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Improved Whole-farm Planning for Mixed-enterprise Systems in Australia using a Four-stage Stochastic Model with Recourse[1]

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Abstract

Farm management occurs against a backdrop of weather-year variation. In Australian mixed enterprise farming systems, how important is it for farm optimisation models to capture this variation and the management tactics matched to that variation? This study compares two whole farm optimisation models of an Australian mixed enterprise farming system. One model represents weather-year variation and the short-term tactical management responses tailored to the unfolding weather-year conditions. The other model is a traditional deterministic steady state model that employs the key assumption that every year is an expected weather-year. Both models require the farm manager to select a profit-maximising suite of enterprises and activities relevant to either the expected weather-year or the suite of weather-years that typify weather-year variation where the farm is located. Comparison of the models' results reveals key differences in farm strategy, farm tactics and farm profit. The model that includes tactics aligned to the weather-year variation reveals that tactical decision-making increases expected farm profit by about 18 per cent.

Keywords: Risk modelling, discrete stochastic programming, farming systems, farm management tactics, Australian Farm Optimisation Model

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Introduction

Australian mixed enterprise farm systems often encompass a range of soil types, crop options and livestock options (Young et al., 2020; Mosnier et al., 2022; Young and Young, 2022). Farmers' enterprise choices are often constrained by a range of factors including labour availability, an existing complement of farm machinery and animal production infrastructure (e.g. dams, yards and fences), access to finance, managerial preferences and past decisions that influence current resource status and feasible future actions (Ewing et al., 2004). Furthermore, price and climate variability can generate significant production and farm income variability (Laurie et al., 2018; Feng et al., 2022) that can complicate the management of the farming system. Furthermore, price and climate variability can generate significant production variability (Laurie et al., 2018; Feng et al., 2022), which can complicate the management of the farming system. In response, farmers tend to implement a long-term strategic plan tailored to their enterprise preferences, their perception of commodity price outlooks, their familial and financial resources and their existing investments in machinery and related infrastructure.

To deal with seasonal variability that affects their production possibilities, farmers implement tactical adjustments that are deviations from their year-in-year-out strategic or initial farm plan. Tactical adjustments are applied in response to unfolding opportunities or threats and aim to generate additional income or to avoid potential losses (Pannell et al., 2000). The combination of some or all of these factors and actions means Australian farming systems can be complex to analyse and manage (Price and Goode, 2009; Kingwell, 2011).

The intricacies of a mixed enterprise farming system suggest that whole-farm modelling may aid agricultural decision-making (Apland and Hauer, 1993; Pannell, 1996). Agricultural or farming systems in Australia, and internationally, are most frequently modelled either by dynamic simulation (Anderson, 1974; Rozman et al., 2013) or mathematical programming (Kingwell and Pannell, 1987; Annetts and Audsley, 2002; Roughsedge et al., 2003; Schäfer et al., 2017). Dynamic simulation (DS) aims to replicate the behaviour of a system. It is frequently applied to represent biological systems within the farming system (Thomas et al., 2018) or a component of the farming system (Keating et al., 2002; Robertson et al., 2002). Mathematical programming (MP) is a group of optimisation techniques that represents a system using variables, constraints and an objective (Norton et al., 1980; Kingwell and Pannell, 1987). Both DS and MP often achieve more than their simple categorisation implies, as it is feasible to specify an objective in a DS model and search for an optimal solution, and MP techniques can represent simulated biological detail (Kingwell and Pannell, 1987; Young et al., 2011).

The focus of this paper is on MP because it can capture biological and economic interactions of a farming system and allow reliable and efficient optimisation techniques to be applied. In their review of the development and use of farm models for policy impact assessment in the European Union, Reidsma et al. (2018) observe that "MP is thus still the major technique for farm level assessments." (p. 114).

One of the common MP methodologies previously applied to farming systems is the deterministic steady state expected weather-year framework (Young, 1995; Roughsedge et al., 2003). Perhaps the best-known Australian example of this framework is *MIDAS* (Model of an Integrated Dryland Agricultural System) that has been widely applied to a variety of farming system issues in Australia (Morrison et al., 1986; Kingwell and Pannell, 1987; O'Connell et al., 2006; Young, 1995). Another framework is stochastic programming with recourse, also known as state-contingent stochastic programming (Crean et al., 2013; Britz et al., 2014; Featherstone et al., 2019). The primary difference between these two frameworks is their representation of uncertainty. The deterministic steady state expected weather-year framework employs the key assumption that the same management decisions are repeated each year, with that year being an unchanging average, median or modal weather-year.

