NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

THESIS

MANAGING UNCERTAINTY IN AGRICULTURAL PRODUCTION: A TWO-STAGE STOCHASTIC PROGRAMMING APPROACH

by

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June 2023

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REPORT DOCUMENTATION PAGE				*Form Approved OMB No. 0704-0188*
Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instruction, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188) Washington, DC, 20503.				
1. AGENCY USE ONLY ***(Leave blank)***	**2. REPORT DATE** June 2023	**3. REPORT TYPE AND DATES COVERED** Master's thesis		
4. TITLE AND SUBTITLE MANAGING UNCERTAINTY IN AGRICULTURAL PRODUCTION: A TWO-STAGE STOCHASTIC PROGRAMMING APPROACH				**5. FUNDING NUMBERS**
6. AUTHOR(S) Sean Cahir				
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Naval Postgraduate School Monterey, CA 93943-5000				**8. PERFORMING ORGANIZATION REPORT NUMBER**
9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES) N/A				**10. SPONSORING / MONITORING AGENCY REPORT NUMBER**
11. SUPPLEMENTARY NOTES The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government.				
12a. DISTRIBUTION / AVAILABILITY STATEMENT Approved for public release. Distribution is unlimited.				**12b. DISTRIBUTION CODE** A
13. ABSTRACT (maximum 200 words)				

Agriculture, a crucial contributor to Australia's GDP, exports, and economy, involves inherent risk and uncertainty. Amidst these challenges, Australian farmers must craft optimal crop and livestock strategies to minimize risk whilst meeting their objectives. Traditional mathematical programming methods have aided resource allocation but fail to adequately address the uncertainty surrounding future market conditions and input parameters. This thesis explores two-stage stochastic optimization to enhance Australian small farm performance under uncertainty. We model uncertain events impacting farm operations as probability distributions, aiming for improved resource allocation and risk management. The stochastic program maximizes mean profit, worst-case profit, and optimizes the superquantile. Compared to deterministic approaches, our model increases the mean profit by 4.3%, raises the lowest 10% profits by 20.5% via the superquantile objective, and elevates the minimum profit by 140.8% when maximizing the worst-case profit. Our approach facilitates strategic planning and risk management within Australia's farming sector.

14. SUBJECT TERMS uncertainty, stochastic optimization, agriculture, two-stage stochastic optimization with simple recourse, optimization, loss-minimization			**15. NUMBER OF PAGES** 73
			16. PRICE CODE
17. SECURITY CLASSIFICATION OF REPORT Unclassified	**18. SECURITY CLASSIFICATION OF THIS PAGE** Unclassified	**19. SECURITY CLASSIFICATION OF ABSTRACT** Unclassified	**20. LIMITATION OF ABSTRACT** UU

NSN 7540-01-280-5500 Standard Form 298 (Rev. 2-89) Prescribed by ANSI Std. 239-18

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MANAGING UNCERTAINTY IN AGRICULTURAL PRODUCTION: A TWO-STAGE STOCHASTIC PROGRAMMING APPROACH

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Submitted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE IN OPERATIONS RESEARCH

from the

NAVAL POSTGRADUATE SCHOOL
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ABSTRACT

Agriculture, a crucial contributor to Australia's GDP, exports, and economy, involves inherent risk and uncertainty. Amidst these challenges, Australian farmers must craft optimal crop and livestock strategies to minimize risk whilst meeting their objectives. Traditional mathematical programming methods have aided resource allocation but fail to adequately address the uncertainty surrounding future market conditions and input parameters. This thesis explores two-stage stochastic optimization to enhance Australian small farm performance under uncertainty. We model uncertain events impacting farm operations as probability distributions, aiming for improved resource allocation and risk management. The stochastic program maximizes mean profit, worst-case profit, and optimizes the superquantile. Compared to deterministic approaches, our model increases the mean profit by 4.3%, raises the lowest 10% profits by 20.5% via the superquantile objective, and elevates the minimum profit by 140.8% when maximizing the worst-case profit. Our approach facilitates strategic planning and risk management within Australia's farming sector.

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List of Acronyms and Abbreviations

ABARES Australian Bureau of Agricultural and Resource Economics and Sciences

DAFF Department of Agriculture, Fisheries, and Forestry

EEV Expected Value Solution

EVPI Expected Value of Perfect Information

GDP Global Domestic Product

NOLH Nearly Orthogonal Latin Hypercube

NSW New South Wales

RP Recourse Problem

WS Wait-and-See Value

VSS Value of Stochastic Solution

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Executive Summary

This thesis provides a comprehensive overview of the development, implementation, and significant findings from a two-stage stochastic programming model for an Australian farm. The integrated model amalgamates crop production, Angus cattle, Merino wool, and prime lamb production, providing a broad spectrum of possible farming strategies. The principal objective of this thesis is to showcase the potential of stochastic programming in managing the uncertainties inherent in agricultural decision-making, while simultaneously delivering precise farming strategies according to farmers' objectives and risk tolerance.

A substantial component of this thesis involves the exploration and review of the existing body of knowledge in stochastic programming and its diverse applications in agriculture. These findings inform the innovative design of the two-stage stochastic programming model, which incorporates multiple objectives and addresses uncertainties in agricultural decision-making.

Implemented using Python, the Pyomo library, and the Gurobi and CBC solvers, the model offers a robust and efficient solution to the optimization problem. The detailed explanation of the model's methodology highlights the importance of selecting suitable objective functions and integrating uncertainty into decision-making.

A critical part of this study involves comparing the stochastic models to a deterministic model, optimized for a specific scenario. When applied across a multitude of scenarios, the deterministic model consistently underperforms compared to its stochastic counterparts. This stark contrast illustrates the shortfalls of decision-making processes that do not account for uncertainty.

The model's key findings demonstrate the feasibility of employing stochastic programming to guide farmers in making informed decisions under uncertainty. By maximizing the mean profit, the average profit increases by 4.3% when compared to a deterministic model, optimized for a specific scenario. Utilizing the superquantile objective raises the bottom 10% profits by 20.5% while the maximising the worst-case profit elevates the minimum profit by an impressive 140.8%.

These results carry substantial implications for farmers. Now, with the insights provided by the model, they can make decisions with greater confidence and significantly reduced risk. This thesis effectively demonstrates the value of stochastic programming as a decision-making tool for Australian farmers, particularly those operating diversified farms. By incorporating uncertainty and risk tolerance into the decision-making process, it provides valuable insights into potential farming strategies, leading to improved efficiency and sustainability in the industry. It ultimately serves as a successful decision aid, paving the way for future research and development in this compelling field.

Acknowledgments

I would like to take this opportunity to thank my family and professors for their support and assistance throughout the completion of my thesis. As an international student, studying overseas away from friends and family has its challenges, but my wife Emily was a constant source of encouragement, accompanying me every step of the way. I am grateful for her support.

I also wish to express my appreciation to my advisor, Prof. Johannes Royset and second reader, Prof. Javier Salmeron-Medrano, who were consistently available to address my queries and offer guidance as I worked on my thesis.

My interest in the subject matter of my thesis was further enriched by the opportunity to discuss it with someone running a farm back home. I am thankful to my father-in-law, Tom Glover, for sharing his insights, which significantly enhanced my understanding and allowed me to complete my thesis to the best of my ability.

My families and professors' guidance, expertise, and encouragement were invaluable, and I could not have achieved this milestone without them and am eager to continue expanding my knowledge and skills in this field.

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CHAPTER 1: Introduction and Background

1.1 Australian Agriculture

Australia's agriculture sector plays a significant role in its economy, contributing to its Global Domestic Product (GDP), exports, and employment opportunities, particularly in rural areas (ABARES 2023). In this thesis, we develop an optimization model that helps small Australian farmers decide which livestock or crops should be produced to maximize their objectives under uncertainty.

The Australian agricultural industry is diverse, encompassing various enterprises ranging from small family-owned farms to large-scale commercial operations. Some of Australia's most common farming practices include livestock production (such as cattle, sheep, and poultry) and cropping (wheat, barley, canola, and other grains). Small businesses are the backbone of Australia's agricultural sector, with many family-owned farms contributing significantly to local communities and economies. However, large commercial enterprises also play a vital role in the industry, as they often drive innovation, create jobs, and contribute to the country's exports.

In recent years, the value of agricultural exports has increased, partly due to growing demand from international markets, particularly in Asia. Despite the challenges faced by the industry, such as droughts, fluctuating global market prices, and trade sanctions, agriculture remains a vital pillar of the Australian economy, and its continued growth and sustainability are essential for the country's overall well-being.

1.1.1 Challenges faced by Australian farmers

Australian farmers encounter numerous challenges that adversely impact their productivity, profitability, and overall well-being. One of the most significant and persistent challenges is the unpredictable nature of weather patterns, including droughts and inconsistencies in rainfall (Hughes and Gooday 2022). Prolonged periods of drought can severely affect crop yields and livestock production, resulting in financial strain and emotional distress for farmers.

Global market fluctuations represent another challenge for Australian farmers. Commodity prices are influenced by demand, supply, and political developments, which can create instability and uncertainty for farmers trying to plan and manage their operations (Greenville et al. 2020). Further, trade sanctions and restrictions, such as those imposed by China in recent years, can occur quickly, without warning, and significantly disrupt the export market for Australian agricultural products (Ferguson et al. 2022).

Labor shortages also pose a considerable challenge for the Australian agricultural sector, particularly for tasks that require specialized skills, such as shearing. The industry often relies on seasonal and temporary workers to fulfill its labor needs. However, factors such as visa restrictions, rural isolation, and competition from other sectors can result in a scarcity of available workers, impacting productivity and increasing operational costs.

In addition to these challenges, farmers must also contend with other issues, such as pests and diseases, climate change, and water management. These uncertainties highlight the difficulties in agricultural decision-making and the need for sound strategies that help farmers manage risks and optimize operations amidst these unpredictable factors.

1.2 Current Methods of Assistance to Australian Farmers

1.2.1 Government schemes and loans

Recognizing the importance of the challenges farmers face, various Australian governments have implemented a range of assistance measures to help support and sustain the agricultural sector. For example, the Australian, New South Wales (NSW) state government has established several programs to provide financial support, promote innovation, and enhance resilience among farmers. One such initiative is the NSW Farm Innovation Fund, which offers funding to support the implementation of innovative and sustainable projects that improve farm resilience and productivity. These projects may include water-saving infrastructure, soil conservation measures, or the adoption of new farming technologies.

To address the financial challenges faced by farmers during droughts, the NSW government also provides drought financial assistance. This assistance aims to alleviate financial pressure on farmers by offering low-interest loans and grants to help them meet their immediate needs, such as purchasing fodder and water, and to support them in investing in long-term drought preparedness measures.

