

Keywords:
Management strategies
Whole-farm simulation modelling
Profitability ranking decisions
Economic analysis
Risk analysis
Time series

ABSTRACT

Context: Grazing enterprises employ a range of management strategies in rain-fed Australian sheep production systems, which alters both production potential and profitability. This research used a stochastic whole-farm simulation modelling methodology to assess the impact of six different management regimes on the long-term profitability of a model farm simulated from August 1971 to July 2018.
Objective: We aimed to 1) compare the whole farm productivity and economics of the different sheep production systems, 2) identify the factors that were driving the differences between systems, and 3) determine if the profitability and ranking of systems changed in response to different market and environmental conditions.
Method: Stochastic simulation whole-farm modelling, combined AusFarm® biophysical simulation data, with forecasted @Risk modelling price time series data. The economic and financial performance of different sheep management systems were assessed using gross margins, cash flows, net present values (NPV), coefficient of variation (CoV) and cash flow modified internal rates of return (MIRR).
Results and conclusions: Decisions on the management of sheep system mating times, breed of ram, type of pasture grazed and retention of ewe lambs affected supplementary feeding costs as well as production of wool and meat. Production differences along with variation in prices received explained why the six sheep systems had

* Corresponding author.
E-mail address: cstorer@csu.edu.au (C.E. Storer).

https://doi.org/10.1016/j.agsy.2025.104407
Received 18 December 2024; Received in revised form 14 March 2025; Accepted 1 June 2025
Available online 16 June 2025

significantly different economic gross margins and NPVs. The systems also had different risks in achieving economic returns. Higher economic returns were associated with higher risks of variable returns and lower returns with lower risk of variation. The earlier mated (February) and terminal systems did not perform economically as well as the later mated (April) systems, but were more reliable with lower risk. The winter lambing Merino system had the lowest gross margins and NPV, but also the lowest risk CoV and MIRR. Investment in additional lucerne pasture for early summer feed paid off with greater gross margins and NPV, but with highest risk CoV and MIRR that these economic returns may vary.

Significance: Modelling incorporating historical long-term price and production risk clarified the complex effects of sheep system management decisions on production and economic returns. The more basic gross margin analysis gave the same ranking of the different sheep production systems as the more complex NPV and MIRR. Potential economic effects and risks of variable returns can be understood by examining past variability in production and prices received (revenues) on gross margins then assessing expected risk of future variability.

1. Introduction

The identification of more profitable sheep production systems has long been a goal of industry. Producers have a choice of enterprise type, lambing time, stocking rate and pasture type with optimal management differing between environments (Warn et al., 2006). Variable seasons also contribute to production and financial risk and tactical management of systems that can result in better economic performance compared with inflexible management (Gicheha et al., 2013). Different enterprises will differ in their ability to generate positive returns and remain resilient in response to variable seasonal conditions and market uncertainty. Frequently changing enterprise type or key management practices may not be cost-effective or practical in response to seasonal variations. Variation in meat, wool and grain prices influence the relative profitability of different livestock production practices (Byrne et al., 2010), and input costs and commodity prices may also vary with seasonal conditions. While these factors are inherently understood by producers, the whole-farm economic consequences of variable seasons and prices for different sheep enterprises is less well defined, making prediction of future profit rankings of alternative sheep systems difficult.

Biophysical simulation modelling is an effective method for exploring the production responses of different sheep management systems to seasonal variation over a long run of years (Amidy et al., 2017; Bywater and Cacho, 1994; Robertson and Friend, 2020c; Warn et al., 2006) or under future climate scenarios (Ghahramani and Moore, 2016), overcoming the usual limitation of field studies with few years of data not being representative of long-term performance (Behrendt et al., 2013; Lodge and Johnson, 2008). Simulation allows assessment of the variability of production and the corresponding financial risk (Godfrey et al., 2022; Nordblom et al., 2021; Nordblom et al., 2020), with this risk being an important factor that influences producer adoption of a practice (Moore, 2014; Tocker et al., 2022). Many have simulated biophysical farm production with highly mechanistic process-based models such as APSIM (e.g. Al Mamun et al. (2023); Bell et al. (2021); Ghahramani et al. (2020); Godfrey et al. (2021); Smith and Moore (2020); Thomas et al. (2018)), the GRAZPLAN suite (e.g Bell et al. (2021); Donnelly et al. (2002); Freer et al. (1997); Ghahramani et al. (2020); Godfrey et al. (2021); Smith and Moore (2020); Thomas et al. (2018)), SGS/DairyMod (Johnson et al., 2008) and PASTOR-DS (Villalba et al., 2019). Livestock models have been used for sheep systems to compare the risk of livestock and cropping enterprises (Bell et al., 2021), increased feeding costs and decreased lamb prices (Bertolozzi-Caredio et al., 2021), increased debt levels on profitability and wealth (Godfrey et al., 2021) and trade-offs between economic and sheep objectives (Villalba et al., 2019). Commonly used gross margin analyses are easily applied to simulated production to compare different sheep management strategies. While gross margins can incorporate risk due to production variability, often static or independent price distributions are used which disregard correlations between season and pricing and the probability distribution of pricing (Amidy et al., 2017). Accumulating debt and interest payments are also important factors determining the feasibility of an investment, which are not considered in partial financial methods (Amidy et al., 2017; Godfrey et al., 2021; Hutchings and Nordblom, 2011; Hutchings et al., 2010). This factor increases in importance when events such as drought or periods of low market prices occur early in the investment period, which can intensify the negative impact on debt or liquidity levels (Godfrey et al., 2021).

A previous gross margin analysis of six common and novel sheep management systems from the 'EverGraze' project in southern Australia identified changes in the gross margin ranking of the systems with decadal seasonal associated production risk (Robertson and Friend, 2020a, 2020b, 2020c). However, that study used static pricing and did not consider whole-farm economic consequences. The objectives of this study were to expand the analysis to: 1) forecast and compare the whole farm productivity and economics of the different sheep production systems described in Robertson and Friend (2020a, 2020b, 2020c) and Robertson et al. (2020) with the long-term price and production risk incorporated, 2) identify the factors that were driving the differences between systems, and 3) determine if the profitability and ranking of systems change in response to different market and environmental conditions.

2. Materials and methods

The study employed a stochastic simulation whole-farm modelling approach. This combined biophysical simulation data with forecasted price data enabling assessment of the economic and financial performance of different sheep management systems (Fig. 1). The whole-farm economic simulation model that integrated price and production data was developed in Microsoft Excel®, to assess six different sheep systems based on Merino ewes and three paddock systems (PS) under equivalent mid-winter stocking rates (SR) with stochastic prices and climatic conditions (Table 1). AusFarm® output and @Risk modelling (to be detailed later) were integrated to produce annual profit and loss budgets, financial position balance sheets and annual cash flows. Monthly AusFarm outputs were aggregated to generate annual livestock trading schedules and enterprise gross margins.

2.1. Biophysical model

Biophysical simulation modelling using AusFarm® software version 1.5.0 (Moore et al., 2007) was used to generate production data for differing sheep systems, with the model having previously been validated against production data from a long-term field experiment at the same location (Robertson and Friend, 2020c). AusFarm uses historical weather data for a location to simulate, on a daily basis, growth of one or more specified pasture species on a user-defined soil type in a number of paddocks in the modelled farm. The pastures are grazed by livestock where key management activities (e.g. genetic base, stocking rate, dates of husbandry events, grazing management, supplementary feeding) are set by the user to represent a production system. Intake of pasture or supplement quantity and quality are simulated to drive animal production (wool, reproduction, growth), mediated by additional effects of weather on energy demand and chill on lamb survival. The model therefore represents a real system with variation in production between land units within a farm, and within and between years. Six sheep systems located at Tarcutta (147°31'E 35°12'S) in southern New South Wales, Australia (Fig. 2) were simulated over the period 1971 to 2018. Data from 1971 was excluded from analyses to allow for an initialisation period in the model. A gross margin analysis has previously been reported in Robertson et al. (2020) and Robertson and Friend (2020a, 2020b, 2020c) based on simulation of these systems. The present study extends the analysis to include whole-farm assessment and time series price forecasting, as well as univariate distributions to more accurately represent the relationships between input and output values and associated risk. The monthly production data (representing August to July for each production year) was compiled in Microsoft Excel® and using @RISK (Palisade Decision Tools, 2021) stochastic simulations calculated enterprise revenues and costs. The production price and cost data were combined with twelve variable input and output prices including sale and purchase of livestock, and feed grain prices, to calculate the whole farm performance and risk for each system. The remaining variable and fixed costs were kept constant in all scenarios.

