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Representing weather-year variation in whole-farm optimisation models: Four-stage single-sequence vs eight-stage multi-sequence

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Abstract

The trade-off between accuracy and complexity is a common issue faced in farm systems analysis. To provide insights into the importance of representing weather-year sequence in farm modelling, two whole-farm optimisation models are constructed and applied to a mixed enterprise farming system in a subregion of Western Australia. The frameworks are (i) four-stage single-sequence stochastic programming with recourse (4-SPR) to capture weather-year variation and management tactics tailored to each weather-year and (ii) eight-stage multi-sequence stochastic programming with recourse (8-SPR) to outline weather-year sequences and management tactics tailored to particular weather-year sequences. Results show that single-year stochastic programming generates similar expected profit and strategic management as multi-year stochastic programming. However, optimal tactical farm management is affected by the outcome of the previous year. Tactical decision-making in response to the outcome of the preceding weather-year increases profitability by 14%. Technology changes over the last decade, particularly the increase in computer speed and computational power, increase the ease of construction and application of the 4-SPR and 8-SPR frameworks. Nonetheless, choosing which framework is best to apply to a particular issue or opportunity remains a challenge.

KEYWORDS

AFO, Australian Farm Optimisation model, discrete stochastic programming, farming systems, risk modelling, tactical farm management, weather-year sequence

JEL CLASSIFICATION
Q15, Q16

1 | INTRODUCTION

Mixed enterprise farm systems often encompass a range of soil types, crop options and livestock options (Young et al., 2020, Mosnier et al., 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. Given the complexities, farm modelling is often used to aid on-farm decision-making (Kopke et al., 2008, e.g. Bathgate et al., 2009; Young et al., 2020).

A further complication for farm management is price and climate variability, which results in significant production variability (Feng et al., 2022; Laurie et al., 2019). For example, Anderson (1979) estimated that climate variability was responsible for just under 40 per cent of the variation in Australia's gross value of agricultural production and farm income. Malcolm and Wright (2016) note that: 'Framing and managing uncertainty will continue to be a daunting and often insurmountable challenge for the bulk of Australian farmers' (p. 516). To handle these variations, previous research has shown that it is optimal for farmers to adjust both long-term strategic and short-term tactical management (Crean et al., 2013; Kingwell et al., 1992; Kingwell et al., 1993; Young et al., 2023). Accordingly, modelling methods that represent uncertainty have been shown to generate more realistic optimal results. For example, Young et al. (2023) compared the more commonly applied steady-state expected framework with a more realistic stochastic framework and found differences in expected profit of 18% along with significant differences in optimal on-farm management.

Mathematical programming (MP) is a useful and widely applied modelling framework that can capture biological and economic interactions of a farming system whilst applying reliable and efficient optimisation techniques (Reidsma et al., 2018; Young et al., 2022). A branch of MP that facilitates the representation of uncertainty is stochastic programming with recourse (Crean et al., 2012; Flaten & Lien, 2007; Kingwell et al., 1991; Schroeder & Featherstone, 1990; Torkamani & Hardaker, 1996, e.g. Britz et al., 2014; Featherstone et al., 2019). Stochastic programming with recourse represents multiple alternative states of nature, each with a given probability, whilst outlining the tactical state-contingent decisions associated with each state or subgroup states of nature (Crean et al., 2013; Rae, 1971). Stochastic programs are brought into equilibrium by making the initial activity levels equal to the probability-weighted average of ending levels.

Most commonly, in farming system applications of MP, the start and end of the decision framework (see Figure 1) corresponds to an average or median year (e.g. Cacho et al., 1999; Crean et al., 2012; Featherstone et al., 2019; Kingwell et al., 1991; Young et al., 2023). A limitation of these MP applications is that they do not consider the impacts of a sequence of years on farm management and profitability. For example, there is no consideration of consecutive drought years. Previous MP studies of Australian farming systems have not considered a multi-year stochastic environment (Crean et al., 2013; Kingwell et al., 1992), so a gap in the literature exists regarding knowing the extent or implications of the failure to embrace a multi-year framework, even though Featherstone et al. (2019) have identified that multi-year effects could be important for decision-making concerning liquidity risk and credit reserve risk.