Hence there is no representation of weather-year uncertainty. By contrast, stochastic programming with recourse represents multiple alternative states of nature, each with a given probability that allows weather-year uncertainty and relevant tactical state-contingent decisions to be represented (Rae, 1971; Crean et al., 2013). Stochastic programming with recourse is brought into equilibrium by making the initial activity levels equal to the probability-weighted average of ending levels (Kingwell et al., 1991; Cacho et al., 1999; Crean et al., 2012; Featherstone et al., 2019).

Previous research that has compared the output from a deterministic steady state expected weather-year model against that of a stochastic programming with recourse model has either been conducted with models that only represent a subsection of the farm system (e.g. Jones et al., 2006), or been conducted in an unsophisticated way that excludes the many intricacies of a farming system and its management (e.g. Crean et al., 2013) or was conducted decades ago (e.g. Kingwell et al., 1992; Cacho et al., 1999). Farming systems, technologies, farm machinery and crop performance have changed greatly in recent decades and these changes bring into question the current relevance and accuracy of the findings of these earlier studies.

These studies identified that weather-year variability and sequential decision making significantly impacted farm management and farm performance metrics and so should not be ignored in farming system analyses. However, for various reasons, much whole-farm research is still conducted using deterministic steady state expected weather-year models (Kopke et al., 2008; Kingwell and Fuchsbichler, 2011; Young et al., 2016; Thamo et al., 2017; Young et al., 2020). Often these models are readily available, relatively easy to use and are regularly updated to maintain their relevance. Nonetheless, due to changes in farm size, farming systems, technologies, farm machinery capabilities, and crop and animal performance over the last three decades it is timely to re-visit the appropriateness of continued reliance on deterministic steady state expected weather-year models and assess once again if stochastic programming with recourse models offer a more accurate and useful representation of farming systems and their optimal management.

Accordingly, in this paper, two modelling frameworks, a deterministic steady state expected weather-year model and a stochastic programming with recourse model, are compared and contrasted to form insights about their relative utility to researchers, farm advisers and farm managers. In this paper, to limit the magnitude of the analysis, we only consider weather uncertainty. The impact of including price uncertainty warrants a separate analysis.

Method

Farm system modelled

The model, with two sub-frameworks, was calibrated to represent a typical farm in the medium rainfall zone of the Great Southern region of Western Australia (Figure 1). The Great Southern region was selected for two reasons. First, the region has been modelled previously for a variety of analyses (Young, 1995; Poole et al., 2002; Young et al., 2011; Trompf et al., 2014) and thus the farm data required is more readily available. Second, the Great Southern region contains 26 per cent of Western Australia's sheep flock (ABARES, 2016), so the selection of this region increases the relevance of the findings from the study to farm businesses dependent on sheep production in Western Australia.

The Great Southern region in Western Australia is characterised by a hot dry summer and autumn, with a winter and spring growing season of 400–650 mm rainfall. Farms are typically a mix of cropping and livestock enterprises. Furthermore, as discussed in the weather-years sub section below, the timing of the start of the growing season, also known as the 'break of season', and the quantity of spring rainfall are key management indicators for farmers in the region.

Figure 1. The Great Southern region in Western Australia

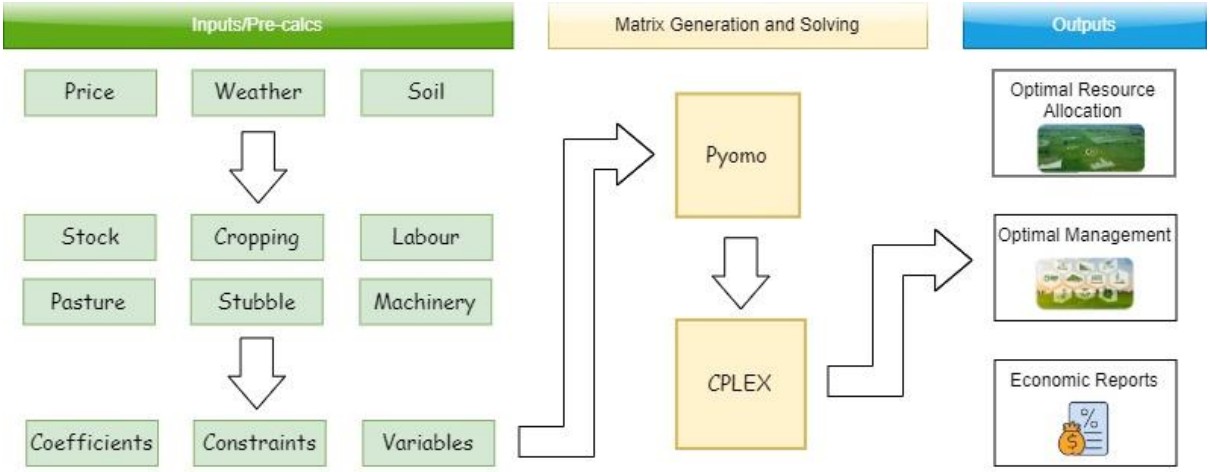
The model was calibrated to represent current farm management technology regarding machinery complement, herbicides and fertilisers used based on discussions with local farm consultants. The tasks contracted and crop and livestock options considered are all consistent with those used currently by farmers in the modelled region and finance availability was not constrained (Tim Trezise *pers. comm.;* Ed Rigall *pers. comm.*).