The simulated sheep systems were an extension of a comparison of four sheep systems undertaken in a grazing experiment on a property near Tarcutta, between 2006 and 2011 (Robertson et al., 2020; Robertson and Friend, 2020a, 2020b, 2020c). For the present simulation study five sheep systems were evaluated when grazing the same pasture base of 20 % lucerne (*Medicago sativa*) and 80 % phalaris (*Phalaris aquatica*). The systems differed in lambing time and/or the proportion of Merino ewes joined to terminal rams (White Suffolk), with Winter Lambing Merino (WLM) being the traditional self-replacing Merino system lambing in July, while Later Lambing (LL) ewes were mated with both Merino and terminal meat breed rams to lamb in September, Split Lambing (SL) produced crossbred lambs in July but also Merino lambs in September, while two Terminal systems did not use Merino rams and produced crossbred lambs either in July after joining in February (Terminal February) or September after joining in April (Terminal April). These five systems include the key types of sheep enterprise found in the region, being either wool or meat focussed and breeding or purchasing replacement Merino ewes. The sixth system (High Lucerne (HL) used 40 % rather than 20 % of pasture area sown to lucerne, but the same sheep management as LL. This system was included to evaluate the impact on sheep production from potentially a longer period of green feed due to growth of lucerne over summer/autumn. A farm size of 1000 ha was used for all systems for ease of comparison, with farms of 600 to 2000 ha being typical of the region (Behrendt and Weeks, 2019; DPI NSW, 2018).

The systems modelled are described in detail in Table 1 and in Robertson and Friend (2020a, 2020b, 2020c) and Robertson et al. (2020). All systems used a similar July stocking rate (dry sheep equivalents (DSE) per hectare) because mid-winter is typically a period of restricted feed availability in cold-winter temperate areas (Moore et al., 2009; Obst, 1987). The different times of lambing meant different numbers of ewes ha^{-1} were used in each system when carrying the same July DSE per hectare. This is due to the increase in energy demand with late pregnancy and lactation, and the energy demand of ewes in winter when pasture supply is limiting, will differ depending on the time of lambing (stage of pregnancy/lactation), therefore altering the potential number of ewes per hectare that can be carried at the same mid-winter grazing pressure.

Apart from the two terminal systems where 18 month old replacement ewes were purchased annually shortly before joining, all systems bred replacement ewes. In the self-replacing systems, young ewes were purchased pre-joining in occasional years when the number of bred replacements was not sufficient due to a low weaning rate. A flexible sale policy was used when selling lambs in all systems which allowed the sale date to reflect variable seasonal conditions, with no supplementary feeding of lambs destined for slaughter. Lambs were sold when the first of any of the three conditions were met: if no live lucerne pasture was available, or if lambs reached an age of 11 months or 45 kg liveweight for Merino wethers and 60 kg liveweight for crossbred wethers, which allowed lambs to be retained to heavy weights in favourable seasons. Shearing was set to 120 days after the start of joining and cast-for age and surplus young ewes were sold pre-joining.

2.2. Price model

Monthly price data were aggregated for key output market prices for meat, wool and skin production, and supplementary feed wheat costs (Table 2) (ABARES, 2019; Meat and Livestock Australia (MLA), 2021a, 2021b), and analysed using the stochastic simulation package @Risk® 8.2.1 (Palisade Decision Tools, 2021). Traditional models rely on single point estimates of a model's variables that leads to inaccurate predictions due to uncertainties in variables used. @RISK is a stochastic simulation Microsoft Excel add-in risk analysis package that incorporates all identified uncertainties into a decision model. Instead of reducing variables to single-point estimates, the simulation model includes a full range of possible values and their probabilities. By running thousands of "what-if" scenarios simultaneously, @RISK provides a comprehensive view of potential outcomes enabling exploration of multiple scenarios and gaining deeper insights into possible risks and uncertainties. The simulation model outcome virtually shows all possible outcomes for any situation, and indicates the likelihood of an event to occur. This type of modelling extends the usefulness of past data, including the production system's management information, historical prices and cost. The results offer more realistic summaries of long-term portfolios, illuminating the business and financial risk profiles.

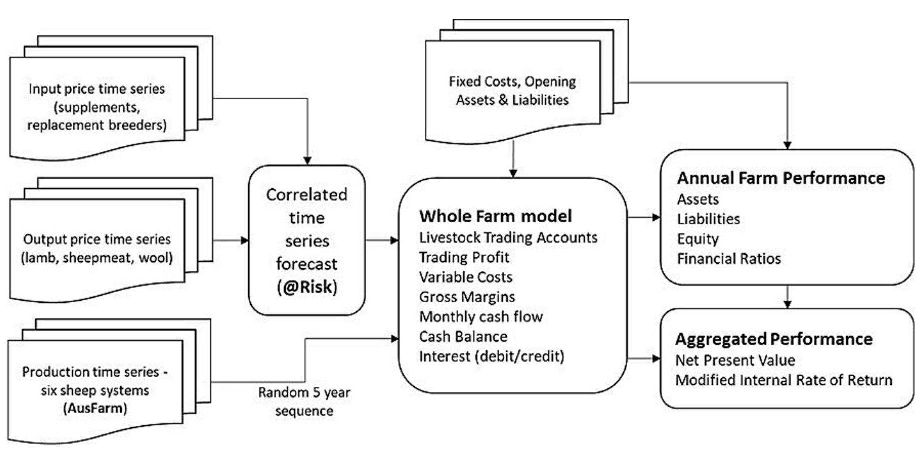


Fig. 1. Conceptual outline of the stochastic whole farm simulation framework.

Once the prices were analysed, they were input into the model. For variable costs, the same prices for purchasing replacement ewes were used for terminal TFeb and TApr systems, with replacement ram prices held constant across all systems and years ($2000 head^{-1} for Merino rams, $1200 head^{-1} for Terminal rams). Historical commodity price data for the period July 2002 – June 2021, i.e., nineteen years or 228 months was used in the model with 2017–18 as the base year to convert the prices from nominal to real. Due to the unavailability of prices for lamb and sheep skins before 2002, the price data used differs from the period in which production outcomes were generated (spanning 1972–2018) using AusFarm simulations. The use of the more recent historical price data was considered to more accurately represent probable variation in future prices, given developments in domestic and global trade.

Three time series forecasting models were fitted to the price data to forecast a period of five years or sixty months (Table 2). The best-fitted time series model for each price input was selected based on the Akaike information criterion (AIC) using the @RISK (Palisade Decision Tools, 2021) auto detect command to achieve stationarity. Stationarity is a statistical property of a time series where its statistical characteristics, such as mean, variance, and autocorrelation, remain constant over time. This property is achieved by modelling and removing any systematic components from the series, leaving behind data that can be treated as random variation (Lehman and Groenendaal, 2020).

Some fitted price time series forecasts were negative, so the minimum prices were restricted to the lower bounds of the best-fitted univariate distributions (Table 2, with distributions shown in Supplementary Material Table SM1) using the AIC. AIC considers both the likelihood (L) and the number of parameters (k) (Eq. 1):

$$AIC = -2\log L + 2k \tag{1}$$

The time series forecasting was governed by a correlation matrix that also configured the outputs, which caused the twelve price time series variables to be dependent of one another, i.e., a multivariate correlation. The Pearson correlation matrix (Table 3) was used to establish the relationship between the input and output prices. There existed strong positive correlations (>0.9) only between lamb and Merino price; wool prices and between medium weight (20.1–24 kg) and light weight skins (16.1–20 kg). Ten thousand iterations using Latin Hypercube sampling were then used to generate five-year input (replacement ewe purchases, feed wheat) and output (meat, skin, wool) price forecasted time series (models and forecast range shown in Supplementary Material Table SM2), and the 5-year sequences of AusFarm modelling output, which were used as price and input variables in the whole-farm simulation model. All other variable costs were determined using data from the 2017–18 NSW DPI gross margin budget estimates for Merino ewes producing 20 μm wool (NSW DPIRD, 2018) (see Table 1).

