An economic analysis of a robotic harvest technology in New Zealand fresh apple industry

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Abstract

The New Zealand apple industry is predominately an export-oriented industry relying on manual labour throughout the year. In recent years, however, labour shortages for harvesting have been jeopardising its competitiveness and profitability. Temporary immigration labour programs, such as the Recognised Seasonal Employer (RSE) program have not been able to solve the labour shortages, urging the industry to consider use of harvesting automation, i.e. robotic technology, as a solution. Harvesting robots are still in commercial trial stage and no studies have assessed the economic feasibility of such technology. The present study for the first time develops a bio-economic model to analyse the investment decision for adopting harvesting robots compared to available alternatives, i.e. platform and manual harvesting systems, using net present value (NPV) as the method of analysis; for newly established single-, bi-, and multi-varietal orchards across different orchard sizes, and three apple varieties (Envy, Jazz, and Royal Gala); and implications of orchard canopy transition and associated sensitivities are considered.

The results of the analysis identified fruit value and yield as the key drivers for the adoption of harvesting automation. For relatively low value and or yielding varieties such as Jazz or Royal Gala, robots are less profitable in single-varietal orchard compared to bi-varietal orchard planted with relatively low value and yielding varieties. In a multi-varietal orchard, a relatively high value and high yield variety, such as Envy, is crucial to compensate for the costs incurred for harvesting other varieties using robots or platforms.

The greatest potential benefit of utilising harvesting robots was reducing pickers required by an average of 54% for Envy and 48% for each of Jazz and Royal Gala across all orchard sizes compared to manual harvesting; and 7% in average for each of Envy, Jazz, and Royal Gala across all orchard sizes compared to platform harvesting system. This study also identified the break-even price for a robotic harvester in a single-varietal orchard, showed that the break-even prices exceeded the assumed price of the robot, and are highly variable depending on the varietal value and yield, where Envy as a relatively higher value and yielding variety returns a break-even price of $2.92 million compared to relatively lower value and yielding varieties, Jazz with $674,895, and Royal Gala with $689,608. Sensitivity analyses showed that both harvesting speed and efficiency are key parameters in the modelled orchard and positively affected the net returns of the investment and must be considered by researchers and manufacturers. However, for developers and potential adopters of robots, it should be more important that robots operate faster, but not necessarily as more efficient in order to generate a high return while substituting the highest number of pickers and leaving less unharvested fruit on trees in the limited harvesting window. Reducing robot price by 12% and 42% can generate an equivalent level of profit similar to manual or platform harvesting, respectively. Increases in labour wages, and decreases in labour availability and efficiency adversely affected the NPV and profitability outlook of the investment, but NPV was more affected by the decreases in labour efficiency and availability than wage increases.

This research has important science and policy implications for policy makers, academics, growers, engineers, and manufacturers. From an economic perspective, for late adopters or those growers who may not be financially able to invest in robots or may be uncertain about their performance, platform harvesting system can be utilised as an alternative solution that is commercially available until robotic harvesting technology improves or becomes more affordable, and commercially available. Alternatively, it may be possible for these orchardists to benefit from utilising the robotic harvester in the form of a co-operative or contract-harvesting business model to avoid the capital costs associated with purchasing and operating the robots.

Besides the economic factors, robotic harvesters have the potential to be considered as a solution for non-economic factors such as food safety problems. This is more apparent in the post-Covid-19 pandemic era, which has not only made it more difficult for growers to source their required workers due to border closures, but also has led consumers to be more cautious about food safety when they make purchase decisions and prefer to have their fresh fruit touchless from farm to plate. This may not be a problem for packhouses as most are automated, but it may be an issue for harvesting operations, because pickers have to pick apples by hand. Even though robots cannot be the only option for growers to rely on for the foreseeable future as they are not commercially available, in the current situation robot harvesting may be the most ideal solution.

Keywords: Robot, labour, bio-economic analysis, net present value (NPV), New Zealand, apple industry.

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List of Acronyms

Acronym	Full phrase
AMS	Automatic Milking Systems
AI	Artificial Intelligence
APAL	Apple and Pear Australia Limited
EDM	Equilibrium displacement models
EU	The European Union
FOPS	Future Orchard Production System
GDP	Gross Domestic Product
GPS	Global Positioning System
GlobalGAP	Global Good Agricultural Practices
GRASP	GlobalGAP Risk Assessment on Social Practice
HSWA	Health and Safety at Work Act 2015
MPI	The New Zealand Ministry for Primary Industries
MSD	The New Zealand Ministry of Social Development
NPV	Net Present Value
NZAPIMB	The New Zealand Apple and Pear Marketing Board
NZAPI	New Zealand Apples & Pears Inc.
IFP	Integrated Fruit Production
IRTA	Institute of Agri-food Research and Technology
IRR	Internal Rate of Return
Pipfruit NZ	Pipfruit New Zealand Inc.
RO	Real Option
RSE	Recognised Seasonal Employer Scheme
SWP	The Seasonal Worker Programme
ITP	Agri-tech Industry Transformation Plan
US	The United States
UK	The United Kingdom
3D	Three-dimensional
2D	Two-dimensional

List of Symbols

Symbol	Description	Unit
Ψ	Adjustment factor for hourly wage	$
ϕ	Salvage rate	%
ϑ	Selected pre-harvest tasks	task
ω	Insurance and housing rate	%
κ	Repair rate	%
$\Phi_{z,i,t}$	Salvage value for robot or platform of variety *i* in *t*	$/machines
ρ	Risk adjusted discount rate	%
χ_z	Harvesting performance for system *z*	%
$\varrho C_{z,i,t}$	Robot operator or platform labour cost of variety *i* in *t*	$/machines
$\varphi C_{z,i,t}$	Fuel cost for system *z* of variety *i* in *t*	$/machines
$\tau C_{z,i,t}$	Insurance cost for system *z* of variety *i* in *t*	$/machines
$\delta C_{z,i,t}$	Oil and lubrication cost for system *z* of variety *i* in *t*	$/machines
$\gamma C_{z,i,t}$	Repair cost for system *z* of variety *i* in *t*	$/machines
$\beta C_{z,i,t}$	Interest cost for system *z* of variety *i* in *t*	$/machines
A_i	Orchard size per variety	ha
$BY_{i,t}$	Biological yield per variety in *t*	kg/ha
K	Initial recurrent costs of the investment	$
$\bar{e}_{z,i}$	Packout or export recovery rate harvested by system *z* of variety *i*	%
F	Harvesting efficiency of pickers to pick unharvested fruit due to inefficiency of robots/platforms	%
F^-	Harvesting efficiency of pickers to pick unharvested fruit from the area not harvested by robots/platforms	%
fc_z	Fuel consumption of gasoline for system *z*	litres/hr
fp	Fuel price	$/litre
ga_i	Fruit weight of variety *i*	grams
g_b	Weight of each bin	kg
$h_{z,i,t}$	Total harvesting operation hours of system *z* for variety *i* in *t*	hr
h_w	Pre-harvest hourly wage utilising platform	$/hr
$h_{3,\vartheta,t}$	Total pre-harvest operation hours required by platform per task in *t*	hr/task
$HA_{z,i,t}$	Mechanically harvested area for system *z* of variety *i* in *t*	ha
$HC_{z,i,t}$	Harvest variable cost for system *z* of variety *i* in *t*	$/ha
HF_z	Harvesting efficiency for system *z*	%
$HS_{z,i}$	Harvesting speed of system *z* for variety *i*	kg/day
HW_i	Harvesting window per variety	days
i	Apple variety	variety

M	The point of indifference between investing or not investing under certainty	integer
MH_w	Manual labour wage	\$/kg
$\overline{MHC}_{z,i,t}$	Pickers cost to harvest unharvested fruit for system *z* of variety *i* in *t*	\$/ha
MHN_b	Number of bins harvested manually	integer
$MVC_{z,i,t}$	Machine-related variable or operating cost for system *z* of variety *i* in *t*	\$/machines
N_l	Number of workers on a platform	integer
$N_{z,i,t-1}$	Number of machines purchased for variety *i* in the previous year	integer
$N_{z,i,t}$	Number of harvesting units required for variety *i* in *t*	integer
$NA_{i,t}$	Number of apples per tree for variety *i* in *t*	fruit/tree
N_l	The number of workers on a platform	integer
$NM_{z,i,t}$	Number of pickers required for system *z* of variety *i* in *t*	integer
NT_i	Number of trees for variety *i*	trees/ha
OF_z	Operation efficiency for system *z*	%
$P_{z,i}$	Price of fruit harvested by system *z* variety of variety *i*	\$/kg
PC_z	Price for each machine	\$/machine
$Pd_{z,i}$	Domestic price for system *z* of variety *i*	\$/kg
PD_i	Daily working hours for platform operation per variety	hr
$Pe_{z,i}$	Export price for system *z* of variety *i*	\$/kg
PH_w	Post-harvest wage	\$/kg
$PHC_{z,i,t}$	Post-harvest cost for system *z* of variety *i* in *t*	\$/ha
$\bar{P}HC_{z,t}$	Pre-harvest costs performed for system *z* in *t*	\$/ha
PHN_b	Number of bins harvested by platform (harvesting team)	bins/hour
$PN_{z,i,t}$	Number of machines purchased new for variety *i* in the current year	integer
q	Percentage of machines' fuel cost for oil and lubrication estimation	%
r	Annual interest rate	%
R_w	Robot's operator wage	\$/hr
R_t	Net returns in *t*	\$
RD_i	Daylight hours per variety for robot operation	hr
$RN_{z,i,t}$	Number of machines replaced for variety *i* in the current year due to reaching useful life	integer
RHN_a	Number of apples harvested by robot per hour	fruit/hour
$\overline{SP}HC_{3,t}$	Costs associated with utilising platform for selected pre-harvest tasks in *t*	\$/ha
$TC_{z,i,t}$	Total cost for system *z* of variety *i* in *t*	\$/ha
TC_t	Cost in *t*	\$/ha

$TFC_{z,i,t}$	Total fixed cost for system z of variety *i* in *t*	$/ha
TK_t	Total cost in *t*	$/ha
$TMVC_{z,i,t}$	Total machine-related operating or variable costs for system *z* of variety *i* in *t*	$/ha
$TN_{z,t}$	Total number of system *z* in *t*	integer
$TPC_{z,i,t}$	Total ownership cost or purchase price for system *z* of variety *i* in *t*	$/machines
TR_t	Revenue in *t*	$/ha
$TR_{z,i,t}$	Total revenue for system *z* of variety *i* in *t*	$/ha
TU_t	Total revenue in *t*	$/ha
$TVC_{z,i,t}$	Total operating or variable cost for system *z* of variety *i* in *t*	$/ha
V	Net present value	$
$Y_{z,i,t}$	Yield for system *z* of variety *i* in *t*	kg/ha
$\bar{Y}_{z,i,t}$	Yield from pickers for system *z* of variety *i* in *t*	kg/ha

Chapter 1. Introduction

1.1. Research background

The New Zealand apple industry is the second-largest fresh fruit export after kiwifruit with an export value of nearly [1]$900 million in 2020 (MPI, 2019 and 2020). The industry relies on intensive labour use in particular for harvest (Pollard, 2018). Consequently, the availability of labour at the time of harvesting is a potential constraint to the industry and its growth, requiring fruit to be harvested within a short harvesting period to ensure optimal quality, or otherwise any unharvested fruit are wasted. This could eventually reduce the profitability and competitiveness of the industry (MPI December 2017 and 2018; Zhang, 2018).