Another notable program is the Farm Business Resilience Program, which offers training to help farmers develop the skills and knowledge to plan for and manage risks effectively. By participating in this program, farmers can learn about risk management, business planning, and decision-making strategies that will enable them to adapt and respond to the uncertainties and challenges inherent in the agricultural sector.

These government schemes and loans demonstrate a clear understanding of the importance of addressing the issues faced by Australian farmers and highlight the commitment to providing targeted support to ensure the ongoing sustainability and resilience of the agricultural sector.

1.2.2 ABARES *farmpredict* Simulation Model

The Australian Government, through the Department of Agriculture, Fisheries, and Forestry (DAFF), has also developed a tool called *farmpredict*, to aid farmers in making informed decisions and managing their farm businesses more effectively (Hughes et al. 2019). This microsimulation model leverages data from the Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) farm survey program and utilizes machine learning methods to predict individual farm business outcomes based on prevailing climate conditions, commodity prices, and other farm-specific factors.

ABARES *farmpredict* is actively used for farm forecasting, drought monitoring, and climate scenario modelling, illustrating the federal government's commitment to creating tools that help Australian farmers manage their operations more efficiently and effectively. By offering farmers access to such advanced predictive tools, the government empowers them to make data-driven decisions that can enhance their farm businesses' resilience, productivity, and profitability in the face of various uncertainties and challenges. This model is further explored in Chapter 2.

1.3 Thesis Overview

1.3.1 Two-stage stochastic programming approach with simple recourse

Stochastic programming is an optimization technique incorporating uncertainty into decision-making by modeling uncertain events using probability distributions. The two-stage stochastic programming approach is a specific type of stochastic programming that divides the decision-making process into two stages: the first stage involves making decisions before the uncertain events occur, while the second stage involves making decisions after the uncertain events are realized to minimize the costs or risks associated with these events.

In a two-stage stochastic programming approach with simple recourse, the second-stage decisions are designed to provide a "recourse" or corrective action to address the consequences of the uncertain events. The objective is typically to minimize the expected cost or risk associated with these recourse actions. This approach offers several advantages over traditional optimization methods, such as deterministic mathematical programming techniques:

- **Explicitly accounting for uncertainty:** Stochastic programming allows for considering multiple scenarios and the associated probabilities, providing a more realistic representation of the uncertainties farmers face in their decision-making processes.
- **Improved risk management:** By incorporating uncertainty and recourse actions into the optimization framework, farmers can make more informed decisions that better balance risks and rewards, enhancing their ability to manage risks and maintain the long-term viability of their farm businesses.
- **Greater flexibility and adaptability:** The two-stage stochastic programming approach enables farmers to make decisions that account for a wide range of potential outcomes, allowing them to adapt to changing conditions and unforeseen events more effectively.

By exploring and applying the two-stage stochastic programming approach with simple recourse to agricultural decision-making, this thesis demonstrates the benefits of this optimization technique in helping farmers make more informed and strategic decisions under uncertainty, ultimately improving their risk management capabilities and resilience of their farm businesses.

1.3.2 Objective functions and risk management strategies

In the two-stage stochastic programming approach, various objective functions can be used to guide the optimization process, each reflecting different risk management strategies and priorities. In this thesis, we will explore the following objective functions:

- **Maximizing mean profit:** This objective function maximizes the average profit across all scenarios, focusing on achieving the highest expected overall profitability without explicitly considering the potential risks or downside outcomes.
- **Maximizing the worst-case profit:** Also known as the "minimax" approach, this objective function seeks to maximize the worst-case profit scenario, ensuring that the farm's performance remains acceptable regardless of the scenario.
- **Maximizing the superquantile:** This risk management measure focuses on maximizing the profit in a selection of the worst-case scenarios, providing a more robust optimization framework that accounts for extreme events and tail risks.

By considering different objective functions and risk management strategies, we can better understand how the two-stage stochastic programming approach can be tailored to address individual farmers' specific needs and risk preferences.

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CHAPTER 2:
Literature Review

2.1 Introduction

This literature review aims to provide an overview of the current state of knowledge in agricultural decision-making, particularly focusing on optimization methods and their applications. The review discusses objective functions, stochastic programming in agriculture, the ABARES *farmpredict* model, normal distribution assumptions, and parameter independence. This organization will facilitate a better understanding of the context within which this thesis is situated and enable us to build upon the existing body of knowledge in our investigation of two-stage stochastic optimization for improving farm performance in Australia under uncertainty.

2.1.1 Objective Functions

Objective functions play a pivotal role in optimization models, representing the goals decision makers aim to achieve through their actions. For example, in agricultural decision-making, objective functions often reflect economic or risk outcomes that farmers seek to optimize. This section discusses various objective functions used in optimization literature, specifically focusing on maximizing mean profit, maximizing the worst-case profit, minimizing variance while maximizing mean, and optimizing the superquantile.

Maximizing Mean Profit: A common objective function in agricultural models, mean profit, seeks to maximize the expected financial returns from farming activities. This objective function is mathematically represented as the sum of each scenario's revenues minus costs (Ruszczyński and Shapiro 2003). In a forestry production setting, the benefits of mean profit maximization have been demonstrated by Alonso-Ayuso et al. (2011). The study shows how this approach can be used to optimize forestry production decisions and highlights its potential for improving profitability in the forestry industry.

Maximizing the Worst-Case Profit: This objective function, also known as minimax regret or minimax criterion, focuses on maximizing the worst-case scenario's profit, effectively minimizing the potential regret in decision-making. Mathematically, it seeks to maximize the minimum value of the profit function across all possible scenarios. Shapiro and Kleywegt (2002) offers a comprehensive analysis of this objective function and its application in traditional decision-making problems such as the news vendor problem. Weintraub and Romero (2006) provides a history of the practical application of maximizing the worst-case profit in agriculture and explores the trade-offs between risk and profit in crop planning.

Balancing Risk and Returns via a Weighted Objective Function: This objective function attempts to balance risk and returns by optimizing a weighted combination of mean profit and its variance. This strategy consolidates the objectives into one by assigning weights to both the mean profit and its variance, striving to enhance the former while mitigating the latter. Azaron et al. (2008) provide an insightful look into this risk-return trade-off and illustrate its practicality in a supply chain scenario through a case study.

Optimizing the Superquantile: This objective function emphasizes risk management, particularly minimizing the risk of extreme losses by optimizing the worst $(1 - \alpha)100\%$ outcomes of the profit. Superquantiles are especially relevant in agricultural decision-making, as it addresses tail risk and the potential for significant losses. Rockafellar and Royset (2015) and section 3.C in Royset and Wets (2022) offer a comprehensive overview of superquantiles and their application in decisions under risk-aversion. They highlight the importance for a decision maker to tailor decisions based on their specific risk tolerance levels.

The choice of the objective function in an agricultural optimization model can significantly impact the model's results and the resulting decision recommendations. Different objective functions may lead to different optimal solutions, emphasizing the importance of selecting an appropriate objective function that aligns with the decision maker's priorities and values. Understanding the trade-offs between different objectives can provide valuable insights for decision makers, helping them make more informed, strategic choices.

In this thesis, we employ three of the four previously discussed objective functions to address various aspects of risk management in small farm operations in Australia. By examining the performance of our two-stage stochastic optimization model under different objective functions, we aim to provide a comprehensive understanding of the trade-offs and opportunities associated with varying criteria of decision-making under uncertainty.

2.2 Stochastic Programming in Agriculture

A stochastic model's objective function and constraints are formulated in terms of random variables, allowing decision makers to optimize their decisions under various scenarios.

A detailed explanation of stochastic programming, including its mathematical formulation and advantages over deterministic linear programming, can be found in Birge and Louveaux (2011). The critical advantage of stochastic programming is its ability to address uncertainty and risk in decision-making, enabling more robust and flexible solutions that account for potential future events.

In agriculture, stochastic programming has been widely used to optimize resource allocation and management decisions under uncertainty. For example, Yan and Li (2018) apply stochastic programming to address water allocation issues in irrigated agriculture, considering uncertain water availability due to factors such as weather variability and climate change. The study demonstrates how stochastic programming can provide better risk management solutions by considering the probability distributions of uncertain parameters, leading to improved water allocation decisions that balance competing demands.

Another example of stochastic programming application in agriculture is found in Ouattara et al. (2019), which uses the method to optimize crop rotation and land-use planning under uncertain market conditions and crop yields. The study shows how incorporating uncertainty through stochastic programming allows for more robust decision-making, reducing the risk of sub-optimal solutions resulting from deterministic models.

Stochastic programming offers significant advantages in agricultural decision-making under uncertainty, providing a more robust and flexible framework for optimizing resource allocation and management strategies. In addition, the method allows decision makers to better account for uncertain future events and their potential impacts, enabling more informed and risk-aware decisions in the agricultural sector.

2.3 ABARES *farmpredict* Model

The ABARES *farmpredict* model is a microsimulation model developed by the Australian Government's DAFF to simulate physical and financial outcomes for Australian farm businesses considering prevailing climate conditions and commodity prices (Hughes et al.

2019). This model is actively used for farm forecasting, drought monitoring, and climate scenario modeling. It employs machine learning methods to predict production outputs, input usage, and changes in farm stocks based on factors like prices, fixed inputs, climate conditions, and other farm characteristics. Accounting rules are then applied to estimate revenues, costs, changes in stock holdings, and profits according to farm survey definitions.

As utilized in the *farmpredict* model, machine learning techniques offer a data-driven approach to agricultural decision-making, allowing for more accurate predictions and adaptive responses to changing conditions. In contrast, two-stage stochastic programming is a more structured approach to modeling decision-making under uncertainty. It involves making decisions sequentially, with recourse actions taken based on the realized outcomes of uncertain events. While the *farmpredict* model primarily focuses on prediction and adapts to observed conditions, two-stage stochastic programming emphasizes optimization by accounting for initial decisions and potential recourse actions.

Both approaches, *farmpredict* and two-stage stochastic programming, have advantages and limitations in agricultural decision-making. Machine learning methods can provide more accurate predictions and adapt to changing conditions, while two-stage stochastic programming offers a structured framework for optimizing decisions under uncertainty. The choice between these approaches depends on the specific decision-making problem and the desired balance between prediction accuracy and optimization.

The ABARES *farmpredict* model is an innovative and valuable tool for Australian agriculture, leveraging machine learning techniques to provide farm-scale results with national coverage. It serves as an example of how modern data-driven methods can complement and enhance traditional optimization approaches, like two-stage stochastic programming, in addressing complex agricultural decision-making problems under uncertainty.