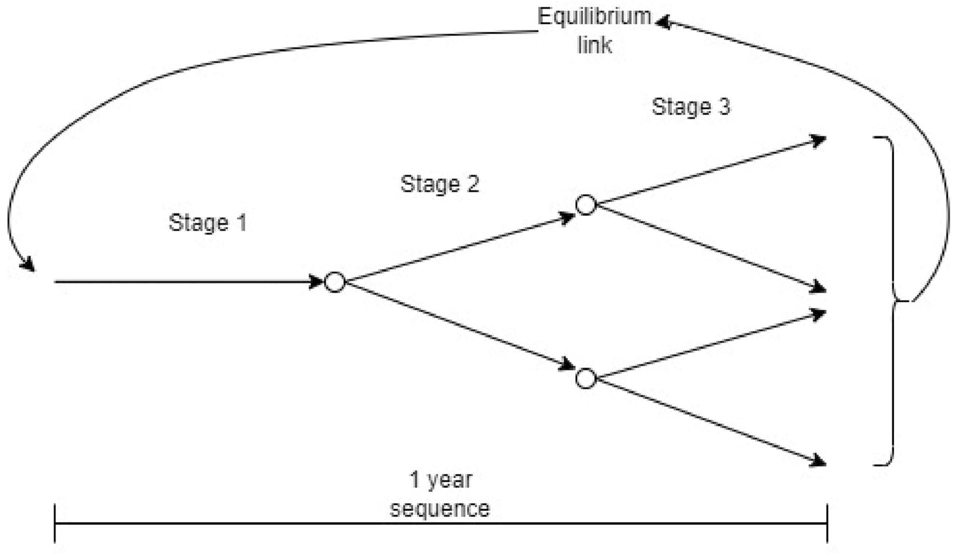

FIGURE 1 General structure of a two-stage, single-year sequence stochastic program with recourse. The starting point is the weighted average of the ending points.

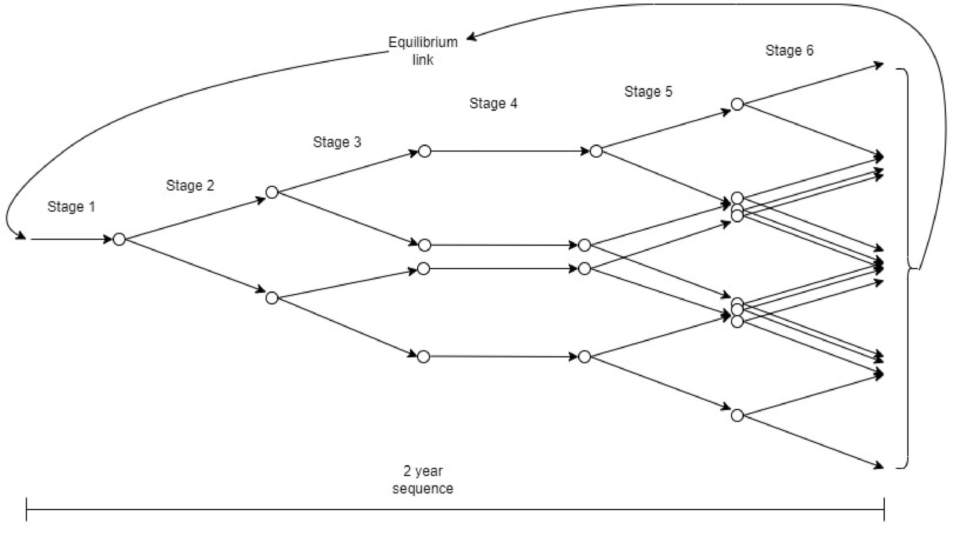

FIGURE 2 General structure of a four-stage, 2-year sequence stochastic program with recourse. The starting point is the weighted average of the ending points.

A multi-year stochastic program framework is illustrated in Figure 2. Each additional year, however, exponentially increases the size and complexity of such a model, causing the problem known as the 'curse of dimensionality' (Burt, 1982). For example, if a single-year stochastic model has 20 terminal states of nature, a two-year sequence model has 400 possible terminal states and a three-year model has 8000 terminal states.

In this paper, we apply a single-year and multi-year stochastic program with recourse to a Western Australian farming system to examine the impact of weather-year sequences and associated decision tactics on optimal farm management and profitability. To limit paper size, we only consider weather uncertainty rather than the additional joint complication of input and output price uncertainty as the latter warrant a similar but separate analysis.

2 | METHOD

2.1 | 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. The Great Southern region was selected for two reasons. First, the region has been modelled previously for a variety of analyses (Poole et al., 2002; Trompf et al., 2014; Young, 1995; Young et al., 2011), and thus, the farm data required are more readily available. Second, the Great Southern region contains 26% of Western Australia's sheep flock (ABARES, 2016), so the selection of this region increases the relevance of the study's findings 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-year subsection 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.

Through discussions with local farm consultants, the model was calibrated to represent current farm management technology regarding machinery complement, herbicides and fertilisers used. Tasks contracted and crop and livestock options considered are all consistent with those used currently by farmers in the modelled region (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 were sourced from the Kojonup weather station (BOM station 10,582) for the period 1970 to 2020. Soil data representing the land management units were sourced from the APSOIL database (Dalgliesh et al., 2012).

2.2 | Model overview

Analyses in this study are derived from applying the **A**ustralian **F**arm **O**ptimisation (AFO) model. A brief summary of the model is provided below. For a more thorough description, see the model's documentation: https://australian-farm-optimising-model.readthedocs.io/en/latest/index.html. In summary, AFO is a Python-based, whole-farm MP model that supersedes the farming system model known as MIDAS (Model of an Integrated Dryland Agricultural System; Kingwell & Pannell, 1987, Pannell, 1996, Young et al., 2020). Australian Farm Optimisation (AFO) leverages an algebraic modelling add-on package called Pyomo (Hart et al., 2011) and IBM's CPLEX solver to efficiently build and solve the farming system model. The model represents the economic and biological details 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.