Temporary immigration labour programs, such as the Recognised Seasonal Employer (RSE) program have been used by New Zealand apple growers to employ seasonal workers, mainly from the Pacific Island communities, during the peak harvesting season (Ashton, 2018; Bartlett, 2018; Eddy, 2018; MPI, December 2017 and 2018) to harvest apples in the limited harvesting time. However, dealing with labour shortages remains a considerable challenge for the industry (Ashton, 2018; Bartlett, 2018; Pollard, 2018; MSD, 2019). In the 2018 apple picking season, the New Zealand Ministry of Social Development (MSD) announced an official seasonal labour shortage across the main apple growing region of Hawke's Bay (Ashton, 2018; Bartlett, 2018). Announcing or extending a labour shortage across affected regions is considered to be the last option when all other measures to source sufficient labour have failed. The announcement allows holders of a visitor visa to apply for a variation of conditions to work on orchards in this region, in addition to local New Zealand people who may be interested or able to work in this context (MSD, 2019).

Lately, the Covid-19 pandemic has put further strain on labour shortages in New Zealand, following the global travel ban and border closure that is put in place by the government as part of series of measures to fight the pandemic (Bonnet, 2020). These measures have been blocking overseas backpackers and visitors, who usually make up about 25% of the workforce in the horticulture industry entering the country (Burry, 2020; Frykberg, 2020; Hill, 2020). Notwithstanding, the Covid-19 pandemic is an

[1]All currencies are in New Zealand dollars.

example to demonstrate that such global disasters and unpredictable events can impose similar risks to the industry, particularly affecting labour availability, given that the New Zealand horticulture industry mainly relies on overseas workers and backpackers.

The challenge for the horticulture industry is to ensure that there is sufficient labour available when required and that this workforce is utilised efficiently. Given that labour is a major cost for tree fruit industry, it is of particular importance for orchardists to make efficient use of labour (Sinnett et al., 2018). Orchardists who grow apples can use machinery to make labour more efficient, however, they cannot completely replace labour with machinery because of the current stage in the evolution of mechanisation and automation of tree fruit production and particularly harvesters (Sinnett et al., 2018).

Among commercially available harvesting solutions, apple growers can use ladder (manual), power ladder (semi-manual), platform (hybrid solution, combining automatic and manual functions), or their combination to assist with not only picking but also pruning, thinning, and tree training (Sinnett et al., 2018; Zhang, 2018). Currently, there are robotic systems developed and commercially trialled in the US and New Zealand that utilise optics, pneumatics, and vacuum technologies to mimic the precision of human pickers, making them better suited for producing apples for the fresh market (Schueller, 2013; T&G, 2019; Zhang, 2018).

Fully mechanised harvesting systems have been used in the past by apple growers mainly for the processed market. Due to the fruit damage caused by the shake-and-catch technology, the harvested apples are not suited for the fresh market (Burks et al., 2018; Zhang, 2018). Although, this research is mainly focused on robot harvesting, platform harvesting is considered as an available alternative to enhance the harvesting speed and efficiency of pickers (Zhang, 2018).

The process of mechanising and automating tree fruit production for fresh market requires changes at the farm level in terms of the cultivar and rootstock selection, traditional orchard practices, orchard design and tree planting density, tree shape and training, labour incentives and dynamics, harvesting logistics, and operating systems (Calvin and Martin, 2010; van der Merwe, 2015). These changes can influence the entire fruit production system leading to better management of inputs and minimisation of waste, while meeting the quality requirements of harvested fruit for fresh market. This requires an automation system with comparable performance to human pickers capable of harvesting ready-to-pick fruits from trees quickly and efficiently without causing damage to the harvested fruit on the tree (Schueller, 2013; Zhang, 2018). Notwithstanding, robotic harvest technology has the potential to fully automate apple harvesting and completely replace manual harvesting labour in the future (Ashton, 2018; Bartlett, 2018; Eddy, 2018).

1.2. Research question and aim

The main question that this research aims to answer is: Is robot harvesting Envy, Jazz, and Royal Gala varieties structured in two-dimensional (2D) tree canopy system economically feasible in New Zealand fresh apple industry?

In order to answer this research question, it is important to remember that at present harvesting robots for fresh market apples are still in their commercial trial phase and no studies have assessed the economic feasibility of such technology. As such, this research develops a bio-economic model to analyse the investment decision to utilise harvesting robots for single-varietal, bi-varietal, and multi-varietal orchards of various orchard sizes using net present value (NPV) of the investment – incorporating various aspects of apple production with respect to robot harvesting including physiological (e.g. tree canopy structure and variety-specific characteristics), technological (e.g. robot harvesting efficiency), and operation and economic trade-offs (e.g. purchase and operating costs of robot).

1.3. Research objectives

The present research aims to achieve the following two objectives:

1. To identify the economic feasibility of utilising robot or platform (an available alternative) on harvest operations of multiple varieties of apples with varying prices and yields across different orchard sizes.

2. To identify the threshold and scale at which investment in a robotic harvester becomes profitable for single-varietal, bi-varietal, and multi-varietal orchards using different scenarios.

1.4. Research contribution

The current research develops a novel bio-economic framework that aims to provide participants in the industry in particular apple orchard operators and robotic harvest technology developers, with an overview of the economic implications of the investment decision in purchasing harvesting robots as a potential solution for addressing harvesting labour shortages. From a policy and strategy making perspective, economic, technological, and horticultural components incorporated into the bio-economic model can assist policy makers and agri-business professionals to identify multi-objective agricultural policies and strategies with a specific purpose of facilitating easier and faster adoption of the technology. This could be achieved by collaborating with and motivating the private sector to engage with the invention and dissemination of new output-increasing practices such as educating orchardists about modern production strategies including suitable orchard architectures and tree maintenance practices (e.g. pruning), that could pave the way towards easier and smoother transition to complete mechanisation and automation of apple harvesting using robotic technology.

In addition, the model can provide a common ground for discussion and cooperation between scientists and experts from various disciplines namely horticulture, economics, and engineering. The outcomes of the model can be used to help policy makers, agri-business professionals, and farmers to make informed decisions about potential management changes to their farm systems that could result in better handling of the constraints associated with the adoption of the technology, including physiological (e.g. tree canopy structure), technological (e.g. robot harvesting performance), as well as operational and economic trade-offs (e.g. purchase and operating costs of robot).

These factors can influence the feasibility of the investment decision, sustainable fruit production, and overall global competitiveness of New Zealand's apple industry. In broader terms, this can create new opportunities in rural communities for better jobs that may require less drudgery than traditional manual field labour such as manual fruit harvesting. In addition, the technology has the potential to improve worker safety and health by reducing the need to use traditional harvesting aids such as ladders for harvesting fruit on trees (Burks et al., 2018).

1.5. Structure of the thesis

This thesis consists of six chapters which are organized as follows:

Chapter 1 (Introduction) provided the background of this research and introduced the research problems as well as the research aim and objectives. The research context, the industry, and the empirical model were briefly introduced.

Chapter 2 (Industry background) overviews the apple industry in the world and in New Zealand contexts. The chapter provides the historical background and identifies the driving forces behind the growth of the industry in New Zealand as well as drivers for switching towards automation in harvesting. Industry production, domestic consumption, trade, and associated challenges are also examined in this section.

Chapter 3 (Literature review) reviews and discusses literature on the issue of labour in agriculture especially in horticulture and the tree fruit industry. Furthermore, the literature on robotic harvesting systems in horticulture and animal agriculture are reviewed in order to provide a broader perspective on the applications of the robotic systems in primary production. Finally, economic studies applied to perennial tree fruit are reviewed with the aim to examine the methods and approaches that have previously been used. This will help to identify the most appropriate method for the current research to assess the investment decision in adoption of the robotic harvest technology.

Chapter 4 (Conceptual model) provides a conceptual framework for the economic feasibility analysis of three apple harvesting systems (manual, robot, and platform), taking into consideration key factors in the investment decision such as yield and value per apple, purchase and operating costs of machines, number of harvesting units required, number of pickers required, harvesting efficiency and speed, and harvesting window of each variety.

Chapter 5 (Empirical model) provides a description of the application and data required to extend the conceptual framework to an empirical model to investigate the investment decision. This chapter analyses the conceptual model discussed in terms of the data collection, analysis, estimations, and assumptions based on literature, online databases, face to face and correspondent communications with representatives from the New Zealand apple industry, which were used to build the base model.

Chapter 6 (Results and discussions) presents and discusses the key findings of the analyses and provides a conceptual framework of information on investment decision making under different scenarios with regard to the ownership and operation of robot versus platform, taking into consideration harvesting systems, orchard types, orchard sizes, and varietal selections.

Chapter 7 (Conclusion) provides an overview of the research chapters and a summary of findings, along with implications and limitations of the research and potential future directions.

Chapter 2. Apple industry overview

This chapter provides an overview of the apple industry in the global and New Zealand contexts. The world apple industry with specific focus on production, domestic consumption, and trades are explained. In addition, an industry overview including key events and development of New Zealand apple industry are reviewed, attempting to identify the driving forces behind the industry's growth. Production and export of New Zealand apples to other countries are explained, the development of exclusive varieties is discussed, and the standardisation of apple production that has made the New Zealand apple industry more competitive globally are elaborated. Following that, the most important challenges of the industry namely labour management and climate change are explained.

2.1. The world apple industry

2.1.1. Production

As presented in Table 2.1, over 70 million metric tons of apples were produced worldwide in the 2018 production year and this is forecasted to increase to nearly 75.8 million for 2019 (USDA, 2018 and 2019). In terms of production, China and the EU followed by the United States were the largest producers of apples in 2018 with production of about 54%, 15%, and 6.1% of total global production; they are followed by Turkey, India, and Iran which together produce nearly 10% of global production (USDA, 2018 and 2019).

Despite low production in the 2018 production year due to severe weather, Chinese production is forecast to rebound to 41 million tons in 2019 (USDA, 2018 and 2019). European Union (EU) production is expected to drop by more than 20% to 11.5 million tons, the second time in 3 years, as member countries, in particular Poland, experienced severe weather conditions, with a combination of drought, heat, frost, and hail (USDA, 2019). United States (US) production is forecast to increase by 300,000 tons to 4.8 million as Washington state production improved due to favourable weather conditions (USDA, 2019). For comparison, New Zealand's total production is forecast at 598,000 tons in 2019, ranking 16th in total world production (Lee-Jones, 2019; USDA, 2018 and 2019).