2.4 Normal Distribution Assumptions in Stochastic Programming

One of the key assumptions in this thesis' stochastic programming model is the use of normal distributions for uncertain parameters. The rationale for this assumption stems from the principle of maximum entropy, which states that the normal distribution maximizes entropy among all distributions with a given mean and variance (Jaynes 1957). This property makes normal distributions a natural choice for modeling uncertainty when limited information is available about the underlying distribution of the uncertain parameters. This is also supported by (Just and Weninger 1999), who found that the normal distribution is reasonable for crop insurance programs and, therefore, for crop production under uncertainty.

There are limitations to the assumption of normal distributions in agricultural decision-making. One significant limitation is that normal distributions are unbounded, meaning they assign non-zero probabilities to extreme values that may not be realistic in real-world applications. For instance, crop yields or livestock populations cannot be negative in agriculture, but a normal distribution could potentially assign a non-zero probability to such values.

Normal distributions do not account for skewness or heavy tails that may be present in real-world data. In agricultural applications, this could mean that the model underestimates the likelihood of extreme events, such as severe droughts or exceptionally high crop yields, leading to suboptimal decision-making. Despite these limitations, assuming normal distributions in stochastic programming models remains popular due to their mathematical properties and widespread familiarity (Plà-Aragonés 2015).

2.5 Parameter Independence in Stochastic Programming

In many stochastic programming models, including those used for agricultural decision-making, the assumption of parameter independence is often made. This assumption implies that uncertain parameters in the model do not influence each other and are uncorrelated. Parameter independence simplifies model formulation and reduces computational complexity, making the model more tractable and easier to solve.

However, the assumption of parameter independence has implications for the accuracy and realism of the model (Plà-Aragonés 2015). In real-world applications, uncertain parameters may be correlated, meaning they influence each other or share common underlying factors. For instance, in agriculture, weather conditions could simultaneously affect crop yields, input prices, and market demand. Ignoring these correlations may result in suboptimal decision-making, as the model does not accurately capture the true relationships between uncertain parameters.

Despite this limitation, some studies have shown that assuming parameter independence can still provide reasonable results in certain contexts (Agrawal et al. 2012).The trade-offs between model simplicity and accuracy depend on the specific problem, the nature of the correlations, and the decision maker's tolerance for potential suboptimality. To account for correlations between uncertain parameters, more advanced stochastic programming techniques can be employed but will not be covered in this thesis. The assumption of independence is utilized in this thesis to simplify the model and facilitate the optimization process.

CHAPTER 3: Model and Formulation

3.1 Introduction

In this chapter, we present the development and formulation of a two-stage stochastic linear programming model with simple recourse to address the uncertainties and risks inherent in agricultural production. Our model focuses on a specific type of farm that combines crop production (canola, barley, lupins, and oats), Angus cattle, Merino wool, and prime lamb production. By incorporating the uncertainties in parameters such as crop yields and stock feed rates as random variables, we aim to provide a robust decision-making tool for farmers to optimize their resource allocation and risk management strategies. All uncertain parameters can be seen in the appendix.

The two-stage stochastic programming approach allows us to incorporate the uncertainties in agricultural production by modeling uncertain events impacting farm operations as probability distributions. By utilizing this information for decision optimization, our model can better account for the inherent variability in agricultural decision-making, which traditional optimization techniques may not adequately capture. The simple recourse structure of our model enables farmers to make informed decisions in the face of uncertainty and adjust their plans as new information becomes available.

In this chapter, we will outline the problem formulation, including the decision variables, objective functions, and constraints. We will also discuss the modeling of uncertainties and the data sources used to estimate the probability distributions for uncertain events. Additionally, we will describe the model implementation, solution approach, and the limitations associated with the model.

Through the development of this two-stage stochastic linear programming model with simple recourse, we aim to provide a valuable tool for Australian farmers, allowing them to make better-informed decisions in the face of the numerous challenges and uncertainties they face in their daily operations.

3.2 Data Sources and Collection Methods

The data sources and collection methods used to develop the two-stage stochastic programming model for the specific type of farm include both official sources, such as the Agricultural Commodities and Trade Data, and direct interactions with farmers through interviews. The Agricultural Commodities and Trade Data, provided by the DAFF, serves as one of the primary sources of information for this study. This official dataset offers valuable insights into market prices, production levels, and other relevant indicators for the agricultural sector. Utilizing this information helps in understanding the broader context of the industry and ensures that the model is built upon a solid foundation of empirical data.

In addition to the official data, we conducted interviews with farmers to gain insights into their local experiences and farming practices. These interactions were particularly valuable in understanding the unique challenges faced by farmers running the specific type of farm focused on in this thesis. By engaging with farmers directly, we were able to gather qualitative data and expert knowledge that would not have been available through official data sources alone. This first-hand information was crucial in fine-tuning the model to better reflect the realities of farming in the specific context studied.

To estimate the probability distributions for uncertain events, we combine data from both official sources and farmer interviews. The official data provides historical information on market prices, production levels, and other relevant indicators that served as the basis for our probability distributions. We then use insights gained from farmer interviews to adjust these distributions, incorporating their expert knowledge and local experiences. By integrating data from both sources, we were able to develop comprehensive and representative probability distributions that account for the inherent uncertainties and variability in agricultural decision-making.

3.3 Problem Formulation

This model formulation is designed for a specific type of farm that combines crop production, Angus cattle, Merino wool, and prime lamb production. The crops include canola, barley, oats, and lupins. The model incorporates multiple sets, parameters, variables, and constraints to provide a comprehensive framework for optimizing agricultural production decisions under uncertainty.

3.3.1 Sets and Indices

The model uses sets and indices to represent various aspects of the farm, such as crop types, stock types, offspring types, and scenarios. The sets and indices are defined as follows:

$c \in C$	set of crops
$fs \in FS$	set of female stock
$ms \in MS$	set of male stock
$o \in O$	set of offspring
$fs \in FGC$	set of female grain feeders
$ms \in MGC$	set of male grain feeders
$o \in OGC$	set of offspring grain feeders
$fs \in FHC$	set of female hay feeders
$ms \in MHC$	set of male hay feeders
$o \in OHC$	set of offspring hay feeders
$ms \in MD$	mating pairs
$fs \in OD$	birthing pairs (offspring)
$fs \in RD$	birthing pairs (replacement)
$i \in I$	scenario number

3.3.2 Parameters (Data)

The model relies on several parameters based on the data collected from official sources and interviews with farmers. The parameters include land carrying capacity, farm size, initial capital, stock prices, crop yields, and expected profits. Parameter sub-indexed by i are considered uncertain and defined by scenario.

$total\_ha$	= total farm size (ha)
$initial\_capital$	= initial funds available
$femalestockcapacity_{fs}$	= land carrying capacity for stock
$malestockcapacity_{ms}$	= land carrying capacity for stock
$offspringcapacity_{o}$	= land carrying capacity for stock
$males\_required_{ms}$	= males stock per female
$grainyield_{c,i}$	= grain yield per crop type
$grainprofit_{c,i}$	= grain profit per tonne
$grainprice_{c,i}$	= grain price per tonne
$hayyield_{c,i}$	= hay yield per crop type
$hayprofit_{c,i}$	= hay profit per tonne
$hayprice_{c,i}$	= hay price per tonne
$femalestockprofit_{fs,i}$	= stock profit per head
$femalestockprice_{fs,i}$	= stock price per head
$femalestockbirthrate_{fs,i}$	= stock birthrate
$femalestockfeedrate_{fs,i}$	= stock feedrate
$femalestockreplacement_{fs,i}$	= stock replacement
$femalestocklossrate_{fs,i}$	= stock loss
$femalestockwoolprofit_{fs,i}$	= stock wool profit
$malestockprice_{ms,i}$	= stock price per head
$malestockfeedrate_{ms,i}$	= stock feedrate
$malestocklossrate_{fs,i}$	= stock loss
$malestockwoolprofit_{fs,i}$	= stock wool profit
$offspringprofit_{o,i}$	= offspring profit per head
$offspringfeedrate_{o,i}$	= offspring feedrate
$offspringlossrate_{o,i}$	= offspring lossrate

3.3.3 Decision Variables

The decision variables in the model represent the choices that the farmers need to make to optimize their resource allocation and risk management strategies. These variables are listed below along with their descriptions:

H_c	= number of hectares allocated to crop c
NF_{fs}	= number of head of female stock of type fs
NM_{ms}	= number of head of male stock of type ms
$GCS_{c,i}$	= tonnes of grain crop c sold in scenario i
$HCS_{c,i}$	= tonnes of hay crop c sold in scenario i
$GCP_{c,i}$	= tonnes of grain crop c to be purchased in scenario i
$GHP_{c,i}$	= tonnes of hay crop c to be purchased in scenario i
$FSS_{fs,i}$	= number of female stock sold in scenario i
$FSP_{fs,i}$	= number of female stock purchased in scenario i
$MSP_{ms,i}$	= number of male stock purchased in scenario i
$OS_{o,i}$	= number of offspring sold in scenario i
$OR_{o,i}$	= number of offspring retained in scenario i
$PROFIT_i$	= profit in scenario i

The $PROFIT_i$ decision variable, while primarily serving as an accounting variable, plays a key role in all three objective functions described below. This variable is fully determined by the other variables in the model, and its inclusion as a decision variable aids in model interpretation and understanding, helping the analysis of the profit under various objectives.

$$
\begin{aligned}
&PROFIT_i \\
&= \sum_{c \in C} CGP_{c,i} \cdot cropgrainprofit_{c,i} + \sum_{c \in C} CHP_{c,i} \cdot crophayprofit_{c,i} \\
&+ \sum_{fs \in FS} FSS_{fs,i} \cdot femalestockprofit_{fs,i} + \sum_{fs \in FS} NF_{fs,i} \cdot femalestockwoolprofit_{fs,i} \\
&+ \sum_{ms \in MS} NM_{ms,i} \cdot malestockwoolprofit_{ms,i} + \sum_{o \in O} OS_{o,i} \cdot offspringprofit_{o,i} \\
&- \sum_{fs \in FS} FSP_{fs,i} \cdot femalestockprice_{fs,i} - \sum_{ms \in MS} MSP_{ms,i} \cdot malestockprice_{ms,i} \\
&- \sum_{c \in C} CGP_{c,i} \cdot cropgrainprice_{c,i} - \sum_{c \in C} CHP_{c,i} \cdot crophayprice_{c,i} \quad \forall i \in I
\end{aligned} \tag{3.1}
$$

3.3.4 Objective functions

The objective functions in the model aim to optimize the variables according to the farmer's goals while accounting for uncertainty and risk-tolerance. There are three different objective functions presented in this thesis:

Mean profit: This objective function aims to maximize the mean profit from farming activities across all scenarios. The mean profit is calculated by taking the average of $PROFIT_i$ across all scenarios i.