A key aspect of AFO that makes it suitable for this analysis is its flexible stochastic representation. In AFO, the user can specify the number of years to include in the weather-year sequence. Variability or uncertainty is represented using the modelling approach of stochastic programming with recourse (Cocks, 1968; Crean et al., 2013; Rae, 1971). Stochastic programming is a formulation of a decision tree (e.g. Figures 1–3) consistent with state-contingent analysis (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 (McCown et al., 2006; Pannell et al., 2000). 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. However, in this study we assume a risk-neutral attitude and the two different AFO frameworks used are as follows:

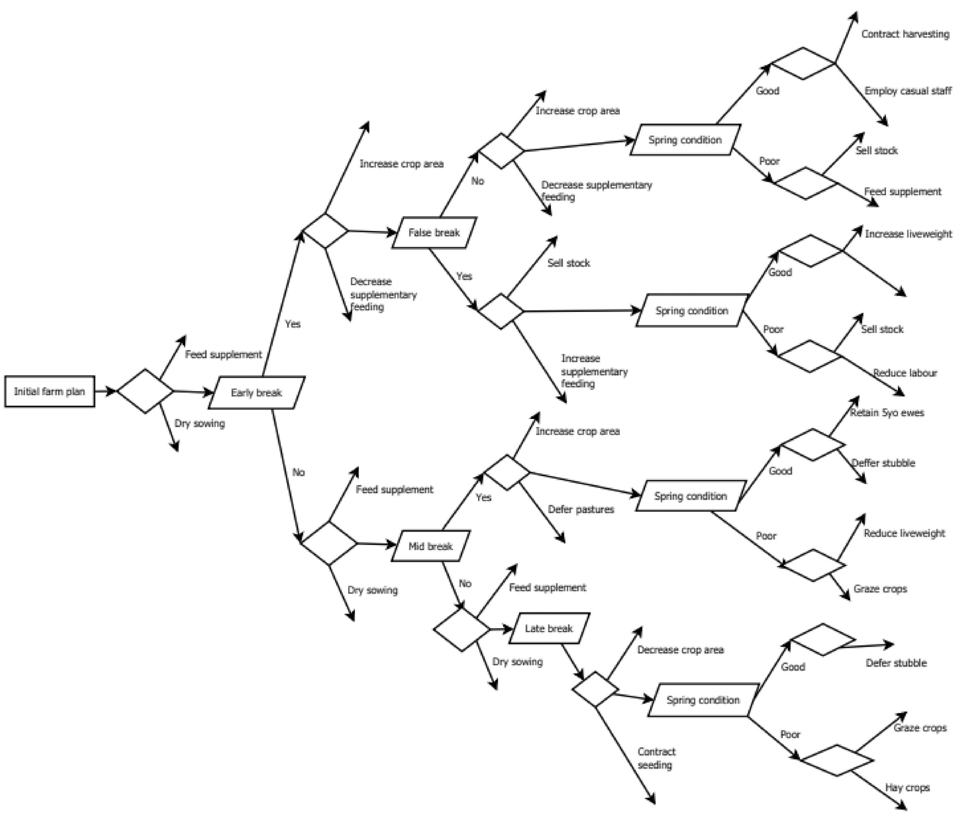

FIGURE 3 Example of a decision tree associated with a weather-year classification. The parallelograms are nodes that identify the type of weather-year, and the diamonds are subsequent decisions. Note, the nodes reflect the Great Southern version of AFO; however, the decisions are not limited to what is depicted.

(i) A four-stage single-sequence stochastic programming with recourse framework (e.g. Kingwell et al., 1991). This framework, known as 4-SPR, represents the farm system with multiple discrete states where each state represents a different weather-year that can have separate inputs to reflect different prices and weather conditions. All states begin from a common point determined by the weighted average of the end of all the weather-years. These states separate at various nodes during the production year to unveil the particular nature of that weather-year. Once a weather-year has been identified, the impact of preceding and subsequent decisions can be 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 typically are made after the break of season is known. In reality, at the break of season the subsequent conditions are uncertain (e.g. 30% chance of a poor spring and a 70% chance of a good spring). Thus, the decisions made at the break of season must factor in future uncertainty about the spring conditions. 4-SPR examines each possible outcome and its probability in determining 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 AFO model that canvasses the four-stage single-sequence stochastic programming with recourse (i.e. the 4-SPR version of AFO) includes 476,113 variables and 237,956 constraints.

(ii) An eight-stage multi-sequence stochastic programming with recourse framework (known as 8-SPR; Xie & Huang, 2018). 8-SPR is similar to 4-SPR with the difference being that the discrete states represent a sequence of weather-years in equilibrium rather than a single year in equilibrium. Optimisation of management within the sequence of weather-years fully accounts for the temporal effects of management change between years. In AFO, the production data in the 8-SPR are the same as the 4-SPR for the individual weather-years. The difference is that the 8-SPR framework more accurately represents carryover management implications from the previous year. For example, if the stock were sold in the previous year, the current year would start with a destocked position. This version of the AFO model includes 4,571,881 variables and 2,140,700 constraints.