2.3. Whole farm model

The AusFarm biophysical data and 5-year stochastic price datasets were combined using a whole-farm model to generate monthly livestock trading schedules, annual activity gross margins, monthly cash-flow statements, annual profit and loss statements, and annual statements of assets and liabilities using the whole-farm financial and economic analysis methods as described in Malcolm et al. (2005) and Behrendt et al. (2014). Risk profiles of the six sheep production systems were determined based on the empirical cumulative distributions of these simulated values.

Each system was set at 1000 ha with land valued at $2500 ha^{-1}. Pasture maintenance annuity costs were included to allow for pasture establishment. Maintenance fertiliser applications were provided by AusFarm simulation outputs that were linked to each systems stocking rate (1 kg P per DSE per ha per year) with the price of fertiliser remaining constant per unit applied. Machinery and equipment were costed at $0.5 million with a 10 % depreciation rate. Starting equity for all systems was set at 84 %, with $700,000 debt set at 7 % annual interest rate. All overhead fixed costs were derived for a typical sheep farm in the case study area from the *agri benchmark* data reported by Behrendt and Weeks (2019) and are detailed in Supplementary Material Table SM3.

2.4. Aggregated performance and risk indicators

Fixed costs and debt potentially impact the performance of production systems Their impacts were considered through use of both an annual and a 5-year planning horizon with various measures. Annual performance measures included gross margin per hectare (GM $ ha^{-1}), and meat and wool production per hectare. The reported 5-year aggregated measures of whole farm performance included net present value

Table 1
Key parameters for the six different modelled sheep systems based on Merino ewes 1972–2018.

	Split Lambing (SL)	High Lucerne Later Lambing (HL)	Later Lambing (LL)	Winter Lambing Merino (WLM)	Terminal February (TFeb)	Terminal April (TApr)
Paddock size (ha)						
Lucerne,	200	400	200	200	200	200
Phalaris,	400	300	400	400	400	400
Phalaris	400	300	400	400	400	400
Stocking rates:						
No. breeding ewes ha^{-1}	6.2	7.2	7.2	4.1	5.2	10
No. ewes + replacements ha^{-1}	8.5	9.5	9.5	6	5.2	10
Stocking rate in July (DSE ha^{-1})	11.9	11.9	11.9	12.2	12.0	11.8
Breeding details:						
Replacement ewes	bred	bred	bred	bred	purchased	purchased
Month mated	Feb. and April	April	April	Feb.	Feb.	April
Ewes mated to Merino or terminal (%)	70 %, 30 %	70 %, 30 %	70 %, 30 %	100 %, 0 %	0 %, 100 %	0 %, 100 %
Lambs details:						
Weaning date	Crossbred: 9 Sep Merino: 23 Nov	Crossbred: 23 Nov Merino: 23 Nov	Crossbred: 23 Nov Merino: 23 Nov	Merino: 9 Sep	Crossbred: 9 Sep	Crossbred: 23 Nov
Median lamb sale date (age in days)	Merino: 28 Jan (142); Crossbred: 2 Jan (175)	Merino: 25 Jan (139); Crossbred: 19 Feb (164)	Merino: 18 Jan (132); Crossbred 24 Jan (138)	30 Nov (142)	1 Jan (174)	27 Dec (110)
Gross Margin* budget estimate	Merino ewes (20 μm)-75 % Merino and 25 % to Terminal			Merino ewes (20 μm)-Merino Rams	Merino ewe (20 μm)-Terminal Rams	

[*] Variable costs for the six sheep systems based on the 2017–18 NSW DPI gross margin (GM) budgets for Merino ewes producing 20 μm wool.

Fig. 2. Location of case study farm in south east Australia: Tarcutta, NSW.
(Source: City and Border Data Spatial from 2019 Esri Data & Maps.)

Table 2
Time series models fitted to historical input and output price data and univariate distributions.

Price variable	Time Series Model	Distribution Type	Minimum	Maximum	Mean	Median	Std. Deviation
Light lamb 12–18 kg ($ kg cwt^{-1})	*ARMA11	RiskTriang	2.3	9.3	5.3	5.1	1.5
Trade lamb 18–22 kg ($ kg cwt^{-1})	*ARMA11	RiskTriang	3.2	9.3	5.8	5.6	1.3
Heavy lamb 22+ kg ($ kg cwt^{-1})	*ARMA11	RiskPert	3.1	10.1	5.7	5.6	1.3
Merino lamb 16–22 kg ($ kg cwt^{-1})	*ARMA11	RiskTriang	1.9	8.7	4.9	4.7	1.4
Restocker/feeder lamb 0–18 kg ($ kg cwt^{-1})	**BMMRJD	RiskTriang	2.2	10.4	5.7	5.5	1.7
Mutton 18–24 kg ($ kg cwt^{-1})	*ARMA11	RiskTriang	0.7	7.2	3.4	3.3	1.4
Skin 16.1–20 kg 1.5" - 2" Free of VM ($ skin^{-1})	*ARMA11	RiskPert	0.7	39.0	9.0	7.7	6.0
Skin 20.1–24 kg 1.5" - 2" Free of VM ($ skin^{-1})	***AR2	RiskPert	3.3	37.0	11.7	10.7	5.5
Skin 24.1 kg + 1.5" - 2" Free of VM ($ skin^{-1})	***AR2	RiskPert	6.1	29.9	14.7	14.3	4.3
Wool EMI 19 μm clean ($ kg^{-1})	***AR2	RiskTriang	10.2	24.2	15.6	15.1	3.1
Wool EMI 20 μm clean ($ kg^{-1})	**BMMRJD	RiskPert	9.1	28.4	13.9	13.3	3.2
Feed Wheat ($ kg^{-1})	*ARMA11	RiskPert	0.2	0.7	0.3	0.3	0.1

($ - AUD, cwt – carcase weight, VM – vegetable matter, EMI – Eastern Market Indicator)
All above were output prices except feed wheat (input). Heavy lamb, Restocker/feeder lamb and associated Skin prices were also used as input prices to accurately value replacement animals as they were required.
[*] ARMA11: A stationary stochastic process where one lagged value and one lagged error are used to predict the next value in a series.
[**] BMMRJD: A continuous-time stochastic process where values of the series revert to a long-term and jumps when random shocks occur.
[***] AR2: A stationary stochastic process where two lagged values are used to predict the next value of a series.

(NPV) as an annuity ($ ha^{-1} year^{-1}) and modified internal rate of return (MIRR) (calculations detailed in Godfrey et al. (2021)).

To analyse simulation outputs Tornado graphs were produced to show regression mapped values of inputs impacting the gross margin for each individual sheep system. Specifically, stepwise linear regressions were performed (Eq. 2):

$$Y = \beta_0 + \sum\nolimits_{i=1}^{m} \beta_i x_i, \tag{2}$$

The length of the bar and value shown (Fig. 3) for each production or price input variable is the amount of change in the output (gross margin) due to a one standard deviation change in the input variable (reported in Table 4) with all other input variables held at their mean values (ceteris paribus). These "mapped" values represent the "beta" coefficients from a multiple linear regression of standardised variables for the inputs (independent variables) and non-transformed values for the output (dependent variable). As per standard tornado charting protocols, input variables were ranked from the highest (top of y-axis) to lowest (bottom of y-axis) in their effect on the output variable. Longer bars (at the top) indicate a greater sensitivity of the output variable to changes in an input variable. Additionally, the direction of the bar indicates whether increasing an input variable by one standard deviation will have a positive or negative effect on the output variable.

Statistical analyses of production outputs were run in MATLAB (Mathworks, 2023). The Tukey's honestly significant difference (HSD) test was used to evaluate differences in pairs of means at 99 % confidence (alpha = 0.01) to control for family-wise error rates and type 1 error (Lane, 2010).