Worst-Case profit: This objective function seeks to maximize the minimum $PROFIT_i$ that occurs in all scenarios, ensuring that the worst-case scenario is optimized. This approach is more conservative as it focuses on minimizing the worst potential downside.

Superquantile profit: This objective function aims to maximize the superquantile of $PROFIT_i$ across all scenarios i, which is a risk measure that focuses on the tail-end (lowest 10% for example) of the distribution of $PROFIT_i$. This approach provides a balance between risk and reward by considering the extreme scenarios and their associated profits, as detailed in Section 3.C of Royset and Wets (2022).

3.3.5 Constraints

Several constraints are imposed on the model to ensure that the optimal solution meets specific requirements and limitations, such as land size, crop supply, stock replacement, and initial capital constraints.

Land Constraint: This constraint ensures that the total land area required for crops and livestock does not exceed the available land area ($total\_ha$):

$$\begin{aligned} & total\_ha \\ & \geq \sum_{fs \in FS} NF_{fs} \cdot femalestockcapacity_{fs} \\ & + \sum_{ms \in MS} NM_{ms} \cdot malestockcapacity_{ms,i} + \sum_{c \in C} H_c \end{aligned} \tag{3.2}$$

Crop Supply Constraints: These constraints ensure that the hay and grain supply from crop production, purchases, and sales matches the demand for feeding livestock:

$$\begin{aligned} & \sum_{c \in C} H_c \cdot crophayyield_{c,i} + HCP_{c,i} - HCS_{c,i} \\ & = \sum_{fs \in FHC} NF_{fs,i} \cdot femalestockfeedrate_{fs,i} + \sum_{ms \in MHC} NM_{ms,i} \cdot malestockfeedrate_{ms,i} \\ & + \sum_{o \in OHC} (OS_{o,i} + OR_{o,i}) \cdot offspringfeedrate_{o,i} \quad \forall i \in I \end{aligned} \tag{3.3}$$

$$\begin{aligned} & \sum_{c \in C} H_c \cdot cropgrainyield_{c,i} + GCP_{c,i} - GCS_{c,i} \\ & = \sum_{fs \in FGC} NF_{fs,i} \cdot femalestockfeedrate_{fs,i} + \sum_{ms \in MGC} NM_{ms,i} \cdot malestockfeedrate_{ms,i} \\ & + \sum_{o \in OGC} (OS_{o,i} + OR_{o,i}) \cdot offspringfeedrate_{o,i} \quad \forall i \in I \end{aligned} \tag{3.4}$$

Crop Sale Constraints: These constraints limit the quantity of grain and hay that can be sold to the amount produced from crop production:

$$GCS_{c,i} \leq H_c \cdot cropgrainyield_{c,i} \quad \forall i \in I,\ \forall c \in C \tag{3.5}$$

$$HCS_{c,i} \leq H_c \cdot crophayyield_{c,i} \quad \forall i \in I,\ \forall c \in C \tag{3.6}$$

Stock Supply Constraints: These constraints ensure that the number of livestock that is replaced is equal to the sum of livestock lost through death and or old age:

$$\begin{aligned} &FSP_{fs,i} + OR_{RD_{fs,i}} \\ &= (femalestocklossrate_{fs,i} + femalestockreplacement_{fs,i}) \cdot NF_{fs} \\ &\forall i \in I,\ \forall fs \in FS \end{aligned} \tag{3.7}$$

Stock Sale Constraints: These constraints calculate the number of livestock to be sold based on the number of age replacements required.

$$FSS_{fs,i} = femalestockreplacement_{fs,i} \cdot NF_{fs} \quad \forall i \in I,\ \forall fs \in FS \tag{3.8}$$

Offspring Retained Constraints: These constraints ensure that the number of offspring retained is at least half of the total offspring born (cannot retain males for breeding):

$$0.5 \cdot femalestockbirthrate_{fs,i} \cdot NF_{fs} \geq OR_{OD_{fs,i}} \quad \forall i \in I,\ \forall fs \in FS \tag{3.9}$$

Total Offspring Constraints: These constraints ensure that the total offspring produced is equal to the sum of offspring retained and offspring sold.

$$OR_{OD_{fs,i}} + OS_{OD_{fs,i}} = femalestockbirthrate_{fs,i} \cdot NF_{fs} \quad \forall i \in I,\ \forall fs \in FS \tag{3.10}$$

Males Required Constraints: These constraints calculate the number of male livestock required based on the number of female livestock.

$$\frac{NF_{MD_{ms}}}{males\_required_{ms}} = NM_{ms} \quad \forall ms \in MS \tag{3.11}$$

Males Replaced Constraints: These constraints ensure that the number of male livestock replaced is equal to the number of male livestock lost.

$$NM_{ms} \cdot malestocklossrate_{ms,i} = MSP_{ms,i} \quad \forall i \in I,\ \forall ms \in MS \tag{3.12}$$

Stock Limits Constraints: These constraints impose upper limits on the number of each type of livestock if required by the farmer:

$$NF_{fs} \leq stock\_limits_{fs} \quad \forall fs \in FS \tag{3.13}$$

Note: the specific model in this thesis limits the Angus cow livestock type quantity to 100 due to the freshwater requirement on the selected farm.

Crop Minimum Constraints: These constraints ensures that a minimum area of land is allocated to crop production if required by the farmer for paddock rotation.

$$\sum_{c \in C} H_c \geq crop\_min_c \tag{3.14}$$

Capital Limit Constraints: These constraints ensures that the total cost of livestock and crop production does not exceed the available capital.

$$\begin{aligned} &available\_capital \\ &\geq \sum_{fs \in FS} FSP_{fs,i} \cdot femalestockprice_{fs,i} + \sum_{ms \in FS} MSP_{ms,i} \cdot malestockprice_{ms,i} \\ &+ \sum_{c \in C} CGP_{c,i} \cdot cropgrainprice_{\mathrm{c,i}} + \sum_{c \in C} CHP_{c,i} \cdot crophayprice_{c,i} \quad \forall i \in I \end{aligned} \tag{3.15}$$

By incorporating these sets, indices, parameters, variables, and constraints, the model provides a comprehensive framework for optimizing agricultural production decisions under uncertainty. The model can be further customized with additional constraints and objectives to better represent specific farming situations and risk management strategies.

For the Worst-Case Profit and Superquantile objective functions, auxiliary decision variables and constraints are added to the model. These additions are necessary for obtaining a linear model, as detailed in Section 3.C of Royset and Wets (2022).

3.4 Model Implementation and Solution

In this section, we describe the implementation of the two-stage stochastic linear programming model with simple recourse using the Python programming language and the Pyomo library (Bynum et al. 2021; Hart et al. 2011). We also explain the solution approach and the solver utilized for the optimization problem.

The model is implemented using Python, a popular programming language known for its versatility and ease of use. Python offers extensive libraries for mathematical programming, data processing, and analysis, making it an ideal choice for implementing such optimization models.

We use the Pyomo library, an advanced open-source optimization modeling tool for Python, to define the mathematical model and constraints. Pyomo allows us to define the decision variables, objective functions, and constraints in a straightforward and natural manner, making the implementation process efficient and robust.

For solving the optimization problem, we employ the Gurobi 10.0 solver, a state-of-the-art mathematical optimization software designed for solving large-scale linear, mixed-integer, and quadratic programming problems (Gurobi Optimization, LLC 2023). Gurobi is known for its superior performance and speed in solving complex optimization problems and was well-suited to handle our two-stage stochastic linear program. The open-source CBC solver was also utilized for a comparison (Forrest and Lougee-Heimer 2005).

We solve the model using a laptop with Intel(R) Core(TM) i5-1035G4 processor running at 1.10 GHz, 8.0 GB RAM, and Windows 10 operating system.

3.5 Model Assumptions and Limitations

For the purpose of this thesis, we concentrate on developing a two-stage stochastic programming model for a specific type of farm that combines crop production, Angus cattle, Merino wool and prime lamb production. This farm type represents a diverse operation, with specific breeding requirements further discussed in the model methodology section. Such a diversified farm serves as an ideal case study for demonstrating the potential benefits and applicability of the stochastic programming approach in managing uncertainty across various agricultural sectors.

The model developed in this study makes several key assumptions to simplify the problem and facilitate the optimization process. It is essential to acknowledge these assumptions and their potential limitations when interpreting the results and drawing conclusions from the model. Some of the main assumptions and limitations include:

- **Independent Variables:** The model assumes that all the variables considered are independent, allowing for a more straightforward modeling approach. However, this assumption may not fully capture the intricate relationships between different variables in the real world. The interdependence of certain factors could lead to different outcomes than those predicted by the model.
- **Perfect Information for Second-stage Decisions:** The model assumes perfect information for second-stage decisions, meaning that farmers have complete knowledge of the outcomes of the first-stage decisions when making their second-stage choices. While this assumption simplifies the model, it is important to recognize that perfect information may not always be available in practice. In reality, farmers often have to make decisions with limited or uncertain information, which could affect the applicability of the model's results in real-world situations.
- **Normally distributed random variables:** This assumption allows for a more straightforward modeling approach and is commonly used in agricultural applications. However, it is important to acknowledge that this assumption may not fully capture the true distribution of the random variables, and other distributions may be more appropriate.

By recognizing these assumptions and limitations, we can better understand the scope and applicability of our two-stage stochastic programming model. It is crucial to consider these factors when interpreting the results and determining their relevance to real-world agricultural decision-making under uncertainty. Despite these limitations, the model can still provide valuable insights into the potential benefits of stochastic programming in managing uncertainty and risk in agriculture, while also highlighting areas for future research and improvement.

CHAPTER 4: Results and Discussion

4.1 Sample Selection Size

These tests aim to assess the model's ideal scenario selection size and determine if using 10,000 scenarios is sufficient for generating consistent optimal decisions. We want a model that provides confidence in the results and ensures that the optimization process is efficient, without using an excessive number of scenarios that could increase computational time and resources.

In the test setup, we compared the results obtained from multiple sets of 10,000 scenarios and then from 100,000 scenarios. The comparison allowed us to evaluate if the model's performance and optimal decisions significantly changed when increasing the number of scenarios. This test provides valuable insights into the model's robustness and sensitivity to changes in the number of scenarios. A more detailed discussion can be found in Chapter 8 of Royset and Wets (2022).

Our key findings, shown in Figure 4.1 reveal that the optimal decisions were within 1% of each other between the 10,000 and 100,000 scenario sets, indicating the model's suitability using 10,000 scenarios. This result suggests that our model provides reliable and consistent solutions even when using a relatively smaller number of scenarios, which is an important aspect of efficient optimization.