The 4-SPR model represents variations between years and tactical management with each year starting with the weighted average end point of all years causing the impacts of consecutive years to not be captured (e.g. late break following a poor spring). However, the 8-SPR model is more realistic because it is an enlarged sequential version of 4-SPR, meaning that variation in management or production in the previous year is reflected in the starting position of the current year. Note, in order to minimise misrepresentation associated with the starting weighted average, the start of the weather-years is defined as the earliest season break.

2.3 | Tactical decisions in the 4-SPR and 8-SPR frameworks

There are many tactical or adjustment options represented in AFO that reflect a farmer's reality. The tactics are similar to, but a greater expansion of those represented by Kingwell et al. (1992) and revolve around 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 remains in 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 is unknown. Typical tactical adjustments include the following:

- 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. Note, in this analysis the input level for each land use on each land management unit in each weather-year is optimised by the user externally to the model, reliant on expert agronomist advice for the study region. The optimisation accounted for the clustering of the 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 is 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 limiting 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 optimised for 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. Note, the assumption that contracting services are available can be changed.
- Dry seeding—A useful tactic to improve timeliness of seeding is to sow into dry soil, before the opening rains, to ensure crops experience the maximum possible growing season.
- Confinement feeding—Confinement feeding can be a good tactic to allow pasture deferment at the beginning of a growing season or to keep ground cover on paddocks in the 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 help meet 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 unfolds unfavourably.
- Retain dry ewes—If the usual 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 and allowing a further decision about 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.

Some aspects of the farm system are represented more realistically in the 8-SPR framework, due to its explicit representation of weather-year sequences rather than assuming each weather-year follows an expected season (as in the 4-SPR framework). These additional aspects include the following:

- Livestock numbers in the year following a destocking event. A valid tactic in a poor production year is to destock. This is represented in the 4-SPR framework as a single occurrence of each weather-year, with the starting stock numbers for the following year being the weighted average of the ending positions of all weather-years. However, if the destocking event involves selling more than one age group of nonreproducing animals or selling reproducing animals prior to them giving birth, then for farmers whose restocking policy is to retain sheep (rather than buy-in), the 4-SPR assumptions do not reflect reality. In practice, the final numbers will be less than the starting numbers, and hence, the following year will start understocked. The 8-SPR framework does represent that if destocking occurs in a current year, then the following year begins with lower stock numbers.
- Requirement for working capital. In the 8-SPR framework, the requirement for working capital varies, based on the closing cashflow position of the previous weather-year. So, years following a poor year may be more constrained by the availability of working capital.
- Feed carried between years. In the 8-SPR framework, the quantity and quality of feed (dry pasture and crop residues or green perennial pasture) carried over will reflect the growing conditions and grazing strategy in the previous spring, summer and autumn.
- Land use sequence. For example, if a previous year was a poor production year, and less canola was grown, then there is more scope to increase the area of canola if the current year is seemingly unfolding to be a favourable production year for canola. This is related to the constraint that canola cannot be grown in consecutive years due to the increased risk of disease.
- Starting liveweight of each animal class. The closing liveweight of animals depends on the growing conditions and grazing strategy in the previous spring, summer and autumn, which affects animal sale values in the following year and in turn may affect subsequent destocking decisions. In the 8-SPR model, the impact of the previous year is fully represented in a destocking decision. By illustration, if a poor year follows a good year so that livestock values are higher, compared with a poor year following a poor year in which livestock values will be lower, the incentive to destock changes.

2.4 | Weather-years

Weather conditions influence crop and pasture growth (e.g. McCown, 1973; Ritchie & Nesmith, 1991). However, modelling the intricacies of weather events leads researchers to experience the 'curse of dimensionality' where myriads of sequences 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 a detailed farm 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's rain-fed farming systems rainfall is often the main limiting factor for crop and pasture yields (Anderson et al., 1992; Stephens et al., 1994). The particular rainfall events that explain the majority of the production variation between years in the simulation modelling are as follows: first, autumn rainfall events that affect pasture germination and crop sowing date; and 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. In the 4-SPR and 8-SPR frameworks, variance in weather-years was approximated by eight discrete states of nature (see Table 1). The effects of each of these states of nature on major input–output relationships of enterprise options are represented in the model.

2.5 | Production assumptions

The production inputs were generated using the same process, data and assumptions for each framework. Importantly, we assume that production in any weather-year is not affected by the previous weather-year; therefore, 4-SPR and 8-SPR use the same inputs. This assumption is unlikely to be valid in regions where stored soil moisture, especially as affected by summer rain, forms a key ingredient to production outcomes. In the Mediterranean-type climate of the study region, the bulk of rainfall occurs from April to October and the hot dry summers limit any carryover of soil moisture and crop pests and diseases. Moreover, unlike the situation in eastern Australia where prolonged dry or wet periods can persist causing production interdependencies across years, repetitious drought or prolonged highly favourable years of production are rare in Western Australia's agricultural region, making the assumption of independence of weather-years more reasonable.

2.6 | 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)

TABLE 1 AFO weather-years.