The increase in New Zealand output is from trees coming into production from expanded planting area (Lee-Jones, 2019; Pollard, 2018). In addition, planting area in New Zealand is projected to continue increasing by reinvesting in existing orchards, replacing older varieties, and more importantly planting higher-density orchards, which has boosted yields from an average 60 metric tonnes per ha from larger woody trees to 80-100 metric tonnes per ha from smaller and more densely planted trees – making New Zealand the country with the highest yield per ha in the world (Lee-Jones, 2019; USDA, 2018 & 2019).

Table 2.1. World apple production, 2014-2019 (1,000 Metric Tons) ranked based on 2019

Rank	Country	2014	2015	2016	2017	2018	2019
1	China	37,350	38,900	40,393	41,390	33,000	41,000
2	EU	13,636	12,453	12,723	10,005	15,030	11,477
3	USA	5,112	4,546	5,010	5,085	4,486	4,665
4	Turkey	2,289	2,740	2,900	2,750	3,000	3,000
5	India	2,498	2,520	2,258	1,920	2,371	2,370
6	Iran	2,500	2,470	2,097	2,097	2,097	2,097
7	Russia	1,409	1,311	1,509	1,360	1,611	1,714
8	Brazil	1,265	1,049	1,301	1,301	1,301	1,301
9	Chile	1,210	1,335	1,310	1,330	1,230	1,144
10	Ukraine	1,180	1,099	1,076	1,076	1,076	1,076
	Total	74,520	74,638	76,432	74,205	70,964	75,722

Source: United States Department of Agriculture (December 2019)

2.1.2. Domestic consumption

As shown in Table 2.2 in terms of domestic consumption of fresh apples, the largest apple producers worldwide are also among the main consumers. In 2019, the countries with the highest consumption are China, EU, Turkey, the US, India, Russia, and Iran. New Zealand is ranked 38th with domestic consumption of 73,150 metric tons.

Table 2.2. World fresh apple domestic consumption, 2014-2019 (1,000 Metric Tons) ranked based on 2019

Rank	Country	2014	2015	2016	2017	2018	2019
1	China	33,470	33,826	34,682	35,371	29,775	38,050
2	EU	7,781	7,544	7,750	6,544	8,197	7,401
3	Turkey	2,064	2,532	2,576	2,452	2,614	2,631
4	USA	2,714	2,553	2,817	2,672	2,518	2,589
5	India	2,681	2,311	2,230	1,919	2,330	2,365
6	Russia	1,803	1,646	1,583	1,807	1,863	1,884
7	Iran	2,358	2,036	1,864	1,372	1,814	1,814
	Total	66,080	66,689	67,825	64,580	65,682	66,907

Source: United States Department of Agriculture (December 2019)

2.1.3. Trade – Imports

In terms of fresh apple imports (Table 2.3), Russia remains the largest fresh apple importer, although greater quantities and improved quality of domestic supplies are expected to ease demand for imports, with imports declining by 80,000 tons to 710,000 in 2019. China is expected to have increased import demand for higher quality apples to a record 100,000 tons due to the low quality of domestic apples (USDA, 2019). Imports into the EU are expected to remain unchanged at 500,000 tons despite lower production as greater supplies of domestic output are diverted to fresh consumption and a smaller share of domestic output goes towards processing. Similarly, US imports are projected to remain unchanged at 145,000 tons, offsetting lower shipments from Chile by higher shipments from New Zealand (USDA, 2019). New Zealand imports a negligible quantity of apples, 150 metric tons, down 9% from 2017, and it is unlikely to increase given a higher domestic output forecast for 2019 (USDA, 2019).

Table 2.3. World fresh apple imports, 2014-2019 (1,000 Metric Tons) ranked based on forecasted 2019

Rank	Country	2014	2015	2016	2017	2018	2019
1	Russia	820	746	657	859	789	710
2	EU	400	451	425	531	493	500
3	Iraq	122	297	241	307	319	330
4	Mexico	314	218	267	287	247	280
5	India	204	202	370	249	277	250
6	Bangladesh	151	203	245	245	188	240
7	Belarus	724	657	544	224	219	220
8	Canada	217	230	221	222	203	220
9	Egypt	201	268	145	72	271	215
10	Vietnam	116	141	150	160	158	190
	Total	6,135	6,474	6,253	6,061	5,764	5,969

Source: United States Department of Agriculture (December 2019)

2.1.4. Trade – Exports

The global apple market is mainly considered as two divided markets. They are the Southern and Northern Hemispheres. In general, the suppliers of these two separate hemisphere markets do not directly compete with each other, due to different peak times of supply. New Zealand directly competes with Chile and South Africa as they are the major Southern Hemisphere apple exporters with the same peak supply periods (Scales, 2014).

Exports (Table 2.4) follows a similar path as production; China, the EU followed by the United States were the largest apple exporters. China's higher supplies are expected to boost exports to over one million tons in 2019. Given reduced production in the EU in 2018, exports are forecast down 200,000 tons to 975,000 in 2019, the second lowest level since 2007 (USDA, 2019). US exports are projected to rise over 100,000 tons to 860,000 as a result of higher supply and the removal of Mexico's 20% retaliatory tariff imposed in May 2019 (USDA, 2019). New Zealand is the sixth largest exporter, with 390,000 tons of exports in 2018; exports are projected to increase by 15,000 tons to 405,000 due to higher supply, with more shipments going to Asian markets (USDA, 2019).

According to Scales (2014), in recent years, there has been a global shift in exporting apples toward markets that are nearby geographically. In the past, Western Europe and North America markets were the main export markets for New Zealand and South Africa. However, now New Zealand has more dependence on geographically closer destinations such as the Asian and Middle Eastern markets, while South Africa has been increasing its dependence on exporting to other African markets and Chile to other South American markets. Moreover, traditional apple markets have had a steady or declining apple consumption, whereas in many Asian markets fresh apple consumption has increased due to rapid increase in per capita income (Scales, 2014).

Table 2.4. World apple exports, 2014-2019 (1,000 Metric Tons) ranked based on forecasted 2019

Rank	Country	2014	2015	2016	2017	2018	2019
1	China	748	1,151	1,381	1,282	818	1,050
2	EU	1,792	1,590	1,487	761	1,176	975
3	USA	1,037	778	868	1,007	742	860
4	Chile	628	765	716	779	705	660
5	South Africa	466	511	553	449	480	570
6	New Zealand	329	347	345	369	390	405
7	Iran	142	435	233	725	283	283
8	Turkey	128	109	215	189	277	260
9	Moldova	135	171	168	269	297	230
10	Serbia	153	233	239	156	184	175
	Total	6,532	6,672	6,679	6,481	5,921	5,969

Source: United States Department of Agriculture (December 2019)

2.2. The New Zealand apple industry

Apple production plays a key role in the growth of the New Zealand horticulture industry. As the largest horticulture industry after Kiwifruit in New Zealand, the apple industry returned export revenue of nearly $900 million in 2020 and is forecast to reach a billion dollars in 2022 and $2 billion in 2030 (Bedford, 2020; Jones, 2020; MPI, 2019 & 2020; Pollard, 2018).

2.2.1. Industry overview

Apples have been grown in New Zealand since 1814. Since then, the industry has undergone challenging phases. New Zealand exported the first shipments of apples to the UK in the 1890s and to the US in 1956. In the 1960s, New Zealand became the world leader in production per hectare after adoption of the central leader shape, M106 rootstock, and higher tree densities from 275 to 670 trees per hectare (Pollard, 2018). In the 1990s, New Zealand developed the Pacific series (Pacific Beauty, Pacific Rose, and Pacific Queen) and Jazz apple varieties. In 1948, the New Zealand Apple and Pear

Marketing Board (NZAPIMB) was established with the aim to bring stability in local prices and to the export market. However, the NZAPIMB was terminated in 1993, which led to opening up the domestic market to competition (Pollard, 2018).

The introduction in 1999 of the Pipfruit Industry Restructuring Act led to the corporatisation of NZAPIMB into ENZA Limited and separation of the regulatory and marketing bodies of the industry (Coriolis, 2006; NZAPI, 2019; Pollard, 2018). In 2001, the deregulation of Pipfruit industry resulted in drastic changes to the industry, which removed the single desk marketing monopoly of ENZA and resulted in an increase in the number of exporters from 1 in 1995 to 85 in 2018, and a reduction in number of growers from 1,600 in 1995 to 257 in 2018 (Table 2.5) (Coriolis, 2006; NZAPI, 2019; Pollard, 2018). In 2005, a Crown Research Institute, HortResearch New Zealand (now the New Zealand Institute for Plant and Food Research) established PREVAR, a joint venture between Pipfruit New Zealand (now New Zealand Apples & Pears (NZAPI)), Apple and Pear Australia Limited (APAL), and the Institute for Crop and Food Research, to commercialize new apple and pear varieties (Coriolis, 2006; NZAPI, 2019; Pollard, 2018; Plant and Food, n.d.).

Table 2.5. Changes in New Zealand apple industry structure (1995, 2001, 2018)

	1995	2001	2018
Number of growers	1,600	1,200	257
Number of exporters	1	80	85
Land in production (ha)	16,000	14,000	10,250
Total production volume (tonnes)	520,000	473,000	577,000

Sources: Freshfacts, 2018; HortNZ, 2020; Lee-Jones, 2019; Pipfruit NZ, 2017; Pollard, 2018; USDA, 2019; NZAPI, 2019.

2.2.2. Production and export

As shown in Table 2.5 over the past decades, land in apple production has decreased from 16,000 ha in 1995 to the current 10,250 ha in 2018 due to decreasing numbers of growers and moving toward high-density plantation and implementing new tree training systems. High-density plantation has allowed apple orchardists to plant more trees per hectare and resulting in more efficient use of land and producing more fruit per hectare, while new training systems have led to better light interception for trees and labour efficiency (Hughes, 2018a; Pipfruit NZ, 2017; Pollard, 2018; NZAPI, 2018). It is forecast that land in production would increase to 15,000 ha by 2030 (Bedford, 2020; NZAPI, 2019). While apples are grown commercially in most regions in the North and

South Islands of New Zealand, historically production has mainly been centred in the Nelson (South Island) and Hawke's Bay (North Island) regions (Pollard, 2018).

In 2019, of the total production of 576,850 tonnes of apples (Lee-Jones, 2019; USDA, 2019), Hawke's Bay accounted for approximately 62%, Nelson 25%, central Otago 4%, and the remaining 9% in Gisborne, Waikato, Wairarapa, and South Canterbury – Figure 2.1 (Pollard, 2018; NZAPI, 2018). Since 2014, there are over 400 ha of unregistered planted areas of 4%, which are not producing fruit for export presently and targeted for local market (NZAPI, 2018; Pollard, 2018). In terms of export volume to different countries, in 2017, about 65% of total New Zealand annual production is exported to over 80 countries worldwide. About 12% of total production is for fresh domestic consumption, the remaining 23% is used for processing into juice and other apple by-products.