The findings have two important implications. Firstly, they reinforce the model's reliability. Each run with a fresh set of 10,000 scenarios consistently generates comparable optimal decisions, underlining the robustness of the model's recommendations, a crucial attribute for decision makers. Secondly, they indicate improved computational efficiency. With stable results achieved using fewer scenarios, the model ensures quicker computations and reduced resource usage. This efficiency translates to a more practical model in real-world applications, making it a valuable tool for optimization in the face of limited resources.

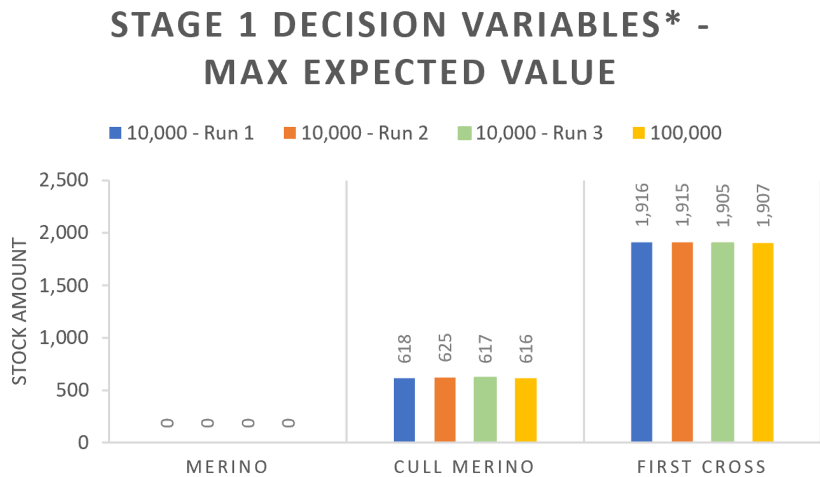

Figure 4.1. Three model runs were completed with 10,000 scenarios, and one with 100,000 scenarios. The stage one decisions returned from the model were within a 1% tolerance. A small selection of stage one decision variables are shown.

4.2 Speed Test and Solver Comparison

The speed test for building and solving the model using different solvers, CBC and Gurobi, is essential to understanding the model's performance and efficiency. Comparing the solvers' speed and effectiveness helps in choosing the most suitable solver for the model, particularly in real-world applications where computation time and resources are crucial factors.

The results of the speed test, shown in Figure 4.2 indicate that as the number of scenarios increases, the time taken to build and solve the model also increases exponentially. However, the model's stability at 10,000 scenarios proves advantageous, as increasing the number of scenarios to 100,000 can significantly increase computation time. This stability allows for a more efficient optimization process, which is particularly important in real-world applications where timely decision-making is critical.

When comparing the performance of the Gurobi and CBC solvers, Gurobi consistently provided faster solutions than CBC, making the model more repeatable and efficient. The speed difference between the two solvers highlights the importance of choosing the most suitable solver to enhance the model's performance, reduce computation time, and ensure reliable and timely results.

The speed test and solver comparison demonstrate the importance of selecting an appropriate solver and using a suitable number of scenarios to achieve a balance between model stability and optimization efficiency. The test results show that Gurobi outperforms CBC in terms of speed, making it the preferred solver for this model. Extrapolating the results found in figure 4.2, the CBC solver would take an expected 30hrs to solve the 100,000 scenario model.

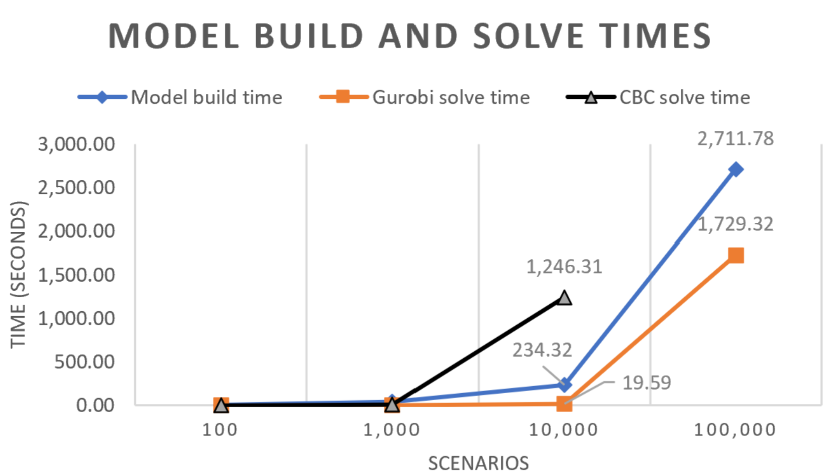

Figure 4.2. This figure shows the time in seconds to build the model, and then solve with both the CBC and Gurobi solver. For 10,000 scenarios, model build time; 4min, Gurobi solve time; 19sec, and CBC solve time; 20min.

4.3 Results from Different Objective Functions

4.3.1 Mean Profit

The model, when tailored to maximize mean profit, advocates for a strategy heavily skewed towards prime lamb production. This strategy is discernible from the stage one decision variables shown in Table 4.1.

The preference for prime lamb production under this objective function is clear from the sizable allocation to firstcross ewes, while the absence of merino ewes suggests that high-quality wool production is not prioritized in this strategy.

Table 4.1. Stage One Decision Variables for Maximizing Mean Profit

Category	Number of Stock/Hectares
Angus Cow	100
Merino Ewe	0
Cull Merino Ewe	764
Firstcross Ewe	2,462
Angus Bull	5
Merino Ram	0
Border Leicester Ram	11
Dorset Ram	35
Canola	0
Barley	7
Oats	6
Lupins	0

When we look at the performance metrics, the model returned a maximum profit of $970,902, a minimum profit of $342,977, and a mean profit of $644,062, summarized in Table 4.2.

Table 4.2. Results Data for Maximizing Mean Profit.

Maximizing Mean Profit	Value
Max Profit	$970,902
Min Profit	$342,977
Mean Profit	**$644,062**
Superquantile	$498,278
Model Build Time (s)	376
Solver Time (s)	46
Number of Constraints	320,008
Number of Variables	370,013

The profit distribution for each scenario is illustrated in Figure 4.3, with markers indicating the mean, min, max, and superquantile profits. When the goal is to maximize mean profit, the model recommends a farming strategy that heavily leans towards prime lamb production through substantial allocation towards firstcross ewes and minimal consideration for merino ewes for wool production.

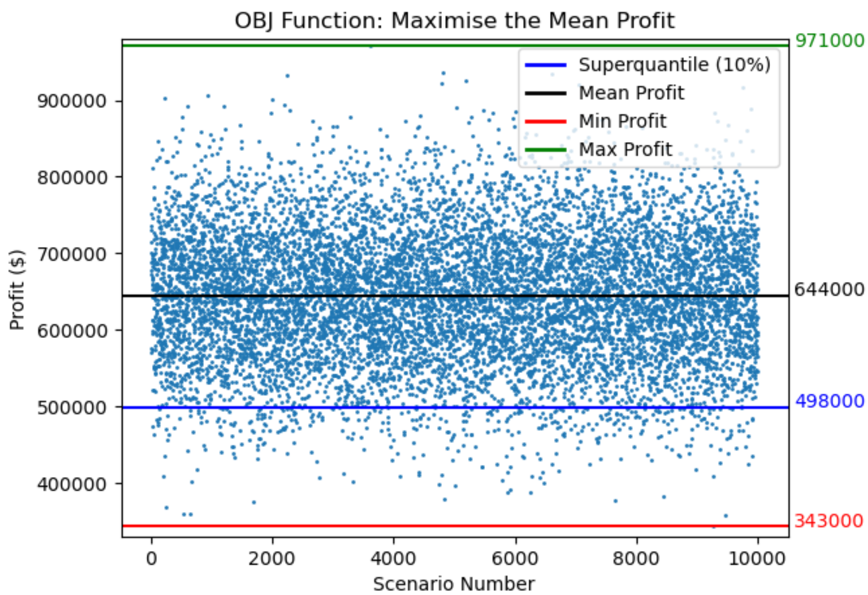

Figure 4.3. This figure shows what the profit will be for each scenario if the optimal stage one decision variables for maximizing the mean are followed.

4.3.2 Worst-Case Profit

Our worst case-based model centers on maximizing the worst-case profit, which changes the landscape of the farming strategy dramatically when contrasted with the mean-based model, optimized for mean profit. A careful examination of stage one decision variables (Table 4.3) underscores a pivot in strategy, deviating from the exclusive focus on prime lamb production to a more balanced approach between wool and lamb production, in addition to a noteworthy allocation towards cropping.

Contrary to the mean-based model, the presence of Merino ewes indicates an integration of wool production into the overall farming strategy. We observe a decrease in Firstcross ewes, denoting a reduction in the focus on prime lamb production. However, perhaps the most significant shift is the introduction of sizeable crop allocation, particularly for canola and oats. This not only diversifies the farming operations but also offers a more resilient buffer against potential uncertainties or adverse events, effectively capping losses.

Turning our attention to the performance metrics (Table 4.4), this model exhibits a maximum profit of $711,296, which, though lower than the first model, is counterbalanced by a

Table 4.3. Stage One Decision Variables for Maximizing the Worst-Case Profit

Category	Number of Stock/Hectares
Angus Cow	100
Merino Ewe	338
Cull Merino Ewe	332
Firstcross Ewe	663
Angus Bull	5
Merino Ram	5
Border Leicester Ram	5
Dorset Ram	14
Canola	110
Barley	0
Oats	121
Lupins	0

significantly higher minimum profit of $419,801. The mean profit in this model is $543,612.

Table 4.4. Results Data for Maximizing the Worst-Case Profit.

Maximizing Minimum Profit	Value
Max Profit	$711,296
Min Profit	**$419,801**
Mean Profit	$543,612
Superquantile	$475,936
Model Build Time (s)	643
Solver Time (s)	14
Number of Constraints	320,001
Number of Variables	370,001

Examining the profits across all scenarios (Figure 4.4), it becomes evident that the farming strategy derived from the worst-case based model is inherently more risk-averse. The distribution of profits showcases a narrower spread than the mean-based model, thereby lowering the risk of low-profit outcomes. In essence, while this model sacrifices potential maximal profits, it fortifies the minimum profit level, which aligns more closely with risk-averse farmers' preferences.