The model represents a typical 2130 ha farm that includes three land management units to reflect soil heterogeneity in the region. The calibration of crop and pasture inputs was completed through a combination of simulation modelling and expert consultation. The growth rate of the pastures and yield of crops in each rotation were generated using *AusFarm* simulation modelling (Moore et al., 2007), with the output for each individual year simulated and then allocated to a weather-year category. The simulation model output grouped by weather-year categories was reviewed by a local agronomist who applied broad brush scaling to align the yields with farmer practice. Climate data was sourced from the Kojonup weather station for the period 1970 to 2020. Soil data representing the land management units was sourced from the *APSOIL* database (Dalgliesh et al., 2012).

Model overview

Analyses in this study are derived from applying the model named ***A**ustralian **F**arm **O**ptimisation* (*AFO*). In summary, *AFO* is a Python-based, whole-farm MP model that supersedes *MIDAS* (Kingwell and Pannell, 1987; Pannell, 1996; Kopke et al., 2008; Bathgate et al., 2009; Kingwell, 2011; Young et al., 2011; Thamo et al., 2013; Young et al., 2020). *AFO* leverages a powerful algebraic modelling add-on package called *Pyomo* (Hart et al., 2011) and IBMs *CPLEX* solver to efficiently build and solve the farming system model. The model represents the economic and biological detail of a farming system and includes modules for rotations, crops, pastures, sheep, crop residues, supplementary feeding, machinery, labour and finance. Furthermore, it includes land heterogeneity by considering enterprise rotations on a limited range of land management units[2].

Figure 2. Visual representation of *AFO*



A key aspect of *AFO* that makes it suitable for this analysis is its flexible representation of uncertainty. Uncertainty in *AFO* can be included or excluded. Variability or uncertainty is represented using the modelling approach of stochastic programming with recourse (Cocks, 1968; Rae, 1971; Crean et al., 2013; Kim et al., 2018). Stochastic programming with recourse is a formulation of a decision tree (e.g.
Figure 3) consistent with state-contingent analysis (Chambers and Quiggin, 2000; Adamson et al., 2007; Mallawaarachchi et al., 2017). It requires the explicit specification of management choices and their possible consequences. The nodes or event forks are usually represented by a relatively small number of discrete outcomes. The inclusion of uncertainty allows the representation of tactical decisions as the year unfolds, which has been noted as an important aspect of farm management (Pannell et al., 2000; McCown et al., 2006). Furthermore, through the use of an expected utility function, *AFO* has the capacity to represent a farmer's risk attitude in response to uncertainty or variability, although in this study a risk neutral attitude is assumed.

The two different *AFO* frameworks used are:

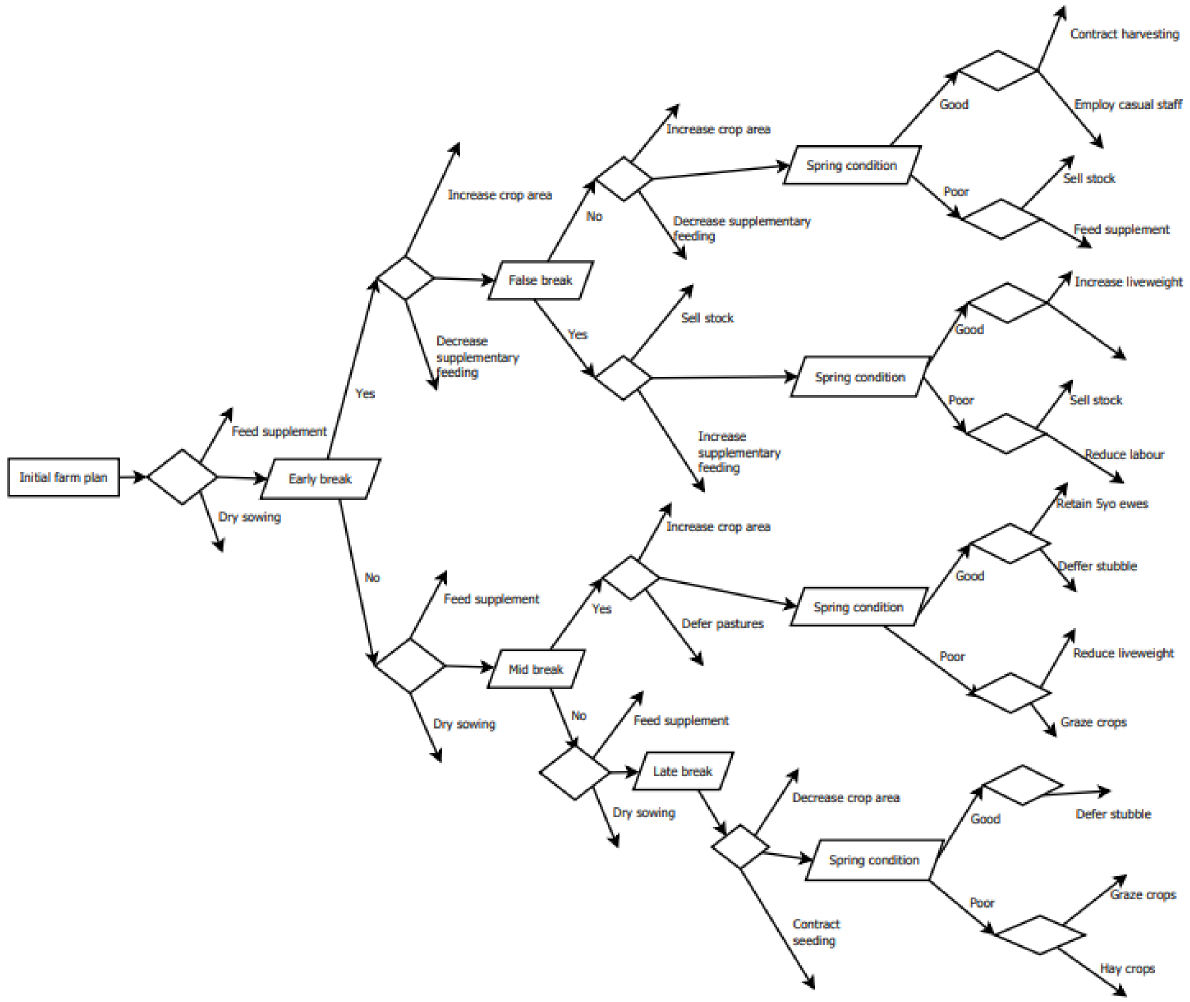
(i) A deterministic steady state expected weather-year framework (DSSE) (e.g. Kingwell and Pannell, 1987). In this framework the farming system is represented as a single discrete state that is statistically the expected weather-year. Representing a farm system by such a single state of nature requires use of expected inputs and outputs (e.g. the wheat yield is the average of all years). It assumes every year is the same and the finishing state equals the starting state. Thus, only strategic (or year-in year-out) management is represented and management does not change between years because there is only one branch of the decision tree being represented. This model includes 83,271 variables and 49,364 constraints.

(ii) A four-stage single-sequence stochastic programming with recourse (4-SPR) (e.g. Kingwell et al., 1991). A 4-SPR model represents the farming system as subject to a portfolio of discrete states of nature where each state represents a different type of weather-year that has separate or unique inputs and outputs to reflect different prices, weather conditions and production outcomes. All states

[2] For a more thorough description see the model's documentation see: https://australian-farm-optimising-model.readthedocs.io/en/latest/index.html.

begin from a common point that is determined by the weighted average of the end of all the weather-years, but then these states separate at various nodes during the production year to unveil the particular nature of that weather-year. To minimise misrepresentation associated with the starting weighted average, the start of the weather-years is defined as the earliest season break. Once a weather-year has been identified, subsequent decisions are differentiated based on the known information about that given weather-year. For example, one node is the start of the growing season or 'break of season'. If that start is what is known colloquially as an 'early break', then after that starting point those types of weather-years can be managed differently to weather-years where the break occurs later. For example, in an early break it may be optimal to crop more area and run a higher stocking rate and vice-versa for a late break, although these decisions can only be made after the break of season is known. However, at the break of the season the subsequent conditions are uncertain (e.g. 30 per cent chance of a poor spring and a 70 per cent chance of a good spring). Thus, the decisions made at the break of season must factor in future uncertainty about the spring conditions. The 4-SPR model examines each possible outcome and its probability to determine the optimal decisions. These decisions are a suite of tactical adjustments made at each node that complement or adjust an overarching farm management strategy. The 4-SPR model is much greater in size, comprising 476,113 variables and 237,956 constraints.

Figure 3. An example of a decision tree associated with weather-year classification



Notes: The parallelograms are nodes that identify the type of weather-year and the diamonds are subsequent decisions. These nodes reflect the Great Southern version of *AFO*, however, the decisions in *AFO* are not limited to what is depicted here.