Code for weather-year	Definition of each weather-year	Probability of occurrence (%)
z0	Early break[a] with follow-up rains and a good spring.[b]	24
z1	Early break with follow-up rains and a poor spring.	20
z2	Early break that turns out to be a false break[c] 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

[a]Early break (i.e. start of the growing season): before 5 May; medium break: between 5 May and 25 May; late break: after 25 May. Season break was defined by soil water reaching 50% of PAWC.

[b]Good spring: above the median (86 mm) rainfall for September and October; poor spring: below the median rainfall.

[c]False break: pasture feed on offer reaches 500 kg/ha followed by 3 weeks of no growth.

it was more likely, for example, that a drought year would cause a dramatic lowering of sheep prices due to destocking decisions by farmers or an increase in fodder prices as demand for supplementary feed increased. However, the state's sheep population is much lower now, about 13 million head thus, 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.

3 | RESULTS

The 4-SPR and 8-SPR models generate similar expected values with the difference in the expected annual profit between the 8-SPR model and the 4-SPR model only being $3276 (0.4%). This difference is due to small changes in the average land use, stocking rate and supplementary feeding (Table 2). However, the 8-SPR model generates a greater range in profit and other farm management indicators across the weather-years compared with the 4-SPR model (see Tables 2 and 3).

The range in profit across weather-years in the 8-SPR model is $1,134,524, and in the 4-SPR model, the range is less at $1,077,700. Yet, in each model the expected profit is similar at $796,191 and $799,468, respectively. This range in profit recorded in the 8-SPR and 4-SPR models reflects the magnitude of variation in crop and pasture production between weather-years and the associated impacts of reliance on short-term tactical management to mitigate or exploit the effects of weather-year variation. In the 8-SPR model, for example, a 5.2 DSE/ha range in stocking rate is observed across the weather-years, along with a 1108 tonne range in supplements fed, a 15% range in the proportion of the farm area that is allocated to pasture and a 43% and 41% range in the proportion of the crop area allocated to canola and cereal, respectively (Table 2).

In the 8-SPR framework, removing tactical adjustments associated with changes in land use, stocking rate, stock sale and stock liveweight targets in response to the end-state of the previous year reduces expected farm profit by $110,247, equivalent to a 14% reduction in expected profit. Removing sequential tactics forces the model to optimise decisions for a given weather-year irrespective of the nature of its preceding weather-year.

4 | DISCUSSION

The results from this study add to the limited MP farm modelling literature that examines the impact of a sequence of years on optimal farm management. In this study, the 8-SPR framework generates an expected profitability and expected management similar to the 4-SPR framework (Table 2). However, importantly, it reveals how the sequence of weather-years generates a larger range in annual profits as well as affects several other aspects of farm management. A previous year's weather and farm management directly affect the initial conditions for the current year and thereby affect subsequent farm management decisions. In extreme sequences (e.g. consecutive poor years or consecutive good years), the allocation of the farm's resources to sheep or crop production shifts further from the expected position due to the weather-year effects. For example, if ewes are retained in good years, the second consecutive good year can have an even greater number of ewes resulting in additional wool and meat income. Overall, this does not affect the expected profit because although the extremes differ from the expected, the probability of these extreme sequences is small and their directional impacts on profit are opposite.

The wider range in features of optimal management, especially for the 8-SPR model, is important to note when using modelling results as the basis of advice to farmers about optimal

TABLE 2 Key descriptors of the optimal farm plans generated by the 4-SPR and 8-SPR frameworks for a typical Great Southern farm.

	4-SPR	8-SPR
Farm profit ($/year)		
Expected[a]	799,468	796,191
Max[b]	1,206,763	1,235,051
Min[c]	129,063	100,527
Stocking rate (DSE/ha)		
Expected	15.9	16.1
Max	17.2	17.8
Min	14.0	12.6
Supplement fed (t)		
Expected	707	705
Max	1470	1500
Min	429	393
Pasture (% of farm area)		
Expected	39	38
Max	43	48
Min	36	33
Cereal (% of farm area)		
Expected	37	38
Max	57	60
Min	28	20
Canola (% of farm area)		
Expected	24	24
Max	36	45
Min	4	2
Flock structure	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.	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.

[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.

management strategies. For example, the optimal proportion of the crop area to plant to canola in a late break year (z6 & z7) varies from a low of 2%, if following a medium break with a good spring (z4), but up to 11% if following a late break with a failed spring (z7; Table 3). This illustrates that compared with single-year analysis, multi-year stochastic programming generates a similar estimated profit but different optimal management of the mixed enterprise farming system, specifically where livestock make a significant contribution to farm income. In short, the nature of optimal farm management, although delivering similar expected profits, is different between the two frameworks.

The 8-SPR model is the more detailed and realistic framework because it represents variation in production associated with a current weather-year as well as the variation in the starting position of the farm associated with the management in the preceding weather-year. An

TABLE 3 Optimal proportion of the crop area sown to canola (%) in the 4-SPR and 8-SPR models. Note, current weather-years that differentiate based on spring conditions have the same land use allocation because land use is selected soon after the break of the season before the spring conditions are known. See Table 1 for descriptions of each weather-year code (e.g. z0).