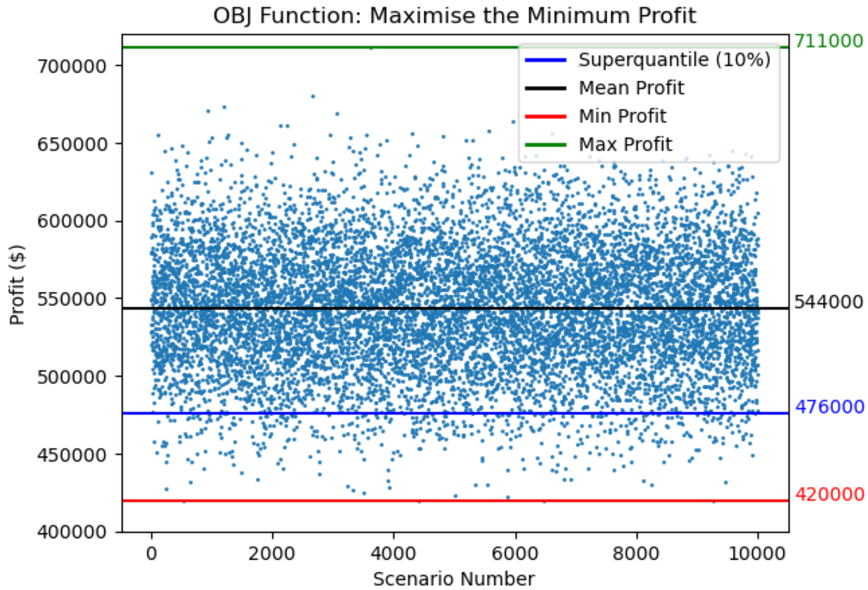

Figure 4.4. This figure shows what the profit will be for each scenario if the optimal stage one decision variables for maximizing the minimum are followed.

4.3.3 Superquantile Profit

The final model under our study focuses on maximizing the superquantile profit, aiming to optimize the balance between risk and reward. The superquantile-based model promotes a strategy that integrates elements from the two preceding results, embodying a hybrid strategy that melds wool and lamb production with a mild focus on cropping.

Table 4.5 presents the stage one decision variables for this model. We observe a considerable number of Merino ewes and cull Merino ewes, similar to the worst-case based model, indicating a continued emphasis on wool production. In addition, the superquantile-based model retains a high allocation of Firstcross ewes, reflecting the benefits of prime lamb production, as seen in the mean-based model.

Table 4.6 details the performance metrics of the superquantile-based model. It reaches a maximum profit of $869,025, a minimum profit of $392,008, and a mean profit of $624,983. Notably, the superquantile profit stands at $510,452, surpassing the superquantile profit of the mean model ($498,278) significantly while only marginally reducing the mean profit.

Table 4.5. Stage One Decision Variables for Maximizing the Superquantile Profit

Category	Number of Stock/Hectares
Angus Cow	100
Merino Ewe	590
Cull Merino Ewe	660
Firstcross Ewe	1,859
Angus Bull	5
Merino Ram	8
Border Leicester Ram	9
Dorset Ram	27
Canola	0
Barley	10
Oats	7
Lupins	0

This result implies that the superquantile strategy enhances the downside risk protection without greatly sacrificing the average profit.

Table 4.6. Results Data for Maximizing the Superquantile Profit.

Maximizing Superquantile Profit	Value
Max Profit	$869,025
Min Profit	$392,008
Mean Profit	$624,983
Superquantile Profits	**$510,452**
Model Build Time (s)	360
Solver Time (s)	14
Number of Constraints	320,001
Number of Variables	370,001

As seen in Figure 4.5, the superquantile-based model harmonizes the best aspects of the mean and worst-case models, creating a balanced and robust farming strategy that protects against downside risks while preserving profit potential. This strategy aligns well with a farmer who seeks to optimize profit while minimizing exposure to poor profit outcomes.

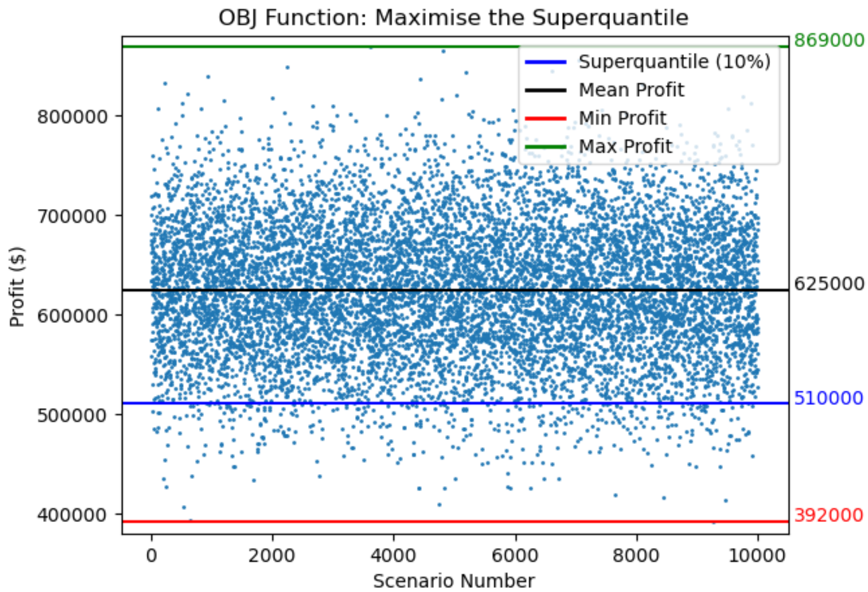

Figure 4.5. This figure shows what the profit will be for each scenario if the optimal stage one decision variables for maximizing the superquantile are followed.

4.4 Comparison of Stochastic and Deterministic Programs

In this section, we compare and contrast the outputs of deterministic and stochastic modeling approaches. Deterministic modeling uses fixed parameter values, eliminating uncertainty and risk, while stochastic modeling incorporates the randomness inherent in real-world scenarios.

First, we ran a deterministic model using the mean values of each unknown parameter. As expected, this model returned very similar results to the stochastic model which sought to maximize mean profit. This similarity stems from the nature of the stochastic model's scenario analysis over 10,000 trials with normally distributed parameters. The scenarios in this context are likely to gravitate towards stage one decisions that perform best with the mean values of these parameters. These observations align with our expectations and confirm the validity of the model assumptions and its overall functionality.

Subsequently, we performed a deterministic run using parameter values that were one standard deviation above the mean. This simulation represents a scenario where a farmer plans for the future using estimated values, but the actual values deviate from the estimates by one standard deviation.

The deterministic model produced a highly focused plan, as seen in Table 4.7, favoring the Firstcross Ewe category almost exclusively. This approach lacks diversification, putting all its eggs in one basket.

Table 4.7. Stage One Decision Variables for Deterministic Model

Category	**Number of Stock/Hectares**
Angus Cow	100
Merino Ewe	0
Cull Merino Ewe	0
Firstcross Ewe	3,226
Angus Bull	5
Merino Ram	0
Border Leicester Ram	0
Dorset Ram	46
Canola	0
Barley	0
Oats	0
Lupins	0

Once we obtained the stage one decision variables, we used them to run the model through the identical set of 10,000 scenarios used by the stochastic models. The profit outcomes, as displayed in Table 4.8, showed a substantial spread, ranging from a minimum profit of \$174,395 to a maximum of \$1,051,259, with a mean of \$617,216.

This comparison reveals the advantage of stochastic modeling over deterministic approaches in managing uncertainty and risk. By considering the distribution of outcomes, stochastic models allow for diversification and robust decision-making that can protect against negative outcomes while still optimizing profit. On the other hand, deterministic models, focusing on a singular scenario, fail to account for the wide variability in potential outcomes, which can lead to exposure to significant downside.

Each of the three stochastic models outperformed the deterministic model (Figure 4.6) in

Table 4.8. Results Data for Deterministic Stage One Decision Variables through 10,000 Scenarios.

Deterministic	Value
Max Profit	$1,051,259
Min Profit	$174,395
Mean Profit	$617,216
Superquantile Profits	$423,526
Model Build Time (s)	325
Solver Time (s)	9
Number of Constraints	320,001
Number of Variables	370,001

their respective areas of focus. The model maximizing mean profit achieved a higher mean profit, the model maximizing worst-case profit secured a higher minimum profit, and the model maximizing the superquantile outperformed the deterministic model as expected.

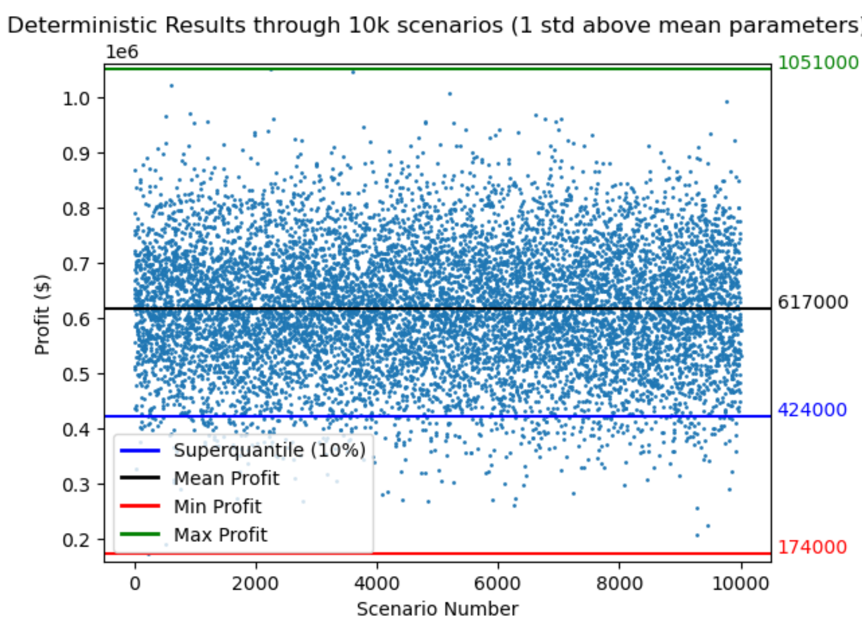

Figure 4.6. This figure shows what the profit will be for each scenario if the optimal stage one decision variables for the deterministic model were followed.

The stacked bar chart (Figure 4.7) provides a clear visual representation of the different strategies produced by the stochastic and deterministic models. Each bar represents a model, with different colored segments indicating hectares allocated to different farming activities. The stark contrast in diversification between the deterministic model and the stochastic models is evident in the chart, further highlighting the advantages of stochastic optimization in uncertainty management.