Tactical decisions in the 4-SPR model

There are many tactical or adjustment options represented in the 4-SPR model. The tactics revolve around enterprise land use area adjustment, land use inputs, whether a crop is harvested or grazed as a standing crop, intensity of machinery use, labour utilisation, seasonal sheep liveweight patterns, tactical sale of sheep, grazing management of pasture and stubble, and supplementary feeding. The same tactical adjustments are made to all weather-years that are indistinguishable from one another at the time a tactical decision is implemented. Such weather-years are clustered at that decision point, as the node that later differentiates these weather-years is still in the future. By illustration, tactical adjustments selected at the early season break node have to be the same for all weather-years that have an early break, because at the time of making the break of season tactical decision the occurrence of follow-up rain and the spring conditions are unknown. Typical tactical adjustments include:

- Rotation phase - The area of each land use can be adjusted depending on the date of season break or other early indicators such as residual soil moisture from summer rainfall. Choice of rotation phase can also be delayed at the break of season, for example waiting to ensure it is not a false break. During this period of delay, pasture will germinate on these paddocks and is able to be grazed (the level of germination is dependent on the rotation history of the paddock).
- Land use inputs – In favourable weather-years additional chemicals and fertiliser can be applied to maximise yields and vice-versa in poor weather-years. In this analysis the input level for each land use on each land management unit in each weather-year was set externally by the model user who relied on the expert advice of experienced agronomists who work in the study region. Their advice accounted for the required clustering of weather-years.
- Fodder crops - In adverse weather-years where either livestock feed is limiting or crops are frosted or are not worth harvesting, saleable crops can be turned into fodder. That is, instead of harvesting a crop it can be grazed by livestock as summer feed.
- Bale crops - Crops planted with the expectation of being harvested for grain can be baled as hay. This may occur in adverse weather-years where either livestock feed is limited or crops are frosted or are not worth harvesting.
- Labour supply - Permanent and manager labour is fixed (i.e. must be the same for all weather-years). However, casual labour can be altered within each weather-year as it unfolds.
- Machinery contracting - If the timeliness of an activity is an issue, contract services can be selected to improve the work rate. This could be valuable in a late break weather-year to ensure the crops get the maximum possible growing season. The assumption that contracting services are available can be changed.
- Dry seeding – This is a useful tactic to improve the timeliness of seeding by sowing into dry soil, before the opening rains, to ensure crops experience the maximum possible growing season.
- Confinement feeding - Confinement feeding can be a useful tactic to allow pasture deferment at the beginning of a growing season or to keep ground cover on paddocks in late summer and autumn.
- Supplement feeding – In-paddock supplement feeding can be used as a tactic to help finish lambs for sale, ensure ewes reach target conditions for reproduction or to help meet their energy requirements during weather-years with poor pasture growth.
- Changing liveweight - Altering livestock liveweight targets can be used as a tactic to handle varying feed availability due to seasonal variation.
- Not mating ewes - If the feed supply is sufficiently poor prior to joining then there is the option of not mating ewes.
- Selling scanned dry ewes or other ewes at scanning – Sale of dry sheep can be a useful tactic if the year is unfolding unfavourably.

- Retain dry ewes - If the strategy is to sell dry ewes, and the weather-year is favourable a tactical adjustment can be to retain the dry ewes until shearing, thereby generating wool income. A further decision can then be made regarding retaining them for mating the following year.
- Selling at other times – The ewes and lambs' sale time can be adjusted, with the value received depending on the liveweight and condition of the animals at sale. In this analysis there were 10 selling opportunities throughout the year for ewes and eight sale opportunities for lambs.

Weather-years

Weather conditions influence crop and pasture growth (e.g. McCown, 1973; Ritchie and Nesmith, 1991). However, modelling the intricacies of weather events leads researchers to experience the "curse of dimensionality" where myriads of different weather events are possible (Burt, 1982). To lessen dimensionality problems associated with representing weather events and their effect on pasture and crop growth, discrete weather states were defined in *AFO* based on their potential to affect farm management. Following a process similar to Kingwell et al. (1991), the classification of weather-years arose, first, from discussions with farmers to identify which features of weather-years most influenced their main farm management decisions, and second, from detailed examinations of the meteorological and farm production characteristics of actual seasons from 1970 to 2020, using the crop growth simulation model, APSIM (Holzworth et al., 2018).

Of main importance to all farmers and advisers were rainfall events. This emphasis placed by farmers on rainfall events, rather than temperature or wind events, was not surprising because in Western Australia rainfall is often the main limiting factor for crop and pasture yields (Pratley and Cornish, 1985; Anderson et al., 1992; Stephens et al., 1994). The particular rainfall events that explain the majority of the production variation between years are first, autumn rainfall events that affect pasture germination and crop sowing date; second, in the case of an early break, whether there are follow up rains or if a false break occurs and finally, the quantity of spring rainfall. Thus, in the 4-SPR framework, variance in weather-years was approximated by eight discrete states of nature (see Table 1).