3. Results

The different sheep systems were first analysed based on data from 1972 to 2018 to see if there were differences in production and if this translated to differences in economic revenues, costs and gross margins. Secondly, the sheep systems were analysed to determine what was driving the differences in gross margins. Finally, the risk in the sheep system performance was analysed based on the longer five-year term.

Table 3
Input and output price correlation matrix for time series modelling.

Price variable	1	2	3	4	5	6	7	8	9	10	11	12
1. Light lamb 12–18 kg ($ kg cwt^{-1})	**1.00**											
2. Trade lamb 18–22 kg ($ kg cwt^{-1})	**0.94**	**1.00**										
3. Heavy lamb 22+ kg ($ kg cwt^{-1})	**0.92**	**0.99**	**1.00**									
4. Merino lamb 16–22 kg ($ kg cwt^{-1})	**0.98**	**0.97**	**0.95**	**1.00**								
5. Restocker/feeder lamb 0–18 kg ($ kg cwt^{-1})	**0.96**	**0.89**	**0.85**	**0.93**	**1.00**							
6. Mutton 18–24 kg ($ kg cwt^{-1})	**0.95**	**0.91**	**0.87**	**0.95**	**0.94**	**1.00**						
7. Skin 16.1–20 kg 1.5" - 2" Free of VM ($ skin^{-1})	−0.41	−0.38	−0.41	−0.44	−0.42	−0.41	**1.00**					
8. Skin 20.1–24 kg 1.5" - 2" Free of VM ($ skin^{-1})	−0.29	−0.28	−0.32	−0.33	−0.30	−0.29	**0.91**	**1.00**				
9. Skin 24.1 kg + 1.5" - 2" Free of VM ($ skin^{-1})	0.17	0.09	0.06	0.10	0.14	0.10	0.61	0.65	**1.00**			
10. Wool EMI 19 µm clean ($ kg^{-1})	0.47	0.40	0.42	0.45	0.37	0.38	0.04	0.01	0.53	**1.00**		
11. Wool EMI 20 µm clean ($ kg^{-1})	0.48	0.40	0.43	0.47	0.37	0.38	−0.03	−0.07	0.45	**0.95**	**1.00**	
12. Feed wheat ($ kg^{-1})	−0.18	−0.05	0.00	−0.10	−0.28	−0.17	−0.06	−0.06	−0.23	0.12	0.13	**1.00**

All above were output prices except feed wheat (input). Heavy lamb, Restocker/feeder lamb and associated Skin prices were also used as input prices to accurately value replacement animals as they were required.
Correlations that were significant (strongly positive >90%) have been shown in bold.

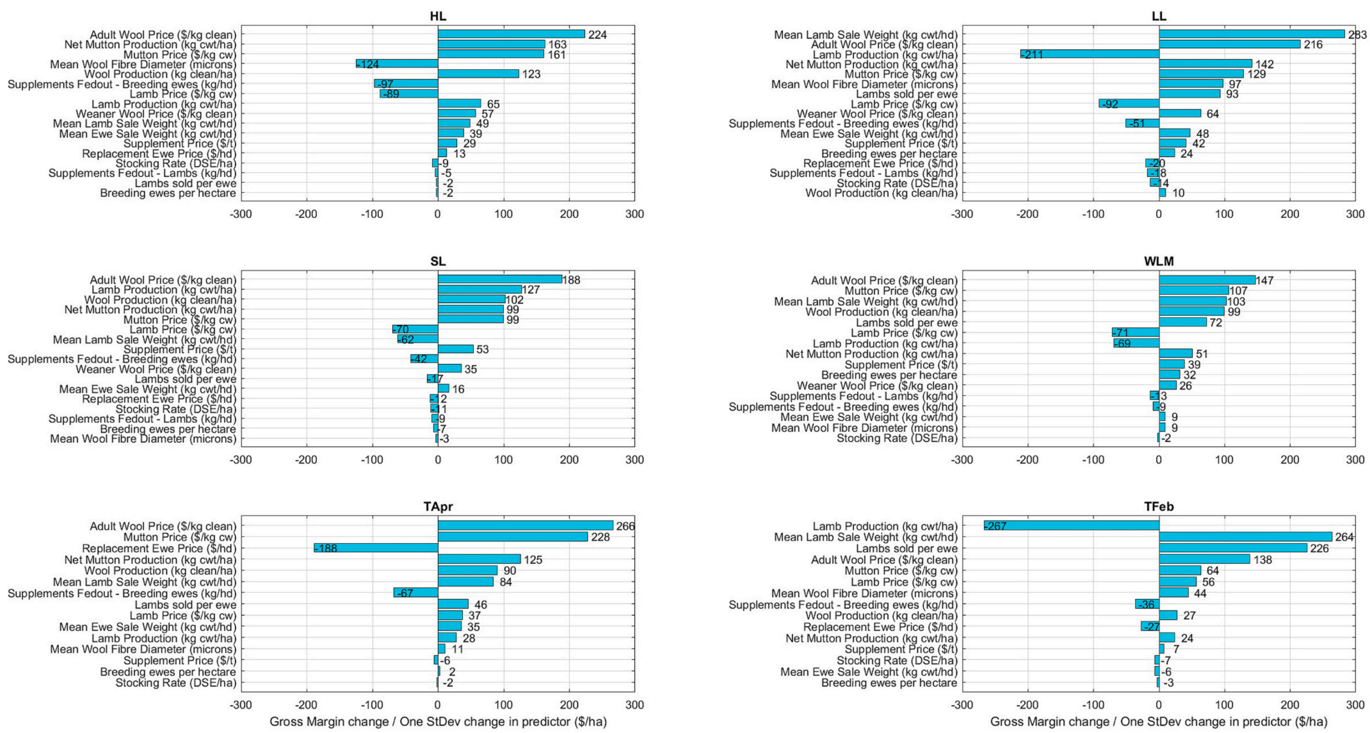


Fig. 3. Regression mapped values for each sheep system (bar length indicates amount of change in gross margin due to a one standard deviation increase in input variable, with the highest impact factors at the top of the chart).
SL Split Lambing; HL High Lucerne later lambing; LL Later Lambing; WLM Winter Lambing Merino; TApr Terminal April; TFeb Terminal February.

3.1. Enterprise production and economic performance

The simulated number of lambs marked per ewe joined and the contributing factor of number of lambs born per ewe joined varied between sheep systems (Table 4). The number of lambs produced tended to be higher in February compared with April joined systems, associated with a higher condition score of ewes at joining. In comparing the different sheep production systems, Table 4 shows that while the total production of lamb and mutton ranged between 94 and 110 kg cwt ha^{-1}, there were large differences in lamb and mutton production in the different systems. The weight of lamb sold was highest for terminal ewes mated in April (TApr 112 kg cwt ha^{-1}) and February (TFeb 93 kg cwt ha^{-1}). For self-replacing systems the high lucerne system mated in April produced the most lamb (HL 66 kg), with production declining with a lower proportion of lucerne and earlier mating systems, being least for winter lambing Merinos (WLM 34 kg). The terminal ewe systems did not retain ewe lambs past 11 months of age for later breeding, allowing 0.33 to 0.49 more lambs sold per breeding ewe in the terminal systems than for those in self-replacing systems. The mean lamb sale carcase weight was highest for the February joined systems but was not increased by using only Terminal rams in the April joined systems where a higher proportion of lucerne achieved the highest carcase weight ((TApr 12 kg, HL 15.8 kg). There was higher lamb production (total kg ha^{-1}) for systems mating in April than in February and production was higher for terminal ewes than breeding replacement ewes. However, mutton production was at least 41 kg ha^{-1} lower in the terminal compared with self-replacing systems. These differences affected revenue in the gross margin as lamb prices were higher than mutton prices, and terminal lambs achieved a higher value per kg of carcase.

The other factor affecting revenue in the gross margin was wool production and price. Wool production was up to 14 kg ha^{-1} higher in April compared with February joined systems, associated with differences in the number of ewes per hectare when stocked at the same mid-winter DSE, with the lowest production for terminal February mating

Table 4
Mean and standard deviation of system variables simulated using AusFarm and Gross Margin for six sheep production systems 1972–2018*.