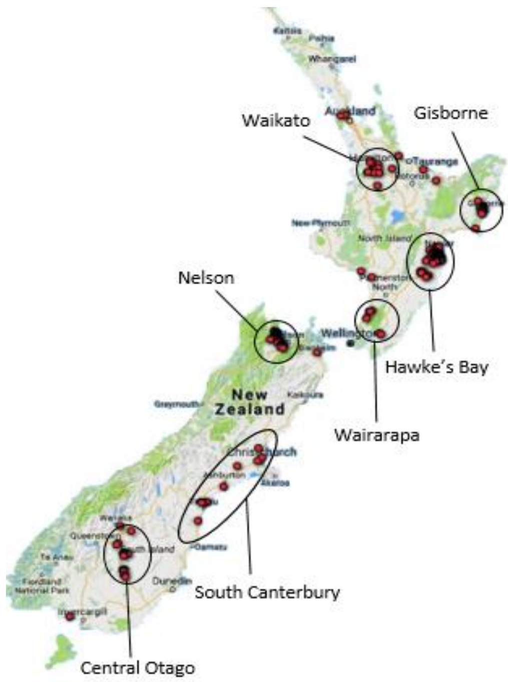

Figure 2.1. New Zealand apple production regions (2018)
Source: NZAPI (2018)

As shown in Figure 2.2, destination markets for export apples have gradually changed during the last decades, a shift from Western to Eastern markets. In 2005, Asian countries imported around 13% of New Zealand's apples and this has significantly increased to about 41% of New Zealand apple production in 2016, followed by Europe with 23%, North America with 16%, and, UK & Ireland with 14%. Asia and the Middle East together accounted for about 47% of New Zealand's exported apples in 2016. This shift means that the potential demand for fresh and quality apples is from countries with large and growing populations and economies that have been going through a shift from low income to middle income populations (Mannering, 2015; Pipfruit NZ, 2017; Pollard, 2018).

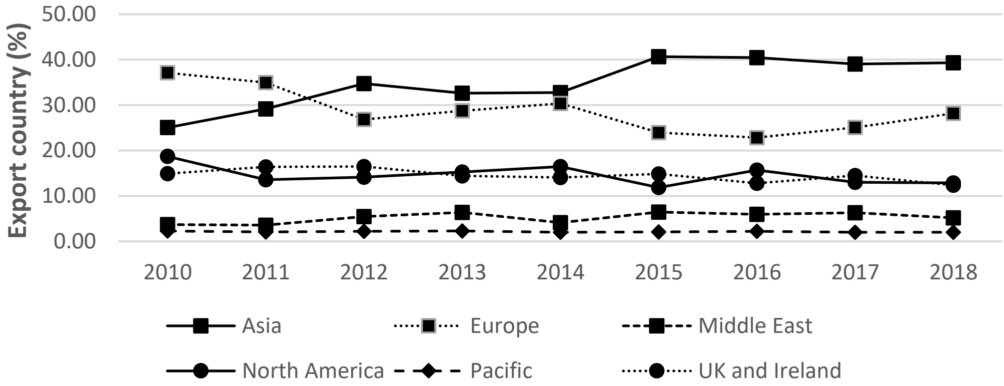

Figure 2.2. New Zealand apple export markets (percentage by continents, 2010-2018). Source: NZAPI (2018).

In terms of export value (Figure 2.3), the New Zealand apple industry doubled its exported value from $360 million in 2012 to over $700 million in 2016 and has further increased by over 13% to nearly $800 million in 2018 (MPI, Dec 2019). More than 70% of the increase was derived from exported value, due to an increase in average export prices to Asian markets, in particular China which experienced poor production due to unfavourable climate conditions (Pipfruit NZ, 2017; NZAPI, 2018; Pollard, 2018; MPI, Dec 2019). It is forecast that export value will reach $2 billion per annum by 2030, driven by the increasing area in production and export values (Bedford, 2020; NZAPI, 2019).

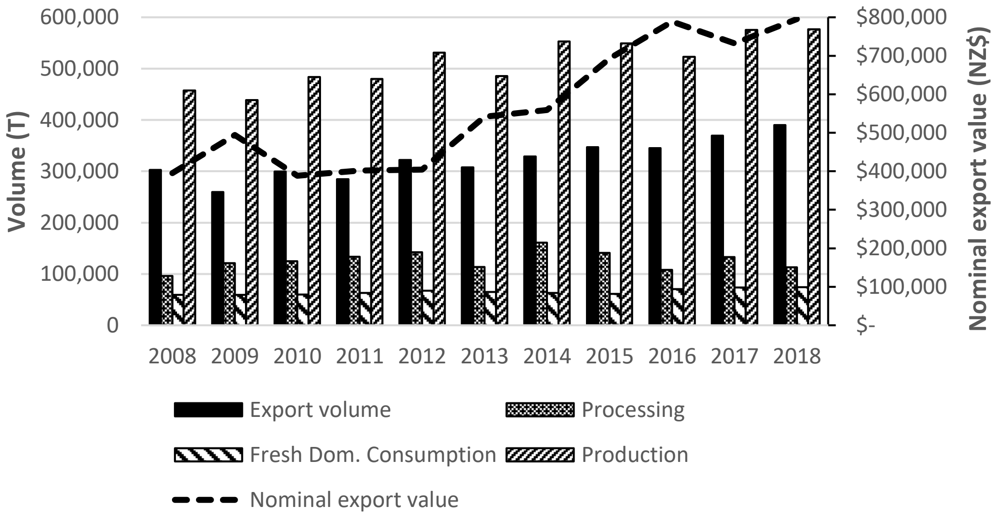

Figure 2.3. New Zealand apple production, fresh domestic consumption, processing, and exports (value & volume), 2008-2018. Source: FAOSTAT

Furthermore, New Zealand has been able to achieve a high yield per hectare in particular for its premium varieties such as Jazz and Envy. As shown in Table 2.6, New Zealand's yield per hectare production surpassed all other countries in 2018; with production of 58.59 tonnes/ha while the global average was 16.62 tonnes/ha. In addition, New Zealand orchards have an average tree density of 1,120 trees/ha, lower than the global average of 1,347 trees/ha while achieving higher yield per ha. This further shows the position of the New Zealand apple industry as one of the most productive producers in the world (Pipfruit NZ, 2017; Pollard, 2018).

Table 2.6. Average apple yields for selected countries 2014-2018 (t/ha)

Rank	Country	2014	2015	2016	2017	2018
1	**New Zealand**	**55.79**	**56.98**	**57.19**	**57.90**	**58.59**
2	Chile	51.24	52.44	53.52	54.41	55.30
3	Belgium	49.43	45.64	40.46	15.42	50.46
4	Italy	49.81	49.83	51.29	39.52	48.34
5	Netherlands	49.58	48.73	47.64	35.99	44.93
7	South Africa	41.30	42.01	42.36	42.99	43.63
8	The United States	45.88	38.33	43.19	43.49	43.52
9	Germany	39.09	34.17	36.34	19.39	38.88
10	France	40.59	43.70	40.07	37.16	37.80

Source: FAOSTAT (Note: Yields are calculated based on the average yield across all areas and varieties).

2.2.3. Development of exclusive varieties

Significant changes have occurred over the past decade with respect to the varietal composition of the apples grown in New Zealand. Orchard areas have expanded with a shift towards higher quality and higher-yield apple varieties mainly because of the strong growth in export markets (Bedford, 2020). The primary focus of the New Zealand apple industry has moved from a commodity producer to a high value producer by introducing and trademarking new premium apple varieties, which has enabled New Zealand to attract high prices and interest in overseas markets while maintaining a higher yield per hectare (Pipfruit NZ, 2017; Pollard, 2018). Size, colour, taste, and texture, as well as sustainable production and consumer demand for safe fresh produce are among some of the priorities for breeding new varieties (Hoang, 2018, Pollard, 2018).

The creation and commercialisation of new apple varieties has been attained through the strategic partnerships between the apple industry and key research and development players such as PREVAR joint, HortResearch, and ENZA (Coriolis, 2006) For example, new variety from the Scifresh cultivar, sold under the trademark Jazz was selected from a cross between Royal Gala and Braeburn and released by HortResearch apple breeding programme in 1985, commercially launched in 2004, and distributed globally by the exporter ENZA and regional partners (Volz et al., 2004; Brown and Maloney, 2009). Jazz is well demanded by overseas consumers with a high price and characterised by excellent features such as firm texture with great eating quality, and a distinctive and attractive appearance with good adaptation to a range of climates in New Zealand, Washington (USA), and France (Volz et al., 2004). Similarly, Scilate apple variety sold under the trademark Envy is a cross between Royal Gala and Braeburn and was developed by HortResearch New Zealand in 2008 (Brown and Maloney, 2009). Envy is characterised by sweet taste, intense flavour, crispness, and large size. Distribution of Envy is managed by ENZA and regional partners, and grown under license in New Zealand, Australia, Washington State (U.S.) and Chile (Charles, 2014), and is predicted to become a billion-dollar brand by 2025 derived from its high demand and price in overseas markets (T&G, 2020). The long leading-in time to develop and launch new varieties shows the long-term planning of these breeding programmes to target the appeal of new/future customers.

Figure 2.4 presents the list of the apple varieties grown in New Zealand according to their share of national planted area in 2018. Envy and Jazz are among premium varieties and are in demand globally such as in the UK (Jazzapple, 2017) and the US (usapple, 2018) markets. As the largest planted variety by area, Royal Gala accounts for 26% of planted area nationally and is ranked as the top variety in export production nationally (NZAPI, 2018). The highest exported volume of apple varieties from New Zealand include Royal Gala, Braeburn, Jazz, Fuji, Envy, and Pink Lady, which made up about 80% of New Zealand apple production in 2016 (Aitken & Hewett, 2017; Pipfruit NZ, 2017).

In 2006, the national planted area of New Zealand's leading variety, Braeburn, was 2,464 ha, this area fell to 1,199 ha in 2018, over 50% reduction in planting. Similarly, exports of Braeburn have dropped from 66% of total crop exports in 2008 to 12% in 2018 (Pipfruit NZ, 2017; NZAPI, 2018), this is mainly due to poor export prices in 2018. As a result, New Zealand apple growers have started to reduce their dependency on old varieties like Braeburn and replace them with newer varieties including Envy and Jazz, which can place New Zealand in a more competitive position in the global market (Mannering, 2015; Pipfruit NZ, 2017; NZAPI, 2018). In addition, growing more diverse apple varieties helps to extend the harvest periods and attract and retain workers longer (Pollard, 2018), given the production and harvest periods vary across varieties. Therefore, a more diverse variety of apples means the harvest season in New Zealand lasts from February (Royal Gala, Early Queen, or Smitten) through to late April and into May (Envy, Fuji, New Zealand Rose, or Pink Lady) (Pollard, 2018).