Table 1. *AFO* weather-years

Code for weather-year	Definition of each weather-year	Probability of occurrence (%)
z0	Early break[1] with follow up rains and a good spring[3].	24
z1	Early break with follow up rains and a poor spring.	20
z2	Early break that turns out to be a false break[2] but is followed up with a good spring.	8
z3	Early break that turns out to be a false break and is followed by a poor spring.	4
z4	Medium break with follow up rains and a good spring.	14
z5	Medium break with follow up rains and a poor spring.	16
z6	Late break with follow up rains and a good spring.	4
z7	Late break with follow up rains and a poor spring.	10

Notes: [1] Early break (i.e. start of the growing season): before the 5th May; Medium break: between the 5th May and 25th May; Late break: after the 25th May. [2] False break: pasture feed on offer reaches 500 kg/ha followed by 3 weeks of no growth. [3] Good spring: above the median (86 mm) rainfall for September and October; Poor spring: below the median rainfall.

By contrast, the DSSE framework has a single discrete state that is an expected weather-year. The effects of each of these states of nature on major input-output relationships of enterprise options are represented in the model.

Production assumptions

The production inputs were generated using the same process, data and assumptions for each framework. As a result, the main model inputs that differ between frameworks are pasture production and crop production. The inputs for the DSSE framework are the weighted average of the inputs for all the weather-years in the 4-SPR framework.

Weather-year prices

Analysis of commodity prices in different weather-years showed that the prices of agricultural products did not significantly correlate with the weather-years experienced in the study region. This is likely to be due to multiple reasons including the region's outputs mostly being sold internationally and so the nature of any weather-year experienced in the region will unlikely affect the international prices received for the region's farm products. In previous decades, such as the 1990s when the state's sheep population exceeded 30 million head (ABARES, 2010) it was more likely, for example, that a drought year would cause a dramatic lowering of sheep prices due to de-stocking decisions by farmers or an increase in fodder prices as demand for supplementary feed increased. However, the state's sheep population is now about 13 million head, and seasonal conditions have far less impact on fodder and saleyard prices (ABARES, 2022). Accordingly, in our analyses, prices were deemed to be unaffected by the weather-year conditions.

Results

The expected profit generated by the 4-SPR framework is $54,549 per year greater than the profit generated by the DSSE framework. The large difference in profit between the models is principally due to the magnitude of additional commercial returns generated by embracing tactical decision-making in the face of weather-year variation. Selection of relevant tactics allows additional profits to be generated in various weather-years, complemented with avoidance of losses in a few other types of weather-years.

The magnitude of additional profits earned, and losses avoided, from embracing tactics is affected by the extent to which the farm strategy involves adopting a crop dominant or livestock dominant enterprise mix. This issue is explored in the Appendix. In the study region the optimal farm strategy typically involves an expected land allocation such that about 60 per cent of the farm's area is devoted to crop production. However, if strategically more of the farm's area is devoted to sheep production, then the difference in expected farm profit generated by each model increases. This reveals that sheep management is particularly sensitive to weather-year variation and tactics. For sheep production the gains in favourable weather-years are not as great as losses in poor years, despite the embrace of various tactical adjustments for the sheep enterprise.

Accompanying these profit differences between the two models are sizable differences in optimal management of the sheep and crop enterprises (Table 2). The strategic 4-SPR farm plans are slightly more crop dominant, especially regarding land allocations to cereal crops, although strategically canola plays a lesser role in the crop mix. Additionally, the 4-SPR modelling results include a 1.5 DSE/ha higher stocking rate accompanied by feeding 76 tonnes more supplements (Table 2). Hence, a more intensive management of the sheep enterprise is revealed in the 4-SPR modelling results.

Table 2. Key descriptors of the optimal farm plans generated by the DSSE and 4-SPR frameworks for a typical Great Southern farm

	DSSE model	4-SPR model
Farm profit ($/year)		
Expected[a]	744,919	799,468
Max[b]		1,206,763
Min[c]		129,063
Stocking rate (DSE/ha)		
Expected	14.6	15.9
Max		17.2
Min		14.0
Supplement fed (t)		
Expected	628	707
Max		1,470
Min		429
Pasture (% of farm area)		
Expected	41	39
Max		43
Min		36
Cereal (% of farm area)		
Expected	30	37
Max		57
Min		28
Canola (% of farm area)		
Expected	29	24
Max		36
Min		4
Flock structure	Ewe dominated flock turning off 90% of lambs at 6 months of age to the prime lamb market.	Ewe dominated flock turning off ~70% of lambs at 6 months of age to the prime lamb market and the remainder at ~12 months of age.

Notes: [a] 'Expected' is the weighted average of all weather-years., [b] 'Max' is the maximum across the weather-years. [c] 'Min' is the minimum across the weather-years.