Variable	SL	std dev	HL	std dev	LL	std dev	WLM	std dev	TApr	std dev	TFeb	std dev
No. lambs born/per ewe joined	1.30abc	0.07	1.21cd	0.07	1.24bcd	0.08	1.34ab	0.06	1.25bcd	0.06	1.32ab	0.04
Lambs marked per ewe joined (%)	97a	6.02	91b	6.94	94ab	7.39	97a	6.86	94ab	6.68	96a	6.06
Lamb sold (kg cwt ha^{-1})	51.7b	9.21	65.9d	14.61	54.5c	10.10	33.6a	4.99	111.9f	15.39	93.2e	41.06
Net mutton production ** (kg cwt ha^{-1})	47.2e	17.43	43.5c	24.19	46.1d	21.55	47.5e	11.85	−5.8a	22.03	2.94b	9.94
Lambs sold per ewe (No.)	0.58b	0.04	0.58b	0.04	0.60c	0.05	0.48a	0.03	0.93d	0.07	0.97e	0.18
Lamb sale weight (kg cwt lamb^{-1})	14.5c	2.50	15.8d	3.74	12.6b	2.45	17.4e	2.47	12.0a	1.62	18.2f	3.57
Ewe sale weight (kg cwt ewe^{-1})	27.6c	2.10	26.1a	2.01	26.7b	2.26	29.2e	1.59	27.9d	1.88	30.8f	1.15
Wool production (kg clean ha^{-1})	26.8c	2.24	32.2e	3.69	31.9d	2.58	20.1b	1.64	30.4f	2.09	15.8a	0.84
Wool fibre diameter (μm)	19.64b	0.26	19.59a	1.37	19.64b	0.26	19.67b	0.24	19.65b	0.25	19.69c	0.21
Breeding ewes per hectare (ewe ha^{-1})	6.17c	0.14	7.25e	0.16	7.19d	0.17	4.07a	0.15	10.00f	0.00	5.20b	0.00
Stocking rate (annual DSE ha^{-1})	13.39c	1.10	14.68e	1.53	14.42d	1.37	10.67b	0.75	15.13f	1.40	10.09a	0.54
Weaner wool price ($ kg clean^{-1})	16.12c	4.04	14.83a	3.91	15.86b	3.97	14.75a	3.64				
Adult wool price ($ kg clean^{-1})	13.67a	3.16	13.66a	3.34	13.69a	3.17	13.71a	3.13	14.00c	3.20	13.89b	3.15
Lamb price ($ kg cwt^{-1})	8.79b	2.28	8.84c	2.28	8.99d	2.44	8.26a	2.15	9.48f	2.51	9.04e	2.27
Mutton price ($ kg cwt^{-1})	7.47d	1.44	7.39c	1.39	7.41c	1.39	7.76e	1.51	6.84b	1.06	6.66a	1.10
Feed wheat price ($ t^{-1})*	327.9	60.76	327.6	59.67	328.2	60.83	328.5	61.73	327.8	61.26	328.1	62.20
Wheat supplements fed to breeding ewes (kg ewe^{-1})	14.3b	23.83	23.4d	30.38	16.0c	26.33	6.55a	16.48	15.2b	24.43	7.30a	16.16
Wheat supplements fed to lambs (kg lamb^{-1})	8.47c	9.99	4.26a	5.82	7.00b	7.73	14.40d	17.25				
Total supplementary feeding costs ($ ha^{-1})*	192.1c	151.9	306.0e	207.7	235.4d	176.0	89.9b	86.6	248.8d	206.9	62.2a	81.0
Replacement ewe price ($ hd^{-1})*	161.3a	33.34	161.7a	33.09	161.3a	33.25			198.1b	40.85	197.6b	40.89
Gross margin ($ ha^{-1})	824.4b	383.31	1012.6f	500.13	964.1e	462.26	764.9a	281.72	935.8d	467.79	859.2c	304.57

a,b,c,d,e,f: Means with different letters within a row indicate means differ using Tukey HSD (alpha = 0.01).
SL Split Lambing; HL High Lucerne later lambing; LL Later Lambing; WLM Winter Lambing Merino; TApr Terminal April; TFeb Terminal February.
* Excludes zero values in calculation of mean, standard deviation and Tukey HSD for supplement price, total supplementary feeding cost and replacement ewe price.
** Net mutton production in the trading account.

(TFeb 16 kg). For adult wool the differences in prices between systems were small with some not statistically different. While weaner wool has a lower fibre diameter, which attracted higher prices than the adult wool, differing prices between systems did not reflect the small differences in fibre diameter. Weaner wool prices were higher for split lambing (SL $16.1 kg clean^{-1}) and late lambing (LL $15.8) than high lucerne and winter lambing Merinos (HL $14.8 and WLM $14.7). Costs varied in the production systems, with less supplementary feeding in terminal systems when lambs were sold before supplementary feeding was needed and there were lower numbers of ewes per hectare (TApr 15.2 kg hd^{-1} and TFeb 7.3 kg hd^{-1}) and more supplements were fed out in self-replacing systems feeding both ewes and lambs. The most supplementary feed was used in April mated systems than earlier mating systems due to the greater number of ewes per hectare and annual average DSE ha^{-1} when carrying the same mid-winter stocking rate (e.g. HL 27.7 kg hd^{-1} fed, 7.2 hd ha^{-1} and 14.7 DSE ha^{-1}; compared to WLM 20.9 kg, 4.1 hd ha^{-1} and 10.7 DSE ha^{-1}). Similarly, higher annual stocking rates for terminal systems required more supplementary feeding (TApr 10 hd ha^{-1} and 15.1 DSE ha^{-1}; TFeb 5.2 hd ha^{-1} and 10.1 DSE ha^{-1}).

3.2. Gross margins

The differences in the production and prices, as well as the quantities of supplementary feed, resulted in significant differences in the average gross margins for the systems (Table 4 at a 99 % confidence). Terminal and earlier mated systems did not produce the highest gross margins. The highest gross margin was in the high lucerne system (HL average $1013 ha^{-1}) followed by late lambing (LL $964), and the lowest gross margin was for winter lambing Merinos (WLM $764). The higher gross margins were achieved in the April mated systems. The high lucerne system had both high lamb and wool production, and the revenue exceeded the increased costs of the supplementary feed. The terminal breeding systems had high lamb production but lower wool production, which did not offset the lower supplementary feeding costs.

The regression mapping approach which predicted the expected gross margin change in response to commonly used variables that were used to generate revenues and costs (Fig. 3) indicated that in most production systems, the gross margins were most sensitive to factors positively affecting revenue. In particular, the highest ranking factors were wool fibre diameter (more so for later-lambing self-replacing systems) or prices, the quantity of mutton production or prices, as well as lamb production, price or sale weight (as indicated by the longest bars at the top of the y-axis). The terminal breeding system with an April mating (TApr) was also strongly negatively affected by increases in the price of replacement breeding ewes. Adult wool prices had the largest positive impact on the HL, SL, TApr and WLM systems, while lamb weight and lamb production positively and negatively impacted LL and TFeb systems, respectively (longest bars). Presumably, for both LL and TFeb, this is a consequence of having insufficient lucerne available to retain lambs to heavier sale weights prior to mid-summer, and potentially presenting implications for future reproduction rate with less feed available for ewes apart from being potentially in lower condition. This is evidenced by the negative sensitivity of Gross Margins to the quantity of supplements fed out to breeding ewes. Whereas other systems, such as TApr tend to sell lambs in less days and prior to summer and may not have the same feed base resource trade-off effects. In WLM, lamb production is a lower component of income.

Gross margin outputs for each system were least sensitive to factors such as mid-winter stocking rate. Similarly breeding ewes per hectare also ranked low in influence across most systems. This reflects, in-part, the design of the sheep systems and their management to maintain similar mid-winter stocking rates, and subsequently, breeding ewe numbers do not vary greatly within a system. Other commonly low-ranking factors such as mean ewe sale weight, replacement ewe prices, and supplement fed out to lambs tended to have either small positive or negative effects, on system gross margins.