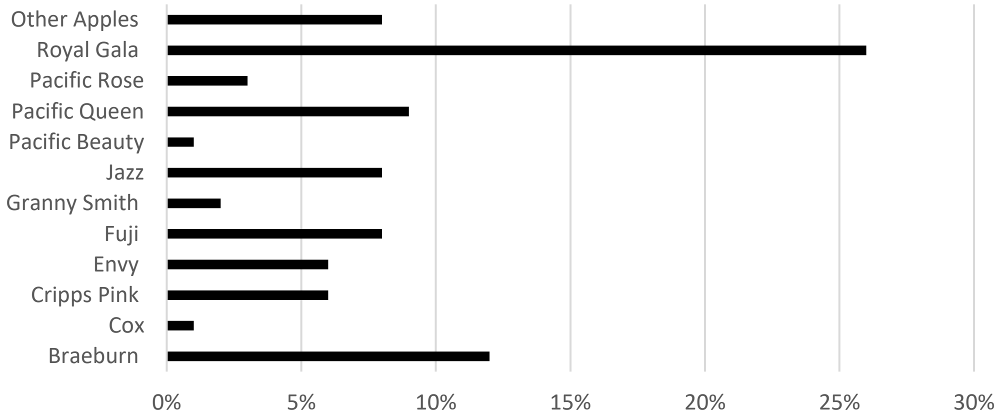

Figure 2.4. Planted area by apple variety grown in New Zealand (%, 2018)
Source: New Zealand Apples and Pears Inc. (2018).

2.2.4. New Zealand trade competitiveness

New Zealand apple growers have faced increasing local and global competition since the deregulation of the New Zealand apple sector in 2001 and global integration of the export fresh market fruit. (Coriolis, 2006; Pollard, 2018). This change in the industry has given export markets the opportunity to set high environmental, technical, and employment requirements for New Zealand growers to meet. Therefore, in order to remain competitive in export markets, New Zealand apple producers need to consider not only economic factors but also environmental and biological factors such as site selection and orchard design, apple variety, rootstock, tree density, tree quality, canopy, and tree size in their initial design in different periods when they make decisions about managing their orchards (Aitken et al., 2004; Busdieker-Jesse et al., 2016; van der Merwe, 2015; Coriolis, 2006; Pollard, 2018).

The New Zealand apple industry has performed strongly in the global market after facing some difficulties in the initial phase of the deregulations (Gray, 2016; Pollard, 2018). This is partly related to meeting the high standards of overseas markets, which has enabled the industry to pass through various quarantine and compliance requirements, and export apples into the most difficult countries and supermarkets. This has turned the New Zealand apple industry into one of the most competitive globally based on factors such as infrastructure and production efficiency (Gray, 2016; Pollard, 2018).

The New Zealand apple industry has continuously sought for innovative solutions to improve productivity and quality of apple production (Aitken et al., 2004; Busdieker-Jesse et al., 2016). For example, the adoption of the Integrated Fruit Production (IFP) framework in 2008, as a holistic system approach for pest management (Damos et al, 2015) enabled New Zealand to market its apples with low chemical residues thus providing access into high standard export markets such as the EU that generated higher orchard returns (Pipfruit NZ, 2017; Pollard, 2018). The IFP framework provides an economic and fruit quality production framework, putting more emphasis on reducing adverse impacts and use of agrochemicals, and improving protection of the environment and human health (Damos et al., 2015). Today, over 90% of New Zealand apples are produced utilising the IFP system (Pipfruit NZ, 2017).

Moreover, New Zealand Pipfruit initiated the Apple Futures program (AFP) in 2007/2008 in response to the changing regulatory requirements imposed by the EU supermarket chains on further reductions in chemical residues for fresh products (Pollard, 2018; Pipfruit NZ, 2017). The program has successfully abolished the use of pesticide chemicals considered as highly dangerous to human health. As a result, the AFP has turned into the marketing slogan of New Zealand apples, “100% Pure Apples from New Zealand” (Plant and Food, 2012). In addition, the industry has introduced a follow up programme – Apple Future II, with an aim to develop new tools and systems to control diseases and pests in apple and pear orchards, and remove insects during postharvest (Jones, 2014). This could provide an easier access to new developing markets across Asia with a growing desire by consumers for reduced pesticide use and increasingly stringent phytosanitary requirements (Jones, 2014; Walker, 2014).

In terms of sustainable and safe production, most New Zealand’s apple and pear growers are certified by the Global Good Agricultural Practices (GlobalGAP) body. GlobalGAP is the world’s leading farm quality assurance programme to assure safe agricultural production. Growers are independently assessed on their compliance with GlobalGAP best practice, including GRASP (GlobalGAP Risk Assessment on Social Practice), which assesses social practices on the orchard such as specific aspects of worker health, safety, and welfare (NZAPI, 2019; Pollard, 2018). Growers need to pass the independent GlobalGAP audit in order to be able to export their products to a specific number of markets (Pollard, 2018).

2.2.5. Industry challenges

There are a number of challenges that threaten the sustainable growth of the New Zealand apple industry among which labour shortage and climate change are the most prominent ones that have attracted the attention of the industry participants (ASA, 2019; Pollard, 2018; NZHerald, 2020a). It should be noted that these challenges are not only specific to the apple industry but across all horticulture industries.

Labour shortages

Labour-intensive industries in horticulture such as apples can create serious labour market issues. This is because of the seasonality operations of these industries that can challenge sourcing sufficient workforce when labour demands are high, given the limited time to perform harvest or other tasks (NZAPI, 2019). For example, during the apple harvesting season, fruit have to be harvested within a limited harvesting window, otherwise any unharvested or late harvested fruit are considered waste and may not be suitable for export market. As a result, this could jeopardise the profitability and competitiveness of the industry (Pipfruit NZ, 2017; Pollard, 2018). In the New Zealand apple industry, the shift towards more productive orchard systems and higher yielding varieties (Bedford, 2020) could in turn create more jobs in the New Zealand apple industry (HortNZ, 2020b). It is forecast that by 2030, there would be 2,349 more permanent and 12,757 more seasonal jobs in the industry (HortNZ, 2020b). There will be 891 permanent jobs in production, 1,080 in post-harvest, and 378 in corporate services. Of the total increase in seasonal jobs, harvest will account for the highest labour demands of 6,177, followed by thinning 2,910, packing 2,531, and pruning 1,139 jobs (HortNZ, 2020b). However, such increases in the number of jobs will require more workers to fill these positions, consequently, drive increasing demand for labour in the industry (Bedford, 2020; HortNZ, 2020b). Therefore, a sustainable supply of labour is crucial in particular for apple harvesting.

The main sources of labour are local New Zealanders, workers mainly from the Pacific working under the Recognised Seasonal Employer (RSE) scheme, and international backpackers who come under working holiday visas (Bedford, 2020; Hill, 2020).The RSE scheme allows the industry to perform all orchard tasks at the right time by facilitating movement of labour across New Zealand, particularly at harvest when workers are required to use ladders and this can free up local labour to perform non-harvest tasks such as supervisory, tractor, and packing roles (NZAPI, 2019). It is estimated that up to 80% of apples and pears are harvested by RSE workers and the Scheme has been recognised as the world's best practice migratory labour aiming to fill in labour shortages in the horticulture and viticulture industries in New Zealand, while ensuring that the migratory labour process is fair and orderly (NZAPI, 2019). However, there is a cap or administrative limit on the number of RSE workers that can be taken up each year. The cap was set at 5,000 when the scheme was established in 2007 and for 2020/2021 season, up to 14,000 workers were supposed to be allowed entering New Zealand, and stay for a maximum of seven months (INZ, 2021; Friesen, 2018; DOL, 2010; Ramasamy et al., 2008; Bedford, 2020; NZAPI, 2019). Workers are required to stay with their original RSE employers while in New Zealand, however, it is possible for the original RSE employer to transfer workers to other accredited RSE employers (DOL, 2010). Overseas visitors usually make up about 25% of the workforce in the horticulture industry, which can work on orchards by gaining permits from the New Zealand Immigration (MSD, 2019). However, labour shortages have remained one of the challenges of the horticulture industry particularly during harvesting season.

At the time of writing, the Covid-19 pandemic has been causing significant uncertainty and disruption around the availability of seasonal labour in New Zealand (NZ Wine and MPI, 2020). This has put more pressure on an already unstable labour market in the industry following the travel restrictions, which stopped overseas backpackers entering New Zealand as part of a series of measures imposed by the government to fight Covid-19 (Burry, 2020; Frykberg, 2020; Hill, 2020). As a result, the cap on the number of RSE allowed into the country has reduced to 7,000 workers (Sharpe, 2021). It is safe to say that post-Covid-19 New Zealand will be characterised by high unemployment but with a large skills shortage (HortNZ, 2020). With Pacific seasonal workers and backpackers down by 50,000 (Jones, 2020), the current labour pool may not satisfy the increasing labour needs in the industry.

The harvest labour market must be considered in the context of the larger tree fruit industry (Calvin and Martin, 2010). There are competing seasonal labour demands across crops and regions in the horticulture industry, and RSE workers are considered as only one element of the industry's total seasonal labour demands. However, these workers cannot stay in the country for long given their visa conditions allowing them to stay in the country for a specific period (Bedford, 2020). Employers can only hire these workers for a certain amount of time to perform specific tasks and once they are finished, they will return to their countries. Therefore, employers could lose productivity because they have to hire another group of RSE workers and train them up, costing them extra cost and time, which could have been spent towards other orchard practices (Bedford, 2020). However, in spite of these factors, the RSE scheme benefits both New Zealand and the Pacific communities (Hill, 2020).

To further deal with increasing labour needs following Covid-19 and lack of access to RSE workers and foreign backpackers, the industry has considered creating full-time year around jobs and employ New Zealanders who have lost their jobs due to the pandemic to keep the labour around permanently rather than on a seasonal basis (Taunton, 2021; Hill, 2020). However, there are constraints to employing locals from urban areas in seasonal jobs including the nature of the work, the long hours, lack of suitable accommodation, and location in rural areas (Bedford, 2020; Hill, 2020). While, students and unemployed living in rural areas may undertake seasonal jobs, it is unlikely that New Zealanders located in urban areas would consider moving to these areas (Bedford, 2020; Hill, 2020). In addition, while RSE workers enter the country with a visa that ties them to their employer to take up a specific seasonal work, New Zealanders have no such restrictions meaning they can leave the job at any time (Bedford, 2020). Despite lack of interest from locals to work in orchards, the industry has considered a number of strategies to encourage them into seasonal work such as providing more flexible work hours, potentially offering higher rates of pay, and using technology (e.g. automated picking platforms) to reduce the physical work requirements (Bedford, 2020).

The New Zealand apple industry has been able to bounce back from the impact of Covid-19, even though the pandemic happened during the production and peak harvest season, which negatively affected sales, particularly in Asia, due to the changes in customer purchasing patterns and logistics (Jones, 2020; O’Callaghan, 2020). This resulted in a lower percentage of fruit sold compared to previous years with higher price pressure particularly in Asian markets. However, this adverse impact was offset by diversifying in geographical markets with a range of both traditional and premium apple varieties (O’Callaghan, 2020). Export returns have reached $870 million, putting the industry on track to teach its goals of $1 billion by 2022 and $2 billion by 2030 (Jones, 2020). However, it is important that the New Zealand apple industry takes advantage of the opportunities post-Covid 19 will bring by working collaboratively with government and across the horticulture sector to identify opportunities domestically and overseas, increasing sustainable job opportunities for New Zealanders, leading the growth and innovation across horticulture, and implementing vaccinations for provinces at a time when really needed (Jones, 2020).