	Current weather-year			
Previous weather-year	**z0 & z1 (%)**	**z2 & z3 (%)**	**z4 & z5 (%)**	**z6 & z7 (%)**
Average—4-SPR	36	31	14	4
Average—8-SPR	34	32	16	3
z0	34	29	13	3
z1	35	29	13	11
z2	31	28	8	2
z3	32	29	8	6
z4	34	34	13	2
z5	35	33	14	10
z6	45	42	21	4
z7	45	42	21	11

example of the tactical adjustment of the area of canola planted in response to the previous weather-year is provided in Table 3. Not reported in this paper, in the interest of brevity, are a myriad of tactical sheep management decisions that allow the profit downside of certain weather-year sequences to be avoided and the profit upside of other weather-year sequences to be exploited. However, accurately including these tactical management options into farm modelling requires data, knowledge and a degree of modelling skill that is rarely available. Additionally, representing weather-year variation more realistically and the myriad of feasible farm management responses to that variation comes at the modelling cost of increased model size and complexity. With just the standard detail of modelling, the 4-SPR model takes 17 minutes to solve. However, the 8-SPR model with a 2-year sequence takes 6 hours and, while not reported here, the solution results for a 3-year sequence take 15 days.

Interpreting the modelling results and testing and debugging the model for errors are also tasks that become more time-consuming as model detail is enhanced. However, in our experience, most time is spent on the initial construction of the base model. The additional time to construct the model's stochastic components regarding weather-year variation and relevant management tactics is substantial but not excessive and is made more efficient by the flexible nature of modern computer programming.

Previous research has shown that tactical management in response to unfolding weather conditions increases profitability (Kingwell et al., 1992; Kingwell et al., 1993; Pannell et al., 2000). However, this previous research is now two to three decades old and was undertaken using a single-year sequence stochastic modelling that neglected the effect of the preceding year's outcome on the implementation of tactics. By contrast, the results from this study quantify the nature and importance of optimal tactical decisions in response to the outcome of the previous year. Tactical decision-making in response to the end-state of the preceding weather-year in this current study increased the expected profit by 16% (Table 2 vs Table 4). These results show that tactical management in response to the unfolding conditions of a current year is important but is only part of optimal farm management. Also important is the response to the preceding weather-year conditions.

In practice, optimal farm management is increasingly complex (Kingwell, 2011), although Malcolm (2000) has noted that: 'A glance through history suggests that in the most important ways, the fundamental elements of managing a farm has altered little' (p. 40). Even earlier,

TABLE 4 Key descriptors of optimal farm plans for the 8-SPR model without tactical adjustments based on the end-state of the previous year (a given weather-year must be managed the same in all sequences).

Farm profit ($/year)	8-SPR
Expected	685,944
Max	1,135,590
Min	26,524

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

Dillon (1980) noted that: 'Farm management is the process by which resources and situations are manipulated by farm managers in trying, with less than full information, to achieve their goals' (p. 257). Current success in farming is not only about getting the big strategic decisions right in an uncertain and volatile environment with ever-changing technologies (Kingwell et al., 2020), but as this study shows, it is also about getting the details right as well.

Previous researchers in this field have identified the constant need to improve farm decision-making (Malcolm, 2000; Schultz, 1939). Schultz (1939) highlighted that two interrelated farm management decisions needed to be made: (i) the amount of needed adjustment and (ii) the method of adjustment. More recently, other researchers have identified the benefits from farmers undertaking small improvements to their practices; the 'one percenters' (Kingwell, 2019; Kirk & Hall, 2015). In this current study, the particular worth of tactical decision-making in the face of unfolding weather-year conditions is highlighted.

5 | CONCLUSION

In this paper, we have compared and contrasted the profit and optimal farm management generated from two different MP frameworks that examine a mixed enterprise farming system in a subregion of Western Australia. These two frameworks were applied using a whole-farm optimisation model called AFO. The principal findings are as follows: first, that multi-year stochastic programming generates a similar expected profit and expected management as single-year stochastic programming. However, optimal farm management in a given year is affected by the outcome of the previous year; and second, tactical decisions associated with the unfolding conditions of a current weather-year are not easily generalisable to a multi-year framework. The implication is that tactical decisions relevant to the unfolding conditions of a current weather-year are rarely reliable and sufficient indicators of what is appropriate in a sequence of weather-years. The end-state of a preceding weather-year significantly alters the nature of subsequently optimal tactical decisions.

Although computational capacity and data availability will likely continue to increase exponentially, in our view the 8-SPR framework is currently too complex for widespread use. By contrast, the 4-SPR framework is quicker and easier to apply, yet its inability to accurately capture important aspects of multi-year effects will constrain its applicability and credibility among potential farmer end users. Overcoming this nexus between ease of applicability and accuracy of impact estimation will be the subject of ongoing research and development.

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DATA AVAILABILITY STATEMENT

All data used in this paper have been referenced and are publicly available.