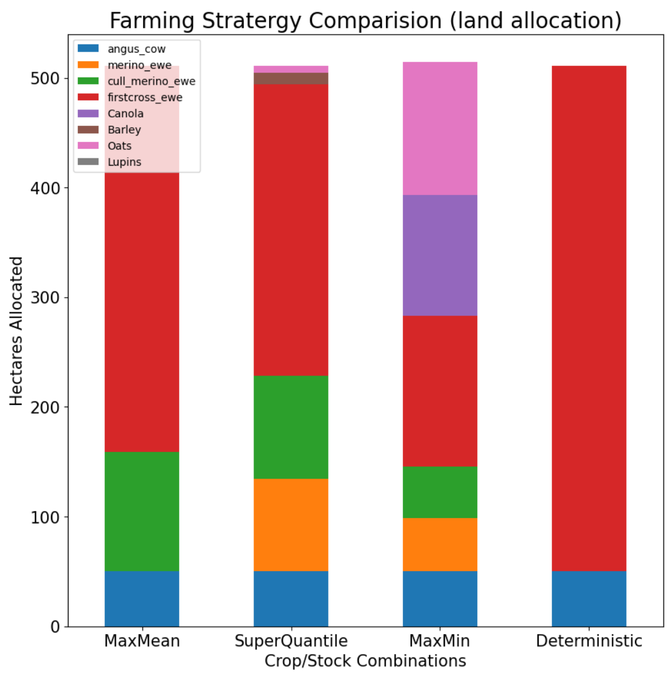

Figure 4.7. The stochastic models show the diversification within the farm, whereas the deterministic model clearly focus on the single scenario it was exposed too.

In comparing the profit distributions of the three stochastic models and the deterministic model, as illustrated in Figure 4.8, we can clearly observe that each model produces results with characteristics of a normal distribution. However, the shape, width, and height of each distribution reveal significant differences in performance and risk profiles for each approach.

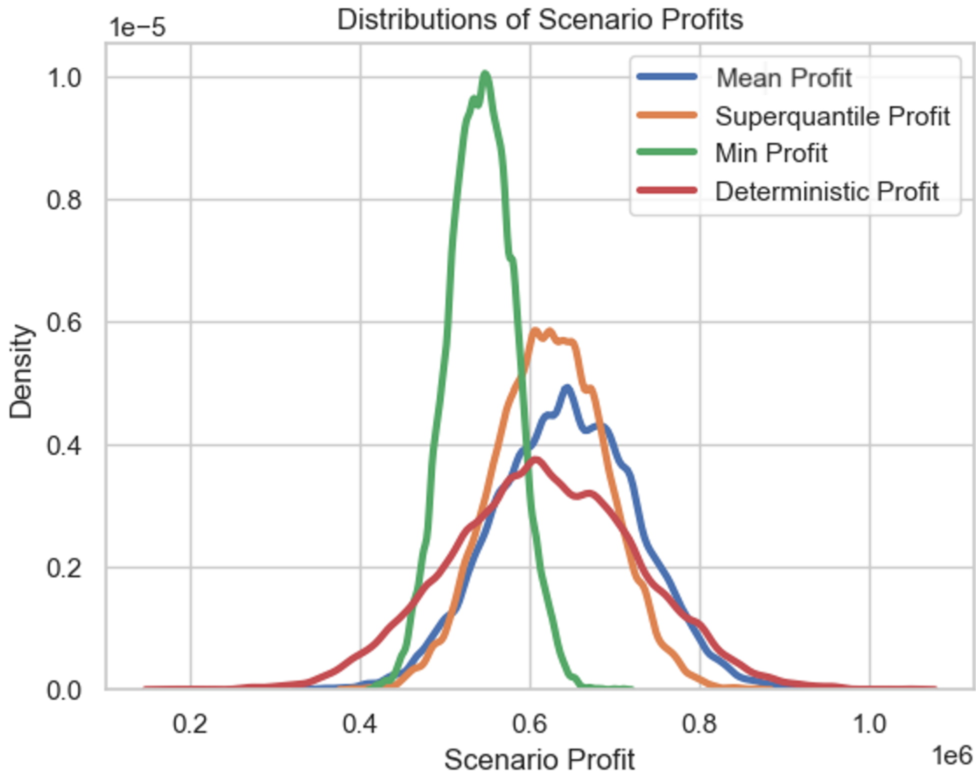

Figure 4.8. This figure shows the distributions of profit from each model. This figure allows for the farmer to make an informed decision.

The deterministic model's profit distribution is the widest, indicating the greatest level of uncertainty in potential profit outcomes. The model's profit range spans from the lowest to the highest observed, reflecting the lack of diversification in the decision variables. Since the deterministic model does not account for uncertainty in choosing stage one decision variables, the spread of potential outcomes is the largest. This highlights the high risk associated with deterministic models: while they may potentially yield the highest profits, they can also result in the lowest ones.

On the other hand, the maximizing worst-case profit model presents the narrowest and tallest distribution. This represents a higher certainty of achieving profits close to its mean value. Such a distribution indicates that the maxmin strategy offers a consistent level of profit with reduced exposure to negative shocks compared to the deterministic model.

The shape of these distributions offers valuable insights to a farmer when making their stage one decisions. Understanding the likely range and distribution of potential profits can help them make informed decisions about the level of risk they are willing to accept. These profit distributions not only reflect the inherent uncertainties of farming but also demonstrate the value of stochastic models in managing these uncertainties. By selecting a model that aligns with their risk tolerance and profit expectations, a farmer can make more strategic and informed decisions about their farming practices.

4.5 Value of Stochastic Solution (VSS) and Expected Value of Perfect Information (EVPI)

When comparing stochastic to deterministic models, two additional statistics provide valuable insights: the VSS and the EVPI.

The VSS is a measure of the potential improvement in decision-making provided by a stochastic model compared to a deterministic model (Maggioni and Wallace 2012). Formally, it is calculated as follows:

$$VSS = RP - EEV \tag{4.1}$$

where Recourse Problem (RP) represents the expected value of the solution obtained by solving the farming model whilst considering uncertainty. In this thesis, we have been refering to RP as the mean profit from the mean-based model. Expected Value Solution (EEV) represents the expected value of the solution obtained by re-solving the RP problem with stage one variables set from solving a deterministic model using mean parameters.

The EVPI measures the maximum amount that one should be willing to pay for perfect information. A detailed description can be found in Chapter 4 of Birge and Louveaux (2011). It is calculated as follows:

$$EVPI = WS - RP \tag{4.2}$$

where Wait-and-See Value (WS) represents the expected value of the solution obtained by assuming that the decision maker will know the outcome of the uncertainty before making a decision. In this thesis, the WS is calculated by finding the average of the optimal solutions for 1000 of the 10,000 scenarios through the use of the deterministic model (see Figure 4.9).

The results for both these statistics in our model are presented in Table 4.9.

Table 4.9. Values of VSS and EVPI

Statistic	Value
VSS	$719
EVPI	$13,773

The VSS is positive, indicating that the stochastic model offers an improvement over the deterministic one. However, the value is relatively small. This is likely due to the model assumptions of no correlation and normal distributions combined with the large number of scenarios (10,000) considered.

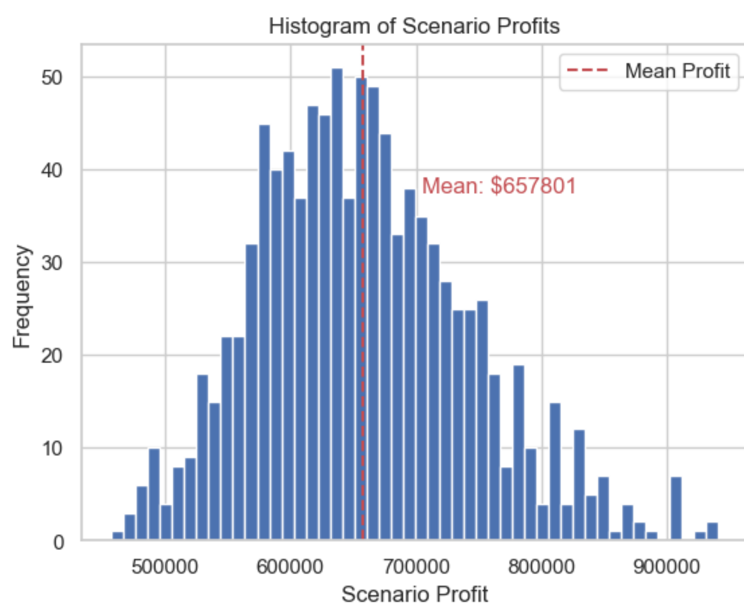

Figure 4.9. Histogram of profits achieved when perfect information is known about 1000 scenarios. The mean highlighted is the WS value.

The EVPI is considerably larger, suggesting a higher potential value in having perfect information about the parameters. This is further visualized in Figure 4.9, which presents a histogram of the deterministic profits across 1,000 of the 10,000 scenarios. The histogram is not exactly normal; it exhibits a longer tail towards higher profits, which reflects the model's attempt to maximize profits for each scenario.

The VSS and EVPI offer valuable insights into the comparative analysis of stochastic and deterministic models. However, they do not fully capture the unique advantage that the stochastic approach provides in terms of its ability to optimize for specific risk measures such as worst-case and superquantile profit scenarios. While the obtained values for VSS and EVPI may not significantly distinguish the stochastic model from the deterministic one, the real strength of the stochastic model lies in its inherent capacity to manage and optimize under uncertainty. This feature, as demonstrated throughout this thesis, permits the effective maximization of worst-case profits and superquantile profits, a feat unachievable with deterministic models. Therefore, the value and benefits of stochastic modeling extend beyond what is captured by VSS and EVPI alone.

4.6 Real-World Implications and Applications

The results from our two-stage stochastic linear programming model have significant implications for real-world decision-making for Australian farmers. By accounting for various sources of uncertainty in agricultural operations, our model provides farmers with a more robust framework for making strategic decisions that can help maximize their objectives while managing risk.

One key finding from our model is that the choice of objective function greatly impacts the optimal farming strategy. For instance, when maximizing the expected value, the model recommends a strategy focused on the production of prime lambs. This insight can be extremely valuable for farmers, as it demonstrates the importance of clearly defining their objectives and risk tolerance when making decisions in the face of uncertainty.

Understanding the impact of different objectives on optimal farming strategies can help farmers make more informed decisions that align with their long-term goals and financial risk preferences. By considering uncertainties in factors such as weather, market prices, and input costs, our model enables farmers to develop strategies that are better suited to withstand the inherent volatility of the agricultural sector.

The results from our model have broader implications for the Australian agricultural sector as a whole. By adopting a stochastic programming approach, farmers across the country can make more robust decisions that account for the uncertainties that define their industry. This, in turn, can lead to more resilient farming operations, improved resource allocation, and more sustainable agricultural practices that benefit both individual farmers and the sector as a whole.