Climate change

In 2018, New Zealand experienced the warmest year on record and it is expected that the average temperature rises over time with diverse impacts on winter chilling, flowering and bud burst, harvest date and yield, fruit quality, extreme high temperatures, and frost and hail (Daly, 2019; Clothier et al., 2012). The average winter temperature in Hawke's Bay, as the largest apple growing region, is expected to rise gradually in future (Fedaeff, 2017; MFE, 2020). Apples require a minimum number of chilling hours during winter to break dormancy (Clothier et al., 2012). Insufficient chilling hours could result in prolonged dormancy, thus not all buds will flower at the same time, resulting in apples maturing up at different time on trees and harvest will not happen simultaneously across an orchard, which could reduce fruit size, weight, yield, and quality (Boudichevskaia et al., 2020; Kumar et al. 2016; Vedwan and Rhoades 2001; Clothier, 2018; Fang et al. 2016; Sharma et al. 2014; Sugiura et al. 2005; Rai et al. 2015).

Elevated temperatures in orchards increases fruit growth, but it will also adversely influence fruit quality such as through more sunburn on apples (Luedeling, 2012; Clothier et al., 2012). In addition, rising temperature can increase the fruit maturity rate, meaning that a lot of fruit maturing at the same time which are required to be picked, otherwise late harvested or unharvested fruit will not suit the export market or even have a reduced shelf life (Else and Atkinson 2010; Tobin, 2021), and in the spring it could increase the invasion and reproduction of plant insect pests and diseases, e.g. fruit flies, resulting in poor-quality apple crop and yield (Patterson et al. 1999; Gautam et al. 2013; Jangra and Sharma 2013; Heyes, 2019; Kenny, 2001).

Impacts of changes in climate conditions can vary across regions, given each of the major apple production regions has its own soil and climatic characteristics (Kenny, 2001). For instance, in New Zealand, low production has been observed in Nelson and Hawke's Bay regions with cold and/or wet conditions (Kenny, 2001). Central Otago has experienced smaller fruit size that could be due to the cooler spring temperatures in the post-bloom period (Kenny, 2001). The summer climate in New Zealand is usually suitable for fruit development, but it could be affected by hotter and drier conditions (Kenny, 2001). Such climatic changes can threaten New Zealand's ability to successfully grow apples like Jazz and Envy with qualities such as crispness, colour, and taste, which are the result of the country's temperate climate – cold nights and warm days (Clothier, 2018). Without such an ideal climate the fruit can suffer different issues such as developing poor colour and soft texture and getting sunburnt as well as not storing well, thus affecting its exportability (Clothier, 2018).

Uncertainty in agricultural water supply and demand as consequences of climate-related variability and changes could also negatively affect agricultural production (Pathak et al., 2018). It is expected that rainfall patterns will change across New Zealand (Clothier et al., 2012). This may be more important for Nelson and Hawke's Bay regions, where climate-related variability could indirectly affect apple production and make climate conditions drier and hotter in these regions (Kenny, 2001; Pathak et al., 2018). While early-season rainfall (i.e. spring and early summer) can provide required water and drop irrigation costs, rainfall later in the season can reduce fruit yield and quality in terms of maturity attributes with fruit maturing earlier on trees (Mpelasoka et al., 2001; Miller et al., 1998; Girona et al., 2006; Clothier et al., 2012).

There are adaptive measures that could help apple growers with changing climatic conditions in their orchards. One solution to cope with prolonged dormancy due to less chilling hours is the use of chemicals for dormancy release – bud-breaking agent, which needs to be applied at an appropriate time to prevent damage to flower buds, however, some European countries have banned use it (Melke, 2015; Close and Bound, 2017). Another option could be to relocate orchards to regions with higher latitude, such as the South Island or Southern part of the North Island. Although from a temperature perspective, it may be logical but other factors such as growing environment, soil characteristics, cultivar, post-harvest operations, transportation, and orchard facilities constructions may hinder orchard relocation (Barden and Neilsen, 2003).

A more suitable option would be the development of climate-resilient apple cultivars that require fewer chilling hours and cold weather to break dormancy as well as being more resistant to diseases and pests (Boudichevskaia et al., 2020; Arya et al. 2014). Scientists in Plant & Food Research in New Zealand have teamed up with Institute of

Agri-food Research and Technology (IRTA) in Spain, to establish a Hot Climate Programme for developing new apple varieties better adapted to hot climates with less chilling hours. T&G Global is set to trial and commercialise these new varieties in New Zealand and overseas (ASA, 2019). The company has already trialled one of these varieties called 'HOT84A1' in Spain and is planning to trial it at Waimea Nursery in Hawke's Bay. The first commercial volumes of 'HOT84A1' will be planted in Spain in February 2021 (NZHerald, 2020b). These varieties will be better adapted to the changing climatic conditions in New Zealand and around the world by being more tolerant to certain diseases and pests, use less water, and or do not require as much winter chilling. In addition to ensuring New Zealand's capability to grow apples in future in regions like Hawke's Bay where warmer temperature are expected, some of these new varieties have the potential to open up new apple growing regions, or to be grown in more marginal regions like Central Otago, which will play an important role in the sustainable growth of the industry (ASA, 2020; Clothier, 2018).

2.3. Conclusion

This chapter provided an overview of the apple industry in the global and New Zealand contexts with specific focus on production, domestic consumption, and trades. Furthermore, significant events and development of the New Zealand apple industry were elaborated. In addition, key components behind the industry's growth and its global competitiveness were identified. These components include production and export of the industry, the development of exclusive varieties, and the standardisation of apple production. Lastly, main challenges of the industry in recent years including labour shortages and climate change were explained.

Chapter 3. Literature review

This chapter discusses the uncertainty in labour management in tree fruit harvesting in order to provide a broader perspective on issues around labour including shortages, costs, and health and safety. Next, the chapter reviews the literature on the robotic systems in the agriculture field and it includes three parts. In the first part, the chapter provides cases of the application of robotic harvesting systems in horticulture and animal agriculture in order to provide a broader perspective on the applications of the robotic systems. In the second part, the chapter elaborates on the application of robotic systems in tree fruit harvesting to identify key developments and limitations of the technology. In the third part, the horticultural aspects of tree fruit production are discussed to identify a set of factors that could impact on the adoption of robotic harvesting technology in apple orchards. Finally, existing economic studies in tree fruit are discussed, keeping in view the gaps in the literature that are apparent, which has helped to identify the appropriate analytical method for the current research.

3.1. Uncertainty in labour management

Labour is an essential input in the production of horticultural crops (Cassey et al., 2016), particularly for deciduous fruit. The seasonal nature of deciduous fruit production operations such as harvesting, training, pruning, and thinning has created seasonal labour demand with harvesting being the most labour-demanding and time-sensitive orchard operations (van der Merwe, 2015; Karkee et al., 2018). A delayed harvesting caused by labour issues such as a labour shortage means growers could make less profit because even a short harvest delay can reduce quality and therefore price. Whereas a longer delay could mean all crop could be lost if quality is reduced to the point that fruit is not marketable (Calvin and Martin, 2010).

It has been predicted that shortages of labour together with high costs of production and increasing competitiveness in the global produce market would be the biggest challenge facing farm businesses in future (Schupp et al, 2011; Valle et al., 2017). For instance, it has been reported that the availability and cost of labour for harvesting are the two most important challenges across all scale of operations and production regions in the US (Grant et al., 2018). Notwithstanding, the issues around labour have mostly been related to pre-harvest and harvest activities in-field or on-orchard than post-harvest operations. For example, for apples as a storable commodity, jobs in warehouse or packing house operations are year-around for large operators. Therefore, compared to pre-harvest or harvest, it is less difficult hiring workers for packing house or warehouse jobs, which are year-around, largely mechanised, and indoor (Calvin and Martin, 2010).

3.1.1. Labour shortage

Generally, a labour shortage is defined as "the difference between the number of workers willing, able, and available to work and the number of workers desired by producers given the going market wage" (Cassey et al., 2016, p.1). Many factors influence the supply and demand of labour such as the minimum wage rate, health and safety issues, and immigration policy (Schmitz and Moss, 2015). The main challenge for the horticultural industry is to ensure there is sufficient labour when needed (Sinnett et al., 2018). A shortage mainly stems from the labour force not interested in undertaking the hard-physical labour required on-farms or in-orchards when higher wages can be earned in other jobs (Sarig, 2005). As a result, labour demanding farms must compete with higher paid urban sector wages to source their labour (Bedford, 2020; Sarig, 2005).

The New Zealand apple industry has been willing to employ locals and train them to become ready and skilled for work and providing them with an opportunity to switch from seasonal to permanent jobs, however, potential workers are still not interested (Bedford, 2020; Pollard, 2018) for various reasons such as the long hours and nature of the work (i.e. physical stress), and locations in rural areas that may not be appealing for locals in urban areas consider relocating to undertake orchard roles (Bedford, 2020; Hill, 2020). As a result, growers mainly relied on backpackers and short term immigration labour programs, e.g. RSE scheme have to cope with increasing labour demands (Bedford, 2020; Mannering, 2015). Similar to New Zealand, the USA uses a similar labour scheme granting a H2-A visa, which allows foreign national workers such as Hispanic workers from Mexico into the country for temporary agricultural work. However, strict immigration policies regarding the employment of immigrants permits only a limited number of labour migrants. Australia is using the Seasonal Worker Programme (SWP) to employ Pacific workers for seasonal work (Bedford, 2020; Calvin and Martin, 2010; Pollard, 2018; McFerson, 2011; van der Merwe, 2015).

Despite employing immigrant workers, labour shortages still remain a challenge for the horticultural industry. This is partly related to the lack of interest from locals to work in orchards as is the case in New Zealand, and partly related to the unpredictable early maturity of various apple crops, which can lead to an urgent demand for harvesting labour (Ashton, 2018; Bartlett, 2018; Pollard, 2018). This can disrupt the supply and demand of the horticulture labour market, i.e. the supply of labour does not match industry demand (Ashton, 2018; Bartlett, 2018; Pollard, 2018). In the 2019 apple picking season, the New Zealand government announced a seasonal labour shortage across regions with labour shortages to raise the awareness about the importance of the issue informing New Zealanders that may be willing and able to work to apply for the opportunities available to them (MSD, 2019). Moreover, the announcement can urge players in the industry such as apple producers to seek alternative solutions and develop more effective and efficient production strategies such as high-density trees planting (Cassey et al., 2016). However, some growers believe that operating modern farming practices such as higher density tree planting with higher yields if performed in the conventional way e.g. using ladders, requires more pickers per hectare, which can exacerbate the shortage of labour (van der Merwe, 2015; Sazo et al., 2010). On the other hand, orchards designed with higher tree densities with short trees that are trellised for more homogeneous trees, reduce the amount of field work performed from ladders, making it easier for pickers to find apples. This can increase the efficiency, productivity, and safety of manual harvesting labour, and more importantly paving the way for mechanical harvesting (Calvin and Martin, 2010).