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REFERENCES

ABARES. (2010) *Australian agricultural commodity statistics: sheep* [Online]. Available from: https://www.agriculture.gov.au/abares/research-topics/agricultural-outlook/data#_2010

ABARES. (2016) *Australian agricultural census 2015–16 visualisations* [Online]. Available from: http://www.agriculture.gov.au/abares/data/agricultural-census-visualisations#production-area-number-and-yield

ABARES. (2022) *Australian agricultural commodity statistics: sheep* [Online]. Available from: https://www.agriculture.gov.au/abares/research-topics/agricultural-outlook/data#_2022

Adamson, D., Mallawaarachchi, T. & Quiggin, J. (2007) Water use and salinity in the Murray? Darling Basin: a state-contingent model. *Australian Journal of Agricultural and Resource Economics*, 51, 263–281.

Anderson, J.R. (1979) Impacts of climatic variability in Australian agriculture: a review. *Review of Marketing and Agricultural Economics*, 47, 147–177.

Anderson, W., French, R. & Seymour, M. (1992) Yield responses of wheat and other crops to agronomic practices on duplex soils compared with other soils in Western Australia. *Australian Journal of Experimental Agriculture*, 32, 963–970.

Bathgate, A., Revell, C. & Kingwell, R. (2009) Identifying the value of pasture improvement using wholefarm modelling. *Agricultural Systems*, 102, 48–57.

Britz, W., Lengers, B., Kuhn, T. & Schäfer, D. (2014) *A highly detailed template model for dynamic optimization of farms*. Institute for Food and Resource Economics, University of Bonn. Model Documentation.

Burt, O.R. (1982) Dynamic programming: has its day arrived? *Western Journal of Agricultural Economics*, 7, 381–393.

Cacho, O., Bywater, A. & Dillon, J. (1999) Assessment of production risk in grazing models. *Agricultural Systems*, 60, 87–98.

Cocks, K. (1968) Discrete stochastic programming. *Management Science*, 15, 72–79.

Crean, J., Parton, K. & Mullen, J. (2012) *A discrete stochastic programming model of a mixed farm in Central West NSW*. Economic Research Report.

Crean, J., Parton, K., Mullen, J. & Jones, R. (2013) Representing climatic uncertainty in agricultural models–an application of state-contingent theory. *Australian Journal of Agricultural and Resource Economics*, 57, 359–378.

Dalgliesh, N., Cocks, B. & Horan, H. (2012) *APSoil-providing soils information to consultants, farmers and researchers*. 16th Australian agronomy conference, Armidale, NSW.

Dillon, J.L. (1980) The definition of farm management. *Journal of Agricultural Economics*, 31, 257–258.

Featherstone, A.M., Baker, T.G. & Preckel, P.V. (2019) Modeling dynamics and risk using discrete stochastic programming: a farm capital structure application. In: *Applications of dynamic programming to agricultural decision problems*. Boca Raton, FL: CRC Press.

Feng, P., Wang, B., Macadam, I., Taschetto, A.S., Abram, N.J., Luo, J.-J. et al. (2022) Increasing dominance of Indian Ocean variability impacts Australian wheat yields. *Nature Food*, 3, 862–870.

Flaten, O. & Lien, G. (2007) Stochastic utility-efficient programming of organic dairy farms. *European Journal of Operational Research*, 181, 1574–1583.

Hart, W.E., Watson, J.-P. & Woodruff, D.L. (2011) Pyomo: modeling and solving mathematical programs in python. *Mathematical Programming Computation*, 3(3), 219–260.

Holzworth, D., Huth, N.I., Fainges, J., Brown, H., Zurcher, E., Cichota, R. et al. (2018) APSIM next generation: overcoming challenges in modernising a farming systems model. *Environmental Modelling and Software*, 103, 43–51.