The real-world implications and applications of our model are far-reaching. By demonstrating the importance of considering uncertainties in agricultural decision-making and providing insights into how different objectives and risk tolerances can impact optimal farming strategies, our model serves as a valuable tool for Australian farmers. By adopting this approach, farmers can make more informed decisions in the face of uncertainty, ultimately leading to a more resilient and sustainable agricultural sector in Australia.

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CHAPTER 5:
Conclusion

5.1 Summary of Key Findings

This research has successfully demonstrated the value of a two-stage stochastic programming approach for managing uncertainty in agricultural production, offering tangible insights and key numerical evidence supporting the model's effectiveness.

Our model emphasized that the farmer's risk tolerance and objectives largely shape the farming strategies. With the objective of maximizing the expected mean profit over 10,000 scenarios, the model strategy leaned towards the production of prime lambs. Comparing this strategy to a deterministic model of a single scenario, the mean profit under the stochastic model increased by $27,000, rising from $617,000 to $644,000.

In the risk reduction scenario where we adjusted the model to maximize the superquantile, the strategy transitioned towards a balanced mix of Merino wool production and prime lamb production. The superquantile value in this case escalated from $423,000 to $510,000 when compared to the deterministic counterpart, effectively increasing the lowest 10% of profits by $87,000.

A significant elevation in the minimum profit was observed when we aimed at maximizing the worst-case profit. The minimum profit escalated from $174,000 to $419,000 in the stochastic model, marking a substantial increase by $245,000 compared to the deterministic model.

These findings further emphasize the superiority of the stochastic model over deterministic approaches in handling uncertainty. By accommodating the inherent uncertainty of future conditions, the stochastic model invariably leads to better decision-making for the farmer. This study, hence, underscores the potential for two-stage stochastic programming to significantly enhance risk management and strategic planning in Australia's agriculture sector.

5.2 Recommendations

Agriculture is inherently defined by uncertainty. Farmers consistently make decisions under these uncertain conditions, impacted by unpredictable weather patterns, fluctuating market prices, and various other risk factors. As such, decision-making strategies that effectively incorporate and navigate this uncertainty are not just beneficial but are essential.

In light of the findings from this thesis, I recommend further investment in stochastic optimization techniques by both the Australian government and commercial farming tools. The benefits, as our research indicates, can significantly improve strategic planning and risk management within the farming sector.

The Australian government has shown initiative in this area with the development of the *farmpredict* model, a microsimulation tool that employs machine learning methods to predict production outputs, input usage, and changes in farm stocks based on factors like prices, fixed inputs, climate conditions, and other farm characteristics. While *farmpredict* is undoubtedly an innovative tool that adapts to observed conditions and provides data-driven predictions, it does not necessarily focus on optimization in the way that two-stage stochastic programming does. Stochastic programming allows for decision-making to be structured sequentially, with recourse actions being made based on the realized outcomes of uncertain events.

The studies conducted by ABARES reveal that farmers who do not adapt to changing conditions are at a significant risk of substantial profit losses. It is clear that the government initiatives need to extend beyond predictive tools to include optimization approaches.

I recommend that the Australian government invest further in integrating stochastic optimization within its agricultural decision-support tools. This investment would not only enhance the predictive capabilities of tools like *farmpredict* but also enable farmers to make more informed, strategic decisions based on optimization. Similarly, commercial farming tools should also explore the integration of stochastic optimization. This approach would provide a competitive edge, offering farmers a more robust and effective tool for managing uncertainties inherent in their profession.

The adoption and implementation of stochastic optimization techniques could profoundly impact Australia's agricultural sector, facilitating improved risk management, greater adaptability, and more sustainable profitability for our farmers.

5.3 Future Research

This study provides a crucial foundation for managing uncertainty in agricultural production. However, several areas would allow for further exploration to refine the model's accuracy and applicability, as outlined below.

5.3.1 Incorporation of Parameter Correlation

This research treated all input parameters as independent for the sake of model simplification. However, the reality of agricultural production is that many variables are interdependent. For example, a drought will likely affect the yield of all crops, not just one, and would also increase the feedrate required for stock. Future work should therefore investigate and implement correlations among parameters. This addition would likely increase the accuracy of the model's results.

5.3.2 Beyond the Normal Distribution Assumption

Although many parameters can be reasonably approximated by a normal distribution, not all variables conform to this pattern. Further research could improve upon the current model by estimating the distribution of data using historical records with greater precision. This approach could provide more accurate representations of uncertainty in agricultural production.

5.3.3 Model Development: Incorporating Paddock Sizes and Resources

The current model does not account for specific resources such as paddock sizes. For example, the model may suggest planting 15 hectares of barley, but the farmer might not have a combination of paddock sizes to accommodate this. Incorporating paddock sizes into the model will require the addition of binary variables, thus making the model more complex but also more realistic.

5.3.4 Incorporation of Stock Mob Sizes

Much like selecting paddock sizes, the model could be expanded to consider mob sizes of livestock. In real-world conditions, different mobs of sheep might need to be kept together, and they may not all fit into a single paddock. The model could be extended to account for scenarios where adjacent paddocks need to be opened and combined to allow for grazing. The inclusion of mob rotation in the model would add complexity, further highlighting the potential need to reduce scenario amounts using techniques such as below.

5.3.5 Use of Nearly Orthogonal Latin Hypercubes (NOLHs)

To manage the increased complexity from incorporating parameter correlations and non-linear constraints, future research could explore the use of NOLH. These mathematical tools can help reduce the number of scenarios the model needs to analyze, saving computation time without sacrificing the quality of insights. By selecting the best combinations of parameters to create scenarios, a NOLH can accommodate a more complex model.

NOLHs are particularly useful in reducing the size of the scenario set in a stochastic program. By carefully selecting a subset of scenarios that are representative of the entire probability distribution, we can reduce the computational effort without significantly sacrificing the quality of the solution. This makes NOLHs a powerful tool for dealing with complex stochastic models where the number of potential scenarios is very large.

APPENDIX: Model Parameters and Inputs

The following tables contain all the model parameters, sets and indices for reproducibility.

Table A.1. Model Static Parameters

Parameter	Value
land_size	520 hectares
sheep_stocking_rate	7 sheep per hectare
cattle_stocking_rate	2 cattle per hectare
available_capital	$1,000,000,000 dollars
stock_limits	100 cattle
crop_limit	0

Table A.2. Sets and Indices

Set/Indices	Elements
commodity_set	Crop, Female_Stock, Male_Stock, Offspring
crop_set (C)	Canola, Barley, Oats, Lupins
female_grain_feeder_set (FGC)	merino_ewe, cull_merino_ewe, firstcross_ewe
male_grain_feeder_set (MGC)	merino_ram, borderleicester_ram, dorset_ram
female_hay_feeder_set (FHC)	angus_cow
male_hay_feeder_set (MHC)	angus_bull
offspring_grain_feeder_set (OGC)	merino_lamb, firstcross_lamb, prime_lamb
offspring_hay_feeder_set (OHC)	angus_calf
female_stock_set (FS)	angus_cow, merino_ewe, cull_merino_ewe, firstcross_ewe
male_stock_set (MS)	angus_bull, merino_ram, borderleicester_ram, dorset_ram
offspring_set (O)	angus_calf, merino_lamb, firstcross_lamb, prime_lamb
scenario_set (I)	1, 2, . . . , n

Table A.3. Mating Dictionary (MD)

Male Stock	Female Stock
angus_bull	angus_cow
merino_ram	merino_ewe
borderleicester_ram	cull_merino_ewe
dorset_ram	firstcross_ewe

Table A.4. Offspring Dictionary (OD)

Female Stock	Offspring
angus_cow	angus_calf
merino_ewe	merino_lamb
cull_merino_ewe	firstcross_lamb
firstcross_ewe	prime_lamb

Table A.5. Replacement Dictionary (RD)

Female Stock	Offspring
angus_cow	angus_calf
merino_ewe	merino_lamb
cull_merino_ewe	merino_lamb
firstcross_ewe	firstcross_lamb

Table A.6. Males Required

Male Stock	Number
angus_bull	20
merino_ram	70
borderleicester_ram	70
dorset_ram	70

Table A.7. Crop Parameters (mean, std)

	Canola	Barley	Oats	Lupins
Grain_Yield	(1.2, 0.15)	(2, 0.25)	(2, 0.25)	(1.5, 0.2)
Grain_Profit	(350, 30)	(90, 10)	(80, 8)	(180, 12)
Grain_Price	(700, 80)	(250, 30)	(200, 25)	(400, 35)
Hay_Yield	(3, 0.8)	(4, 0.5)	(4, 0.5)	(2.5, 0.3)
Hay_Profit	(60, 8)	(40, 5)	(35, 4)	(60, 8)
Hay_Price	(200, 30)	(150, 20)	(135, 15)	(200, 30)

Table A.8. Female Stock Parameters (mean, std)

	Angus_Cow	Merino_Ewe	Cull_Merino_Ewe	Firstcross_Ewe
Profit	(1000, 100)	(90, 30)	(70, 25)	(80, 30)
Price	(2500, 300)	(240, 40)	(180, 30)	(280, 50)
Birthrate	(0.9, 0.04)	(1.1, 0.05)	(1.2, 0.05)	(1.5, 0.05)
Feedrate	(0.5, 0.02)	(0.2, 0.01)	(0.2, 0.01)	(0.2, 0.01)
Replacement	(0.08, 0.015)	(0.08, 0.015)	(0.1, 0.015)	(0.1, 0.015)
Lossrate	(0.08, 0.015)	(0.1, 0.015)	(0.1, 0.015)	(0.1, 0.015)
Wool_Profit	(0, 0)	(45, 5)	(20, 4)	(14, 2)

Table A.9. Male Stock Parameters (mean, std)

	Angus_Bull	Merino_Ram	BorderLeicester_Ram	Dorset_Ram
Price	(6000, 750)	(1250, 100)	(1300, 150)	(2000, 200)
Feedrate	(0.5, 0.02)	(0.2, 0.01)	(0.2, 0.01)	(0.2, 0.01)
Lossrate	(0.08, 0.015)	(0.1, 0.015)	(0.1, 0.015)	(0.1, 0.015)
Wool_Profit	(0, 0)	(60, 7)	(30, 8)	(30, 8)

Table A.10. Offspring Parameters (mean, std)

	Angus_Calf	Merino_Lamb	FirstCross_Lamb	Prime_Lamb
Profit	(2500, 200)	(90, 15)	(110, 15)	(150, 20)
Feedrate	(0.15, 0.02)	(0.05, 0.005)	(0.05, 0.005)	(0.05, 0.005)
Lossrate	(0.05, 0.008)	(0.12, 0.016)	(0.11, 0.016)	(0.15, 0.016)

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