The labour shortages issue has worsened in the world including in New Zealand, Australia, and the US, following the Covid-19 pandemic due to travel restrictions, which has stopped foreign national workers and overseas backpackers into the country. This has made it more difficult for the horticulture industry to source the workforce they require (Burry, 2020; Frykberg, 2020; Hill, 2020).

3.1.2. Labour costs

Farming production costs are one of the key factors in competitiveness of farmers (van der Merwe, 2015). Labour costs especially harvesting labour accounts for a great portion of total production costs (Karkee et al., 2018). For example, in the USA, labour costs account for half the variable costs of fruit production (van der Merwe, 2015). For a typical apple orchard in USA, labour accounts for 58% of total production costs with thinning, training, and pruning accounting for 46% of variable labour costs, and harvesting 44%, making it the most expensive orchard operation (Calvin and Martin, 2010; Karkee et al., 2018; West et al., 2012). In New Zealand, of the total cost to produce apples in 2018, 52% was accounted for orchard costs and 48% for post-harvest.

For orchard costs, 70% was for labour expenses, and harvest accounted for 24% of labour costs (MPI, 2018). This indicates the importance of labour availability in fruit production. Any disruption in supplying sufficient labour can impact the whole value chain of industry (Cassey et al., 2016). For example, labour shortages for pre-harvest and harvest operations can impact post-harvest operations such as disruptions in timely transportation and delivery of harvested fruit to market (Cassey et al., 2016).

Experienced labour is highly demanded during harvest time (Schupp et al., 2011) to minimise the damage to the fruit and maintain the quality of the fruit for the fresh market (Sinnett et al., 2018). In addition, in the case of a labour shortage, growers can become more vulnerable to unfavourable weather conditions during harvest (McFerson, 2011). This may become more problematic for fresh market fruit especially apples as a labour-intensive perennial crop, which requires fruit to be picked in a relatively short picking window due to the susceptibility of the fruit to bruising or over-ripening (Sinnett et al., 2018). Any unharvested fruit due to labour shortages is considered wasted and unsuitable for fresh market. This may cause significant losses to producers and reduce the overall profitability of the orchard industry, thus leading growers to leave the industry (Cassey et al., 2016; McFerson, 2011).

3.1.3. Health and safety

Growers believe that creating a productive and efficient working environment with good team relations and attractive labour remuneration can attract an efficient and productive workforce (Warner, 2008). It has been recognised that agricultural production is among the most dangerous jobs and associated with significant risk to health and safety (Otero and Preibisch, 2010). Meeting the health and safety requirements of farmworkers can create a more productive, safer, and attractive working environment for them (Fragar and Franklin, 2000; Otero and Preibisch, 2010).

Occupational health and safety problems in agriculture can stem from various factors. Some of the most commonly reported hazards include technology used to increase agricultural production (e.g. exposure to chemicals from applied pesticides, and injuries or diseases due to noise or vibrations from mechanisation); farm or work-related injury or disability (e.g. stress or fatigue due to repetitive and intense long physical farm work); exposure to ambient environment (e.g. diseases from sun, heat, cold, rain, and dust); work and life close to animals (e.g. bacteria, fungi, parasites, or respiratory diseases from diseased animals); and health status and risks of local and immigrant seasonal workers, and potential risk of infectious diseases and poor hygiene and unsuitable facilities at farming workplaces and in housing places (Fragar and Franklin, 2000; Otero and Preibisch, 2010).

Regular labour inspections are a routine in developed countries to ensure the health and safety of labourers; inspecting how physically demanding and hazardous the work is and whether it imposes pressures on body postures (van der Merwe, 2015). In the agricultural sector in New Zealand, WorkSafe New Zealand has created extensive guidance to developing safety management systems based on the Health and Safety at Work Act 2015 (HSWA), which contains relevant information and practices to meet the health and safety of workers (WorkSafe New Zealand, n.d.). The HSWA guideline identifies key components of a health and safety management system that are deemed important in New Zealand agriculture, and farmers need to follow those that are appropriate for themselves, their workers, and visitors to their farms (WorkSafe New Zealand, n.d.).

In the horticulture industry, health and safety in orchards has become an important topic. Normally, harvesting tree fruit manually requires use of ladders to reach fruit on the top part of the tree canopy, which demands repetitive movements with heavy loads of fruit up and down ladders and to and from the collection bin, which can expose fruit pickers to ergonomic injuries such as the risk of falling from the ladder (Karkee et al., 2018). Therefore, considering such working styles and environment, orchard workers can suffer from different types of injuries. Back and shoulder injuries can happen due to carrying heavy bags or gear up and down the ladders, bending and lifting, and the pressure on harvesting fruit as quickly as possible, particularly for workers paid piece rate (Carrabba, n.d., 2005, 2008; Brower and Scofield, 2008; Fiske, 2010; Meyerhoff, n.d., 2009, 2010; Scott, n.d.), because they can earn more money if they can pick more volume of fruit (i.e. bins), thus requiring to work more hours usually 60 hours per week, but this makes them more vulnerable to sickness and physical stress, whereas in hourly rate payment they are not required to work as much hours per week regardless of how much they pick. However, pickers prefer the piece-rate payment over hourly rate because they can earn more money by picking more volume of fruit (Flaws, 2020; O'Sullivan, 2020). Other commonly reported hazards include skin injuries or irritation caused by exposure to pollen and dust, insects, sun, or chemicals used in orchards. Moreover, orchard workers involved in harvesting, pruning, thinning, or tree training tasks are not legally required to wear protective equipment such as gloves and hats to protect themselves from injuries or reduce the indirect exposure to hazardous materials (Carrabba, n.d., 2005, 2008; Brower and Scofield, 2008; Fiske, 2010; Meyerhoff, n.d., 2009, 2010; Scott, n.d.).

In regard to using orchard aid tools such as ladders, according to the Washington State Department of Labour and Industries, there are over 500 workers reported each year falling off ladders in orchards while harvesting fruit, 200 of which are left with serious injuries to the extent of not being able to return to harvesting (Carrabba, n.d., 2005, 2008; Brower and Scofield, 2008; Fiske, 2010; Meyerhoff, n.d., 2009, 2010; Scott, n.d.). Considering that ladders are still widely used in harvesting tree fruit, most of the current safety regulations in orchard are focused on their proper use to avoid injuries. For example, in the USA the current regulations require that safety of ladders is inspected prior to using, while making sure to properly set them up before climbing especially in orchards planted on slopes. For example, workers are required to set up ladders away from power lines and not allowed to use them in windy conditions, and ladders must be sized appropriately according to workers and for the trees (Carrabba, n.d., 2005, 2008; Brower and Scofield, 2008; Fiske, 2010; Meyerhoff, n.d., 2009, 2010; Scott, n.d).

3.2. Alternative solutions for labour efficiency

When labour is relatively scarce and wages rise, producers seek alternatives in dealing with labour issues (Calvin and Martin, 2010). For example, growers may use less labour by harvesting less orchard area, thus reducing labour costs by accepting lower yields (Calvin and Martin, 2010). While the current research is mainly focused on mechanical harvesters, the mechanisation of any task requiring manual labour such as spraying, insect or disease scouting, pruning, thinning, weeding, and cultivating can reduce labour requirement and costs, and allow labour to be allocated for other tasks that are not yet mechanised (Calvin and Martin, 2010). Therefore, growers may consider using labour assist tools to use labour more efficiently and safely by making work physically less demanding (Sinnett et al., 2018). As a result, this could increase the size of the workforce that can comply with work standards (Calvin and Martin, 2010; Schmitz and Moss, 2015; Sinnett et al., 2018). Currently, apple growers rely on available labour aids such as ladders (Figure 3.1A), power ladders (Figure 3.1B), or platforms (Figure 3.1C), or a combination, to make labour more efficient in undertaking orchard tasks such as harvesting, pruning, thinning, and tree training (Sinnett et al., 2018).

Another alternative is the use of robotic harvest technology (Figure 3.2). Robotic harvesters use precision technologies such as sensors, machine vision, and Global Positioning System (GPS) to maximise productivity through better management of inputs (e.g. labour), minimising waste, and improving the quality of harvested products for fresh market fruit (Noguchi et al, 1997; Schueller, 2013). Research is being done regarding this technology and its ability to substitute labour in the case of labour shortages in particular in labour-intensive and high-value crops such as tree fruit (Schmitz and Moss, 2015).

(A) (B) (C)

Figure 3.1. Available labour aids: Ladder (A), power ladder (B), and platform (C).
Source: Sinnett et al. (2018)

There are machines developed by different robotic companies and commercially trialled, and some still in the prototype stage (Baeten et al., 2008; Bulanon and Kataoka, 2010). A robotic apple harvester developed by Abundant Robotics is one of the first example of such developments that were recently trialled commercially in the USA and New Zealand – Figure 3.2 (Chumko, 2019; Zhang, 2018).

Figure 3.2. Robotic apple harvester with suction mechanism (Commercially trialled) Sources: Dininny and Mullinax (2016) and Chumko (2019).

3.3. Research into the robotic systems in agriculture

This section provides a general overview and description of various characteristics of mechanised and automated fruit harvesting systems. The section will also introduce different fruit harvesting technologies including shake-and-catch (mechanical mass harvesting) and pick-and-place (individual robotic) (Karkee et al., 2018). In addition, applications of robotic harvesting systems in horticulture and animal agriculture are reviewed in order to provide a broader perspective on the applications of the robotic systems in agricultural production systems.

3.3.1. Automation and mechanisation in agriculture

In the past, commercial adoption of agricultural technologies such as tractors, planters, sprayers, combine harvesters, and irrigation systems have changed the structure of agriculture (Silwal et al., 2016a) and coincided with replacement of farm labour (van der Merwe, 2015). Mechanisation has been one of responses farmers have to increasing labour uncertainties and risks such as shortages, costs, or health and safety while taking other measures. These measures include using less labour or labour more efficiently by adopting management and farming practices such as precision farming, pest control, irrigation systems, and improvement in cultivars (Calvin and Martin, 2010; van der Merwe, 2015).

Mechanisation and automation in agriculture encompasses precision agricultural technologies such as auto-steering systems, controlled traffic farming, autonomous systems (Lee et al., 2013; Mandel et al., 2010; Pedersen and Lind, 2017; Sui and Thomasson, 2013; Swinton and Lowenberg-Deboer, 2001), machine vision, Global Positioning Systems (GPS), soil sensors, drones, satellite images, efficient irrigation, and post-harvest automation (Schimmelpfennig, 2016; Zhang, 2018).

Application of these modern practices and technologies can provide farm operators with detailed information that can be used to manage the spatial and temporal variability aspects of agricultural production (Schimmelpfennig, 2016; Zhang, 2018) and to fine-tune their production practices based on detailed and within-field information (Schimmelpfennig, 2016). Some of the applications of such technologies are in mapping and monitoring yield with GPS equipped harvesters and tractors, and soil mapping in order to deal with variability of soil condition and crop growth, soil compaction, nutrient management, fertiliser application, and herbicide resistance (Lusk, 2016; Andrew and Moss, 2015; Redhead et al., 2015; Schimmelpfennig, 2016; Zhang, 2018).