Further differences in optimal management when weather variation is included are listed below:

(i) More canola is grown in weather-years where there is an early break and more cereals are grown in weather-years with a late break.

(ii) More contract seeding is employed in years with a late break because it is more profitable to pay for additional contracting services to accelerate seeding and mitigate yield losses due to late sowing in these weather-years. Additionally, in weather-years that favour an enlarged cropping program, it is optimal to contract seed in those years (e.g. in weather-years that break early). Additional contract seeding helps ensure crops are established promptly, and any negative impacts of a false break are mitigated when the seeding operation is interrupted due to lack of soil moisture. A false break has little impact on the yield of early sown crops provided they are established while moisture is available early. However, the impact of a false break on pasture production early in the growing season is severe.

(iii) In late break years more dry sowing occurs because it is more profitable to get crops established as quickly as possible and pay for additional in-crop herbicides later in the year, (due to foregoing knock down sprays). Losing crop yield due to later establishment of the crops is a greater expense than the additional cost of herbicides associated with dry sowing.

(iv)In early break years an additional knock down spray is used, which reduces the total crop costs. The additional knock down spray is optimal because it lowers the total herbicide package cost more than the labour and machinery cost incurred with the additional knock down application.

Some of the management tactics listed above (e.g. contract seeding and dry sowing) arise from avoiding crop yield reductions due to untimely sowing of cropping programs. The deterministic steady state expected weather-year framework has only one time of season break and does not represent a false break, so it understates the impacts of certain weather-years on crop production.

Removing the tactical adjustments associated with land use, stocking rate, stock sales and stock liveweight targets from the 4-SPR framework greatly reduces expected farm profit by $144,573 (Table 2 versus
Table 3). This 18 per cent reduction in expected farm profit, caused by removing these tactics in the 4-SPR framework, reveals the worth of embracing these management tactics in the face of weather-year variation.

Table 3. Profit from the 4-SPR model without tactics (all weather-years must have the same management)

	4-SPR with tactics Farm profit ($/year)	4-SPR without tactics Farm profit ($/year)	Difference (%)
Expected	799,468	654,895	18.1
Max	1,206,763	1,019,302	15.5
Min	129,063	41,817	67.6

Note: the tactics constrained were rotation, stocking rate, liveweight targets and dates of sheep sales. The models still optimised grazing management tactics including use of pasture, supplements and crop residues.

Discussion

The comparison between the DSSE and 4-SPR frameworks (Table 2) shows that the inclusion of weather-year uncertainty and relevant management tactics in farm optimisation modelling results in different estimated profits and different strategic farm plans. This is consistent with the results reported by Kingwell et al. (1992), Cacho et al. (1999), Jones et al. (2006) and Crean et al. (2013). Accompanying the strategic farm plans of the 4-SPR model are a suite of associated farm management tactics that bolster farm profit and show how sensitive optimal farm management really is to weather-year variation.

The results from this study contribute to the limited Australian farm management modelling literature on the role and impact of weather-year variation. This current study compares modelling frameworks by applying a newly constructed, full scale, bioeconomic model that accurately represents current farming systems in the Great Southern region of Western Australia. The modelling results reveal important differences between the frameworks regarding key features of farm management such as selection of stocking rate, supplementary feeding and enterprise allocation. The steady state expected weather-year framework overlooks and understates how weather-year variation and associated management tactics impact farm management.

The results from this study support the contention that farm models that explicitly account for weather-year variation and associated tactics are more likely to reveal the nature of optimal farm management regarding the strategic and tactical use of farm resources more accurately. However, an additional gap in our knowledge remains, namely, how similarly or differently will each framework respond to price changes in farm inputs and outputs. For example, if livestock prices increased by 15 per cent would both frameworks respond in the same way? Filling this gap in our knowledge is a subject for further research.

In this study detailed options for tactical adjustment in response to the stochastic outcomes were included. Similar to Kingwell et al. (1992) this study's results showed that it is optimal to apply short-term tactical management adjustments in response to unfolding weather conditions. The 4-SPR results showed that without fully representing tactical management in response to the current weather-year conditions, estimates of profit were reduced by $144,573, or 18 per cent of expected profit (Table 2 vs

Table 3). This is 6 to 8 per cent more than reported by Pannell et al. (2000), which is likely to be the result of regional differences, inflation and the more detailed representation of tactical management in this paper.

The practical implication of these finding is that a farmer with a strategic “set and forget” type management attitude would be substantially worse off by failing to exploit either favourable opportunities or avoid threats associated with weather-year variation. Additionally, the findings suggest that a farm adviser who solely focuses on farm strategy and who does not accurately consider the dynamic nature of farming, and the relevant management tactics applied by farmers, is likely to provide misleading or potentially unhelpful advice.