Kingwell, R. (2011) Managing complexity in modern farming. *Australian Journal of Agricultural and Resource Economics*, 55, 12–34.
Kingwell, R. (2019) Disruptive change in the international grain trade: implications for Australia. *Farm Policy Journal*, 16, 55–62.
Kingwell, R., Islam, N. & Xayavong, V. (2020) Farming systems and their business strategies in South-Western Australia: a decadal assessment of their profitability. *Agricultural Systems*, 181, 102827.
Kingwell, R., Morrison, D.A. & Bathgate, A. (1991) *MUDAS: model of an uncertain dryland agricultural system: a description*. Western Australian Department of Agriculture: South Perth.
Kingwell, R., Morrison, D.A. & Bathgate, A.D. (1992) The effect of climatic risk on dryland farm management. *Agricultural Systems*, 39, 153–175.
Kingwell, R. & Pannell, D. (1987) *MIDAS, a bioeconomic model of a dryland farming system*. Wageningen, the Netherlands: Pudoc.
Kingwell, R.S., Pannell, D.J. & Robinson, S.D. (1993) Tactical responses to seasonal conditions in whole-farm planning in Western Australia. *Agricultural Economics*, 8, 211–226.
Kirk, G. & Hall, E. (2015) *Drivers of farm business – what keeps the top 25% at the top?* [Online]. Available from: https://grdc.com.au/resources-and-publications/grdc-update-papers/tab-content/grdc-update-papers/2015/03/drivers-of-farm-business-what-keeps-the-top-25-at-the-top
Kopke, E., Young, J. & Kingwell, R. (2008) The relative profitability and environmental impacts of different sheep systems in a Mediterranean environment. *Agricultural Systems*, 96, 85–94.
Laurie, A., Curtis, M., Heath, R., Mcrobert, K. & Darragh, L. (2019) *Australian agriculture: an increasingly risky business*. Surry Hills, NSW: Australian Farm Institute.
Malcolm, B. (2000) *Farm management economic analysis: a few disciplines, a few perspectives, a few figurings, a few futures*. Annual Conference of Australian Agricultural and Resource Economics Society.
Malcolm, B. & Wright, V. (2016) Antipodean agricultural and resource economics at 60: farm management. *Australian Journal of Agricultural and Resource Economics*, 60, 516–530.
Mallawaarachchi, T., Nauges, C., Sanders, O. & Quiggin, J. (2017) State-contingent analysis of farmers' response to weather variability: irrigated dairy farming in the Murray Valley, Australia. *Australian Journal of Agricultural and Resource Economics*, 61, 36–55.
Mccown, R. (1973) An evaluation of the influence of available soil water storage capacity on growing season length and yield of tropical pastures using simple water balance models. *Agricultural Meteorology*, 11, 53–63.
Mccown, R., Brennan, L. & Parton, K. (2006) Learning from the historical failure of farm management models to aid management practice. Part 1. The rise and demise of theoretical models of farm economics. *Australian Journal of Agricultural Research*, 57, 143–156.
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. *Agricultural Systems*, 95, 37–48.
Mosnier, C., Benoit, M., Minviel, J.J. & Veysset, P. (2022) Does mixing livestock farming enterprises improve farm and product sustainability? *International Journal of Agricultural Sustainability*, 20, 312–326.
Pannell, D.J. (1996) Lessons from a decade of whole-farm modeling in Western Australia. *Applied Economic Perspectives and Policy*, 18, 373–383.
Pannell, D.J., Malcolm, B. & Kingwell, R.S. (2000) Are we risking too much? Perspectives on risk in farm modelling. *Agricultural Economics*, 23, 69–78.
Poole, M., Turner, N.C. & Young, J. (2002) Sustainable cropping systems for high rainfall areas of southwestern Australia. *Agricultural Water Management*, 53, 201–211.
Rae, A.N. (1971) An empirical application and evaluation of discrete stochastic programming in farm management. *American Journal of Agricultural Economics*, 53, 625–638.
Reidsma, P., Janssen, S., Jansen, J. & Van Ittersum, M.K. (2018) On the development and use of farm models for policy impact assessment in the European Union–a review. *Agricultural Systems*, 159, 111–125.
Ritchie, J.T. & Nesmith, D.S. (1991) Temperature and crop development. *Modeling Plant and Soil Systems*, 31, 5–29.
Schroeder, T.C. & Featherstone, A.M. (1990) Dynamic marketing and retention decisions for cow-calf producers. *American Journal of Agricultural Economics*, 72, 1028–1040.
Schultz, T.W. (1939) Theory of the firm and farm management research. *Journal of Farm Economics*, 21, 570–586.
Stephens, D., Walker, G. & Lyons, T. (1994) Forecasting Australian wheat yields with a weighted rainfall index. *Agricultural and Forest Meteorology*, 71, 247–263.
Torkamani, J. & Hardaker, J.B. (1996) A study of economic efficiency of Iranian farmers in Ramjerd district: an application of stochastic programming. *Agricultural Economics*, 14, 73–83.
Trompf, J., Young, J., Ferguson, M., Anderson, G., Tocker, J., Vogt, S. et al. (2014) *More lambs more often – bullet proofing your business against variable seasons*. Hamilton Victoria: Rural Industries Skill Training.

Xie, F. & Huang, Y. (2018) A multistage stochastic programming model for a multi-period strategic expansion of biofuel supply chain under evolving uncertainties. *Transportation Research Part E: Logistics and Transportation Review*, 111, 130–148.

Young, J. (1995) *MIDAS: model and documentation for the great southern model (version GSM92-3)*. Nedlands, Western Australia: University of Western Australia.

Young, J., Thompson, A., Curnow, M. & Oldham, C. (2011) Whole-farm profit and the optimum maternal liveweight profile of merino ewe flocks lambing in winter and spring are influenced by the effects of ewe nutrition on the progeny's survival and lifetime wool production. *Animal Production Science*, 51, 821–833.

Young, M., Kingwell, R., Young, J. & Vercoe, P. (2020) An economic analysis of sheep flock structures for mixed enterprise Australian farm businesses. *Australian Journal of Agricultural and Resource Economics*, 64, 677–699.

Young, M., Vercoe, P.E. & Kingwell, R.S. (2022) Optimal sheep stocking rates for broad-acre farm businesses in Western Australia: a review. *Animal Production Science*, 62, 803–817.

Young, M., Young, J., Kingwell, R. & Vercoe, P. (2023) Improved whole-farm planning for mixed-enterprise Systems in Australia using a four-stage stochastic model with recourse. *Australian Farm Business Management*, 20. Available from: https://blog.une.edu.au/afbm-journal/2023/08/15/improved-whole-farm-planning-for-mixed-enterprise-systems-in-australia-using-a-four-stage-stochastic-model-with-recourse/

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