3.3. Gross margin variability

To ascertain the expected variability in gross margin performance for each sheep system, the co-efficient of variation for each 5-year gross margin sequence (i.e., iteration) was calculated (Table 5). The coefficient of variation shows the variation around the mean expressed as a percentage to allow for the differences in each system to be compared relative their mean performance. There was more variation in the median and 75th percentile values for the April mating systems (HL, LL, TApr) than February mating systems (WLM, TFeb), with the Split Lambing system intermediate. The variation in Terminal systems was similar to that of systems using only Merino or both Merino and terminal rams, with month of mating having a larger impact. This indicates that February mating provided more reliable gross margin outcomes regardless of breed. While the winter lambing Merino (WLM) average gross margin was lower on average than the other systems, the terminal breeding with February mating (TFeb) was higher than both winter lambing and split lambing (SL) (Table 4). Therefore, if a farmer was concerned about risk and preferred less variation in gross margins, they would target the winter lambing, or for a slightly higher gross margin would target the terminal breeding with a February mating.

3.4. Longer term five-year performance

Net Present Values (NPV) equate the five-year cash flows to present day values as an annuity in dollars per hectare. Fig. 4 shows the distribution NPVs through box and whisker plots which show the middle 50 % of responses as well as potential extreme values in the tails and outliers (all system NPVs were statistically significantly different at alpha = 0.01). The highest median NPV were for the high lucerne system (HL). All systems have some years where the NPV has no value, but the upside higher values were more pronounced in high lucerne (HL median NPV \$586, 70th percentile \$705), later lambing (LL median NPV \$530, 70th percentile \$638) and terminal breeding with April mating (TApr median NPV \$492, 70th percentile \$611). Terminal breeding with an April mating also indicated the largest downside risk with negative and high potential NPV extreme outlier values.

Another way to consider risk and aggregated performance is through the modified internal rate of return (MIRR) that translates the NPV into a percentage return over a five-year investment and uses the cost of capital as the reinvestment rate (Barry et al., 1999). The MIRR cumulative distribution functions (CDF) for each sheep system are shown in Fig. 5 and indicate whether one system stochastically dominates another (Hardaker et al., 2015). The CDF distributions indicate that the high lucerne system (HL) displayed first-degree stochastic dominance over all other systems, and the winter lambing Merino system (WLM) was stochastically dominated by all other systems. This suggested that the high lucerne system was the most stochastically efficient option for farmers considering these sheep systems.

While all of the farming systems had a small chance that there would be no return (MIRR 0 %), 70 % of the time returns would be greater than 9 % (decile 0.3: HL 11.9 %, LL 11.2 %, SL 10.9 %, TFeb 10.5 %, TApr 10.3 %, WLM 9.5 %) and half the time (50 %) the returns were forecast to be between 11 and 13.5 % (decile 0.5: HL 13.5 %, LL 12.7 %, SL 12.3 %, TFeb 11.9 %, TApr 11.8 %, WLM 10.8 %). More rarely, 30 % of the time returns reached for high lucerne were 15 %, late lambing 14.2 % but other systems 12 % to 13 % (decile 0.7: HL 15.1 %, LL 14.2 %, TApr 13.3 %, TFeb 13.2 %, SL 12.3 %, WLM 12.1 %,). While MIRR for both terminal systems were not statistically significantly different from each other (alpha = 0.01), all other systems had different MIRR. This indicates the potential upside returns were forecast to be higher for high lucerne and late lambing systems. There were less upside returns for winter lambing Merino and split lambing systems.

Table 5
Coefficient of Variation* in Gross Margins at key percentiles for the six sheep systems across each 5-year forecast iteration**.

	SL	HL	LL	WLM	TApr	TFeb
25th Percentile	31.4 %	34.2 %	32.8 %	23.8 %	32.9 %	21.4 %
Average	44.6 %	47.8 %	46.3 %	34.2 %	47.4 %	30.5 %
Median	41.9 %	45.4 %	43.8 %	32.1 %	44.2 %	29.1 %
75th Percentile	54.6 %	58.9 %	56.7 %	42.4 %	58.6 %	37.9 %

SL Split Lambing; HL High Lucerne later lambing; LL Later Lambing; WLM Winter Lambing Merino; TApr Terminal April; TFeb Terminal Feb.

* Coefficient of Variation is the ratio of the standard deviation of gross margins to the mean gross margin.

** 5 year forecast based on the historical modelled production and pricing.

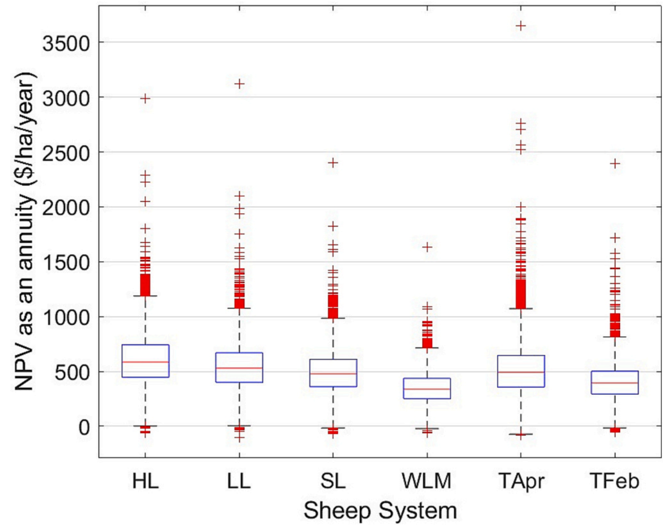


Fig. 4. Box plot indicating Net Present Value as an annuity (\$ ha^{-1} yr^{-1}).
HL High Lucerne later lambing; LL Later Lambing; SL Split Lambing; WLM Winter Lambing Merino; TApr Terminal April; TFeb Terminal February.

4. Discussion

This work captured and reflected long-term economic and production variability using multi-year stochastic price and deterministic production modelling that involved time series price forecasting. The

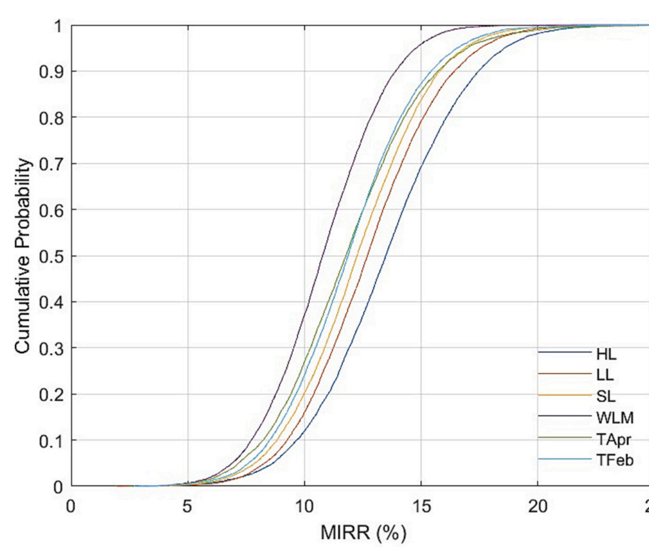


Fig. 5. Cumulative Distribution Functions indicating Modified Internal Rate of Return (%).
HL High Lucerne later lambing; LL Later Lambing; SL Split Lambing; WLM Winter Lambing Merino; TApr Terminal April; TFeb Terminal February.

univariate distributions were bounded by a correlation matrix to more accurately represent the relationships between input and output prices and associated risk. The different sheep production systems modelled varied with the breed of ram, timing of rams mating ewes for different lambing times while having equivalent mid-winter DSE/ha^{-1}stock rates, the type of pasture grazed (higher proportions of lucerne than phalaris), if lambs were all sold (terminal systems) or replacement Merino ewes kept which influenced supplementary feeding costs. Production variation as well as different supplementary feeding costs and prices received when meat, wool and animal were sold, resulted in different gross margins and net present values (NPV) of longer term five-year cash flows.