Furthermore, the importance of accurately representing tactical decision-making also has implications for other types of farming system modelling; for example, when applying dynamic simulation models that represent variation in climate (e.g. CSIRO's *AusFarm*). Accurately describing weather-year variation is only a partial aid to improving farm planning or farm management decision-making. A necessary complementary action is to accurately capture tactical management options relevant to each main type of weather-year. The results reported here show that a farmer's tactical responses to weather-year variation can unleash opportunities to increase farm profitability. However, identifying optimal choices for tactical management, particularly for livestock, is difficult and time-consuming due to the complexity of interactions and the myriad of options and ramifications. Lack of focus or rigour in this area can generate inaccurate findings, which would result in suboptimal allocation of farm resources and financial losses.

Accurately including uncertainty and tactical management into farm modelling requires data, knowledge and a degree of modelling skill that is rarely available. Additionally, the more realistic representation comes at the modelling cost of increased model size and complexity. The DSSE model in this study currently takes 4 minutes to build and solve whereas the 4-SPR model takes 17 minutes. Interpreting the results and model debugging are also tasks that become more time-consuming as model detail increases. However, in the experience of the authors, most time was initially spent on constructing the base DSSE model. The additional time to construct the stochastic component that captured weather-year variation and relevant management tactics was substantial but not excessive and was made more efficient by the flexible nature of modern computer programming. The trade-off between accuracy and complexity, however, raises the question about which framework should be used for different types of analyses. This is an ongoing dilemma faced by many researchers: what is the appropriate level of detail from which to derive valid and relevant findings? (Kingwell et al., 1992; Cacho et al., 1999; Malcolm, 2000; Pannell, 2006).

Conclusion

In this paper the profit and optimal farm management generated by two different farm modelling frameworks that examine a mixed enterprise farming system in the Great Southern region of Western Australia were compared and contrasted. These two frameworks were applied using a whole-farm optimisation model called *AFO*. The principal findings from applying the two separate frameworks are first, that inclusion of weather variation and associated tactical management generates different results from the more commonly applied steady state expected weather-year modelling; and second, tactical decision-making associated with unfolding conditions of the current weather-years generates substantial opportunities to boost farm profit and/or avoid losses.

Despite exponential computational progress that facilitates application of more complex frameworks, choosing the correct framework for an analysis remains a challenge. The model framework applied needs to be relevant to the problem or opportunity or innovation being analysed. The financial reward of responding to that problem, opportunity or innovation needs to be sufficiently large to justify the costs of model construction and application.

Appendix

The underlying nature of the farming system, whether crop dominant or livestock dominant, does affect the value of weather-year tactics available to the farm manager. By illustration, the crop enterprise, as represented by a farm with 100 per cent crop, has similar profitability when weather-year variation is included (Table A1). This indicates a symmetric profit response for lower and higher crop yield. In contrast, the livestock enterprise, as represented by a farm with 100 per cent pasture, has a lower profitability when weather-year variation is included (Table A2), which indicates an asymmetric profit response to lower and higher pasture growth. In the DSSE framework the model can optimise the number of stock for the feed budget which is the same each year and equates to the weighted average of all weather-years. However, in the 4-SPR framework, the feed supply changes each year, with the number of stock being less flexible and this is reflected in the larger requirement for supplementary feed in the 4-SPR model (Table A2).

The inflexible nature of livestock feed requirements between years can be mitigated, to some extent, through tactical livestock management. The tactical management includes retaining or selling an extra age group of stock, adjusting the timing of the livestock sales within the year, altering the target liveweight profile and adjusting the grazing management strategy through altering the target feed-on-offer profile during the year. However, even with the inclusion of these tactical management options, the gains in the favourable years are not as great as losses in poor years for the sheep enterprise and there is a change in farm strategy to reduce the number of livestock carried (Table A2). Hence, the outcome of a symmetric profit response for the crop enterprise and an asymmetric profit response for the livestock enterprise, is that the optimum crop area for the 4-SPR model is higher than in the DSSE model. The need to carry sheep across weather-years restricts the tactical options for flexible sheep management and increases the relative attractiveness of cropping enterprises with their associated tactics.

Table A1. The expected profit, and optimal land allocations to cereals and canola for the DSSE model and 4-SPR model when constrained to all crop

	DSSE model	4-SPR model
Expected profit ($)	435,512	438,626

Cereal (% of farm area)	77	72
Canola (% of farm area)	23	28

Table A2. The expected profit, and optimal stocking rate and supplement feeding for the DSSE model and 4-SPR model when constrained to all pasture

	DSSE model	4-SPR model
Expected profit ($)	571,696	488,270
Expected stocking rate (DSE/ha)	11.4	10.5
Expected supplement fed (t)	1,135	1,376

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