The winter lambing Merino system (WLM) had the lowest average gross margin (\$764 ha^{-1}) with lower lamb production (34 kg cwt ha^{-1}), lower wool production (20 kg ha^{-1}) but higher mutton production (47.5 kg cwt ha^{-1}). While winter lambing Merinos had lower supplementary feeding (20.9 kg hd^{-1}) and costs, the higher mutton production did not generate as much revenue as the lost lamb revenue (lambs received higher prices than mutton) so gross margins were the lowest of the systems. Regression mapping (Fig. 4) indicated that system gross margins were generally most sensitive to increases in wool price and production, as well as mutton prices and lamb production. Similarly, the cash flows over five years NPV had the lowest median value for winter lambing Merinos. In assessing the risk, the winter lambing Merinos had the lowest CoV of gross margins and the MIRR cumulative distribution function had lower returns over five years compared to the other systems. This indicates that while the returns were lower, winter lambing Merinos were more reliable due to lower risks of variable returns. This is in line with risk return trade off theory where higher returns are expected to be related to activities with high risks with greater variability in the returns (Behrendt, 2014; Hardaker et al., 2015). It may be one of the reasons that the winter lambing Merino production system predominates in regions of Eastern Australia where lower stocking rates and earlier lambing reduces the risk of poor nutrition of lambs when it is dry from spring to summer (Robertson and Friend, 2020a, 2020b, 2020c).

If growers were willing to take on more risk and aim for higher returns, which system could they look at? While some of the decision in which system to choose may be made on farmer preferences for supplementary feeding, reliability and pattern of feed pasture supply etc., the economic returns and risks forecasted in the long term may assist decision making. The highest average gross margin was in the high lucerne system (HL \$1013 ha^{-1}) followed by late lambing (LL \$964), terminal breeding with April mating (TApr \$936) and February mating (TFeb \$859). The high lucerne system had higher supplementary feeding costs that were more than compensated by high lamb and wool production revenue. The terminal breeding systems lower supplementary feeding costs were offset by high lamb revenue and lower wool revenue. The NPV of longer-term cash flows into current day values had higher median and 70th percentile values for high lucerne (HL median NPV \$586 ha^{-1}, 70th percentile \$705), followed by later lambing (LL median NPV \$530 ha^{-1}, 70th percentile \$ 638) and terminal breeding with April mating (TApr median NPV \$492 ha^{-1}, 70th percentile \$611). These production systems also had higher risk with larger gross margin coefficients of variation (HL median 45.4 % & 75th percentile 58.9 %; TApr median 44.1 % & 75th percentile 58.6 % and LL median 43.8 % & 75th percentile 56.7 %). The higher risk can pay off in some years as a higher modified internal rate of return on the five-year cash flows with 30 % of the time returns reaching 15.1 % for high lucerne, later lambing 14.2 % and terminal breeding with April mating 13.3 %. In considering the simulated production outcomes and economic returns using forecasted values for input and output prices, the farmer can understand the scope of potential returns and the risk rather than relying on recent seasons or heuristic decision making.

It is recommended to evaluate this forecasting method in other climates and geographical regions where production and market prices are different. Kimura and Anton (2011) found Australian farm prices of wheat and barley varied 50 % most of the time (average CoV) but prices varied much less in Estonia and Italy and to a lesser extent the UK. Production was even more varied in Australia, often twice as much for wheat, barley and oil seeds. These differences in variability may affect the results of modelling in other locations. Further research could extend the results of this research by considering the impact of production systems on carbon and water footprints. While further research is recommended to evaluate how this forecasting method is useful in assessing other farming systems, the case studies reported here show significant differences due to the farmer tactical decisions made in different sheep production systems. In this modelling, these tactical decisions were primarily constrained to supplementary feeding and lamb selling policies. As such, it would be expected that the variability of enterprise return from simulation modelling with non-embedded risk (Hardaker et al., 2015) as reported here are much higher than one might expect in real world situations due to the mitigation opportunities livestock farmers have to manage timing of mating, breed of ram, pasture management, stocking rates, supplementary feeding and time of sale of animals and wool. The regression mapping provides an indication of the factors that different system enterprise gross margins are most or least sensitive to. With a focus by management on the highest-ranking factors, it would be possible for managers to minimise potential downside consequences and maximise upside opportunities. Further development into supporting tactical decision making through stochastic dynamic systems modelling and the integration of real-time input and output price forecasting, provides a logical pathway to improve on-farm decision making. The inclusion of other measures of environmental and social performance would further enhance the applicability of such decision support.

Results of this type will assist farmers to understand the complex economic impacts of their decision making and use gross margins with confidence. The proviso is that models have been based on forecast production and prices generated from historical records that may vary in the future.

5. Conclusions

The use of the stochastic whole-farm simulation modelling approach using the AusFarm decision-support tool showed management decisions using six different management regimes impacted forecast production outputs and costs, annual gross margins and the NPV cash flow. Of note the more basic gross margin analysis gave the same results as the more complex NPV providing confidence that farmers can use this easier method in evaluating decisions.

Higher economic returns were associated with higher risks of variable returns and lower returns with lower risk of variation. The earlier mated (February) and terminal systems did not perform economically as well as the later mated (April) systems but were more reliable with lower risk. The winter lambing Merino system had the lowest gross margins and NPV, but also the lowest risk CoV and MIRR. Investment in additional lucerne pasture for early summer feed paid off with greater gross margins and NPV, but with highest risk CoV and MIRR, these economic returns may vary. The farmer needs to forecast their production and prices based on the expected season and market conditions while considering if they want to take on greater risks in aiming for higher returns.

CRediT authorship contribution statement

Christine E. Storer: Visualization, Validation, Project administration, Investigation, Writing – review & editing, Writing – original draft. **Sosheel S. Godfrey:** Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization, Writing – review & editing, Writing – original draft. **Susan M. Robertson:** Visualization, Validation, Resources, Project administration, Methodology, Investigation, Data curation, Conceptualization, Writing – review & editing, Writing – original draft. **Michael A. Friend:** Visualization, Validation, Project administration, Investigation, Conceptualization, Writing – review & editing, Writing – original draft. **Karl Behrendt:** Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization, Writing – review & editing, Writing – original draft.

Funding sources

The work upon which this study is based was supported by the CRC for Plant-Based Management of Dryland Salinity (grant, 2006-2007) and the Future Farm Industries CRC (OPA 3910, 2008-2011).

Declaration of competing interest

The authors have no interests to declare

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2025.104407.

Data availability

Data will be made available on request.

References

ABARES, 2019. Agricultural Commodity Statistics 2019. Australian Bureau of Agricultural and Resource Economics and Sciences, Canberra.

Al Mamun, M.A., Garba, I.I., Campbell, S., Dargusch, P., deVoil, P., Aziz, A.A., 2023. Biomass production of a sub-tropical grass under different photovoltaic installations using different grazing strategies. Agr. Syst. 208, 103662.

Amidy, M.R., Behrendt, K., Badgery, W.B., 2017. Assessing the profitability of native pasture grazing systems: a stochastic whole-farm modelling approach. Anim. Product. Sci. 57, 1859–1868.

Barry, P.J., Ellinger, P.N., Baker, C.B., Hopkin, J.A., 1999. Financial Management in Agriculture, 6th ed. Interstate Publishers, Inc.

Behrendt, K., 2014. Price risk exposure of Australian Merinos – is it in the bloodline? Anim. Product. Sci. 54, 1317–1322.

Behrendt, K., Weeks, P., 2019. How Are Global and Australian Sheepmeat Producers Performing?: Global Agri Benchmark Network Results 2018, MLA Market Information Report. Meat & Livestock Australia, North Sydney, Australia, p. 18.

Behrendt, K., Scott, J.M., Mackay, D.F., Murison, R., 2013. Comparing the climate experienced during the cicerone farmlet experiment against the climatic record. Anim. Prod. Sci. 53, 658–669.

Behrendt, K., Malcolm, B., Jackson, T., 2014. Beef business management. In: Cottle, D., Kahn, L. (Eds.), Beef Cattle Production and Trade. CSIRO Publishing, Collingwood, Australia, pp. 739–769.

Bell, L.W., Moore, A.D., Thomas, D.T., 2021. Diversified crop-livestock farms are risk-efficient in the face of price and production variability. Agr. Syst. 189, 103050.

Bertolozzi-Caredio, D., Soriano, B., Bardají, I., Garrido, A., 2021. Economic risk assessment of the quality labels and productive efficiency strategies in Spanish extensive sheep farms. Agr. Syst. 191, 103169.

Byrne, F., Robertson, M.J., Bathgate, A., Hoque, Z., 2010. Factors influencing potential scale of adoption of a perennial pasture in a mixed crop-livestock farming system. Agr. Syst. 103, 453–462.

Bywater, A.C., Cacho, O., 1994. Use of simulation models in research. In: Proceedings of the New Zealand Society of Animal Production, pp. 403–412.

Donnelly, J.R., Freer, M., Salmon, L., Moore, A.D., Simpson, R.J., Dove, H., Bolger, T.P., 2002. Evolution of the GRAZPLAN decision support tools and adoption by the grazing industry in temperate Australia. Agr. Syst. 74, 115–139.

DPI NSW, 2018. Riverina Murray Region - Agricultural Profile. NSW Department of Primary Industries and Regional Development.

Freer, M., Moore, A.D., Donnelly, J.R., 1997. GRAZPLAN: decision support systems for Australian grazing enterprise. II. The animal biology model for feed intake, production and reproduction and the GrazFeed DSS. Agr. Syst. 54, 77–126.

Ghahramani, A., Moore, A.D., 2016. Impact of climate changes on existing crop-livestock farming systems. Agr. Syst. 146, 142–155.

Ghahramani, A., Kingwell, R.S., Maraseni, T.N., 2020. Land use change in Australian mixed crop-livestock systems as a transformative climate change adaptation. Agr. Syst. 180, 102791.

Gicheha, M.G., Edwards, G.R., Bell, S.T., Burtt, E.S., Bywater, A.C., 2013. Embedded risk management in dryland sheep systems II. Risk analysis. In: Agricultural Systems.

Godfrey, S.S., Nordblom, T., Ip, R.H.L., Robertson, S., Hutchings, T., Behrendt, K., 2021. Drought shocks and gearing impacts on the profitability of sheep farming. Agriculture 11, 366.

Godfrey, S.S., Ip, R.H.L., Nordblom, T.L., 2022. Risk analysis of Australia's Victorian dairy farms using multivariate Copulae. J. Agric. Appl. Econ. 54, 72–92.

Hardaker, J.B., Lien, G., Anderson, J.R., Huirne, R.B., 2015. Coping with Risk in Agriculture: Applied Decision Analysis, 3rd ed. CABI.

Hutchings, T., Nordblom, T., 2011. A financial analysis of the effect of the mix of crop and sheep enterprises on the risk profile of dryland farms in south-eastern Australia. Austr. Farm Bus. Manag. 8, 19–42.

Hutchings, T., Nordblom, T.L., Guangdi, L., Conyers, M., 2010. Economics of Managing Acid Soils in Dryland Mixed Cropping Systems: Comparing Gross Margins with Whole-farm Analysis Derived Using a Business Process Model, 54th Annual Conference. Australian Agricultural & Resource Economics Society, Adelaide, South Australia, pp. 1–28.

Johnson, I.R., Chapman, D.F., Snow, V.O., Eckard, R.J., Parsons, A.J., Lambert, M.G., Cullen, B.R., 2008. DairyMod and EcoMod: biophysical pasture-simulation models for Australia and New Zealand. Aust. J. Exp. Agric. 48, 621–663.

Kimura, S., Anton, J., 2011. Risk Management in Agriculture in Australia, OCED Food. OECD Publishing, Paris, France, Agriculture adn Fisheries Papers.

Lane, D.M., 2010. Tukey's Honestly Significant Difference (HSD), Encyclopedia of Research Design. SAGE Publications, pp. 1566–1570.

Lehman, D.E., Groenendaal, H., 2020. Practical Spreadsheet Modeling Using @Risk. CRC Press, Boca Raton, FL, USA.

Lodge, G.M., Johnson, I.R., 2008. Agricultural drought analyses for temperate Australia using a biophysical pasture model. 2. Relationship between rainfall and the start and end of predicted droughts. Aust. J. Agr. Res. 59, 1061–1067.

Malcolm, B., Makeham, J., Wright, V., 2005. The Farming Game: Agricultural Management and Marketing, 2nd ed. Cambridge University Press, Melbourne, Australia.

Mathworks, 2023. Matlab & Simulink, Academic Version Release R2023a ed. The Mathworks Inc., Massachusetts, USA.

Meat & Livestock Australia (MLA), 2021a. Saleyard Sheep and Lamb Indicators (New South Wales, Australia).

Meat & Livestock Australia (MLA), 2021b. Sheepskin Prices: Merino Sheep (New South Wales, Australia).

Moore, A.D., 2014. The case for and against perennial forages in the Australian sheep–wheat zone: modelling livestock production, business risk and environmental interactions. Anim. Product. Sci. 54, 2029–2041.

Moore, A.D., Holzworth, D.P., Herrmann, N.I., Huth, N.I., Robertson, M.J., 2007. The common modelling protocol: a hierarchical framework for simulation of agricultural and environmental systems. Agr. Syst. 95, 37–48.

Moore, A.D., Bell, L.W., Revell, D.K., 2009. Feed gaps in mixed-farming systems: insights from the grain & graze program. Anim. Product. Sci. 49, 736–748.

Nordblom, T.L., Penfold, C., Whitelaw-Weckert, M., Norton, M., Howie, J., Hutchings, T. R., 2020. Financial comparisons of under-vine management systems in four south Australian vineyard districts. Austr. J. Agric. Resour. Econ. 65, 246–263.

Nordblom, T.L., Hutchings, T.R., Godfrey, S.S., Schefe, C.R., 2021. Precision variable rate nitrogen for dryland farming on waterlogging Riverine Plains of Southeast Australia. Agr. Syst. 186.

NSW DPIRD, 2018. Livestock Gross Margin Budgets: Sheep Gross Margins 2017–18. NSW Department of Primary Industries and Regional Development.

Obst, J.M., 1987. Grazing management and pasture utilization by sheep, goats or cattle. In: Wheeler, J.L., Pearson, C.J., Robards, G.E. (Eds.), Temperate Pastures their Production, Use and Management. Australian Wool Corporation/CSIRO, Melbourne, Australia, pp. 477–485.

Palisade Decision Tools, 2021. @RISK, Decision Tools Suite 8.2. Palisade Corporation, Ithaca, NY USA.

Robertson, S.M., Friend, M.A., 2020a. The performance of sheep systems grazing perennial pastures 3. Fertility, fecundity and lamb survival. Anim. Product. Sci. 60, 414–422.

Robertson, S.M., Friend, M.A., 2020b. The performance of sheep systems grazing perennial pastures. 2. Wool quality and lamb growth. Anim. Product. Sci. 60.

Robertson, S.M., Friend, M.A., 2020c. Performance of sheep systems grazing perennial pastures. 4. Simulated seasonal variation and long-term production. Anim. Product. Sci. 60, 423–435.

Robertson, S.M., Broster, J.C., Friend, M.A., 2020. The performance of sheep systems grazing perennial pastures. 1. Pasture persistence and enterprise productivity. Anim. Product. Sci. 60, 388–405.

Smith, A.P., Moore, A.D., 2020. Whole farm implications of lucerne transitions in temperate crop-livestock systems. Agr. Syst. 177, 102686.

Thomas, D.T., Moore, A.D., Bell, L.W., Webb, N.P., 2018. Ground cover, erosion risk and production implications of targeted management practices in Australian mixed farming systems: lessons from the grain and graze program. Agr. Syst. 162, 123–135.

Tocker, J., Malcolm, B., Heard, J., Ho, C., Behrendt, K., 2022. Profitable sheep farming in south-West Victoria: specialisation or diversification under volatile prices, costs and climate. Austr. Farm Bus. Manag. J. 19, 21–47.

Villalba, D., Díez-Unquera, B., Carrascal, A., Bernués, A., Ruiz, R., 2019. Multi-objective simulation and optimisation of dairy sheep farms: exploring trade-offs between economic and environmental outcomes. Agr. Syst. 173, 107–118.

Warn, L., Webb Ware, J., Salmon, L., Donnelly, J., Alcock, D., 2006. Analysis of the Profitability of Sheep Wool and Meat Enterprises in Southern Australia: Final Report for Project 1.2.6. Sheep Co-operative Research Centre.