These technologies and their applications have already been utilised in field crops such as in the production of wheat and corn (Karkee et al, 2017; Zhang, 2018).

Adoption barriers

From a technical point of view, mechanisation often introduces complex technical challenges (Calvin and Martin, 2010). Adoption of mechanisation and automation systems is easier in industrial settings, as the environment and limiting variables are amended and designed according to the machine's attributes for its optimal performance. Whereas in agricultural settings, environmental and production limiting factors may not be easily managed or eliminated for optimal automation performance (Burks et al., 2013 and 2018). From an operational point of view, the intelligence and skill of experienced farm workers are not easy for a machine to imitate, in particular when crops do not mature evenly, and labour must determine what can be harvested during several passes through orchards or fields, which is normally the case for most fruit tree crops (Burks et al., 2013 and 2018; Zhang, 2018).

A mechanical harvester that harvests the crop in one-off time – nonselective harvesting, regardless of maturity, could decrease useable yield per hectare due to creating unacceptable levels of damage to the harvested produce or plants, which may not be suitable for some markets, e.g. the fresh apple market (Calvin and Martin, 2010). Hence, harvesting machinery has advanced more for vegetables than for fruit and the advancement has been more common for produce for processed market than the fresh market. For instance, fresh table grapes are harvested manually, whereas many raisins, wine, and juice grapes are largely harvested mechanically (except grapes harvested manually to produce premium wine) (Calvin and Martin, 2010). One consideration is that most vegetables are annual crops, thus any damage to plants during harvest operation is less concerning for growers than when machines harvest perennial fruit such as apples – any damages done to perennial trees during harvest operation could negatively affect production next year (Calvin and Martin, 2010).

In addition, it is easier to develop and utilise harvesting machines for annual crops planted in rows than with perennial fruit from trees where fruit location is not as predictable and requires more precision (Calvin and Martin, 2010). Therefore, mechanisation may not only entail adopting a single tool or technique, rather it is about the adoption of a system approach. For example, in a horticultural setting, it includes adoption of new plant breeding and growing techniques, which are interconnected with harvest and post-harvest operations. This coupled with external factors such as economic and policy changes can influence the adoption of novel agricultural technologies (Burks et al, 2013 and 2018; Gallardo and Zilberman, 2018; Sunding and Zilberman, 2001; Thompson and Blank, 2000; Rasmussen, 1968).

Adoption rate

Despite the significant benefits that agricultural technologies offer, the rate of adoption has not been uniformly temporally or geographically distributed (Pedersen and Lind, 2017; Swinton and Lowenberg-Deboer, 2001). The perceived profitability of agricultural technologies relies on many factors such as farm size, crop and soil types, extent of specialisation at the farm, costs of on-farm labour, and accessibility to finance and collateral for the individual farmer (Pedersen and Lind, 2017). For example, adoption of precision agriculture technologies is mainly driven by higher expected profits and often happens in countries with limited labour resources and abundant land (Pedersen and Lind, 2017; Swinton and Lowenberg-Deboer, 2001). High commodity prices and low interest rates may speed up adoption rate in these countries (Pedersen and Lind, 2017; Swinton and Lowenberg-Deboer, 2001).

Similarly, adoption of a mechanical harvester that is available commercially could be limited due to economic obstacles (Calvin and Martin, 2010; Schimmelpfennig, 2016). Growers may prefer manual harvesting for tree crops due to better quality of harvested crops and lower costs. In addition, switching to mechanical harvesting is costly and risky, requiring a major change in operations of the farm such as using new plant varieties or growing new crops (Calvin and Martin, 2010). Even with a technology that generates high farm profits, adoption is slow initially and later becomes faster depending on characteristics of farm and the learning curve to integrate new technology with existing practices (Schimmelpfennig, 2016). Furthermore, the adoption decision-making for individual farmers is dependent on present investments in machinery and estimated time of replacement and access to training and extension services (Pedersen and Lind, 2017). It should be noted that from a broad perspective, adoption of a robotic future for the agricultural industry, e.g. a robotic apple harvester, requires collaboration and engagement of farmers in the technology transition. Farmers can make their current orchard related decisions based on anticipating the prospective of utilising robotic technologies using artificial intelligence (AI) and prepare aspects of their orchard for the smooth technology transition (Legun and Burch, 2021).

Notwithstanding, despite wide commercial adoption of automation and mechanisation technologies in the production of field crops like wheat and corn, commercial adoption of mechanisation and automation technologies in fruit tree crops especially for fresh market has been limited (Karkee et. al, 2018). This is because advancements in mechanisation for fruit and vegetable has lagged in general and being limited to products for the processing market, and for fresh market fruit harvesting is still mainly dependant on manual labour (Gallardo and Zilberman, 2018). For example, in the USA, mechanical harvesting is being used for fruit tree for the processed market including Florida oranges, Michigan tart cherries, California olives, and California tree nuts (Gallardo and Zilberman, 2018). Recently, there have been some advancements in developing robotic harvesting technologies for commercial utilisation in fresh-market fruit. Some of the developments and application of robotic harvesting systems in horticulture including strawberry, tomato, and capsicum/pepper productions, as well as animal agriculture including Automatic Milking Systems (AMS) are reviewed in the subsequent sections.

Case study: Robotic strawberry harvesting

Currently, there are prototype trials of agricultural robotic systems underway for automatic strawberry harvesting by two robotics companies - Harvest Croo (Figure 3.3A) and Agrobot (Figure 3.3B) in the USA. Harvest Croo has developed a robot mainly for in-field strawberry harvesting while Agrobot has focused on greenhouse strawberry harvesting (Siegner, 2018; SPW, 2019). The technology requires high precision handling given strawberries are fragile and can easily be damaged during handling. The robots mimic human pickers and operate based on the current farming practices and do not require any changes to how the farmer grows their crops like investing in a more expensive growing system such as tables or vertical frames. The robot can pick a single strawberry plant in 8 seconds then move to the next plant in 1.5 seconds. A robot is able to harvest nearly 3.3 ha per day without a break, translating into a replacement of 30 pickers per machine (Siegner, 2018; SPW, 2019).

Similarly, a robotic hand has been developed and trialled in the UK for picking raspberries and strawberries without damaging the fruit (Ley, 2019). The robot could be important to British farm sector given that the country is leaving European Union (EU), which can limit fruit pickers and other seasonal workers from neighbouring European countries entering the country (Ley, 2019). Another UK based robotic company, Dogtooth Technologies (Figure 3.3C) has taken a different approach in developing and testing a strawberry harvesting robot. To identify ripe fruit, the robot uses computer vision together with machine learning to enhance its harvesting efficiency techniques. The robot is also able to sort, and grade harvested fruit based on their size, quality, and move them directly into a designated basket (Hooker, 2018). Moreover, the robot operation is compatible with the existing infrastructure, thus growers do not need to adopt a new growing system (Hooker, 2018). The first prototype was tested in 2016 and first field trial was recently conducted in Australia, but it has not been commercially tested (Bogue, 2020). Another similar project has recently been introduced by Robot Highways a consortium between Berry Gardens, Saga Robotics, the University of Lincoln, the University of Reading, the Manufacturing Technology Centre, British Telecom (BT), and strawberry grower Clock House Farm in the UK to develop a robot to harvest strawberries (Barker, 2020). Note that no commercial launch date has been announced for these robots.

(A) **(B)** **(C)**

Figure 3.3. Robotic strawberry harvesters: CROO (A), Agrobot (B), and Dogtooth (C). Sources: Giles (2018) and SPW (2019).

Case study: Robotic tomato harvesting

The Virgo, a robotic greenhouse tomato harvester for fruit to the fresh market has been developed and tested recently by Root AI (Figure 3.4A), a robotic company in the US. The robot uses a combination of precision agriculture and automation technologies such as range image sensor, camera, artificial intelligence (AI), and robotic arms with a pick-and-catch technique to locate and remove ripe tomatoes without bruising them (Black and Kolodny, 2019). The robot has already been tested in commercial greenhouses in the U.S. and Canada. In addition, the robot can also be used to pick other crops; through reprogramming the robot, writing new AI software and adding additional add-ons such as sensors or grippers for picking and handling different crops (Black and Kolodny, 2019).

Another similar robotic tomato harvester has been developed and trialled by Panasonic in Japan (Figure 3.4B) that uses a set of precision agriculture and automation technologies while implementing a robotic arm with a precise cut-and-catch technique that locate and cut the stem of the ripe fruit and moves them to a collection bucket (Murison, 2017). The robot can be mounted on a rail for easy and quick sliding along the vines from one end to another end. The robot is expected to mimic human picking speed, picking at an average speed of 10 tomatoes per minute (Murison, 2017). No commercial launch date has been announced for these robots.

(A) **(B)**

Figure 3.4. Robotic tomato harvester: Root AI (A), and Panasonic's robot (B).
Sources: Black and Kolodny (2019) and Murison (2017).

Case study: Robotic pepper harvesting

Sweeper, a robotic greenhouse pepper harvester has been prototyped in Europe (Figure 3.5). The robot uses precision agriculture and automation technologies including a camera to identify the colour of a pepper, computer vision to recognize the fruit ripeness level for picking, and a robotic arm with small razor to cut-and-catch peppers and dropping into a collection basket (Arad et al., 2020; Petrova, 2018).

Figure 3.5. Robotic pepper harvester (Sweeper).
Sources: Arad et al. (2019) and Petrova (2018)

Sweeper can pick a single pepper in about 24 seconds, as the speed has been slowed down purposefully for safety reasons. Moreover, the robot is equipped with LED lights, enabling the robot to operate at any time of the day, for approximately 20 hours a day. However, the robot can only pick ripe fruit with 61% accuracy, which is far from perfect, but it is the first robot of its kind harvesting sweet pepper with this level of performance in a commercial greenhouse trial (Arad et al., 2020; Petrova, 2018). However, no commercial launch date has been announced for the robot.

Case study: Automatic Milking Systems (AMS)

The abovementioned technologies are still in the trial phase and not commercially available, thus no definite studies have yet been done about different aspects of technologies and their feasibility. However, one of the major agricultural robotic systems that has been well-adopted commercially is the Automatic Milking System (AMS) in the dairy industry. Even though it is not directly applicable to field crops, the concepts and ideas used in developing AMS can give insight as to what factors have been involved in developing and adopting a robotic system in an agricultural context. From a technological perspective, AMS uses robotic technology, sensing, and imagining of milk cows in dairy farms (De Koning and Rodenburg, 2004). Similarly, a robotic tree fruit harvesting uses similar sets of precision agriculture and robotic technologies such as robotic arms, vision systems, or sensors (Zhang, 2018). Therefore, the two systems although from different industries could be considered similar from a technological point of view.

The dairy industry became interested in AMS or robotic milking systems in mid-1970 as labour costs started to increase in Europe. The first AMS was commercially built in 1992 (De Koning and Rodenburg, 2004). Since 1998, AMS adoption has resulted in significant changes in different aspects of dairy farming namely the operation and organisation, and reforming the associations between farmers, employees, technology, animals, and the environment. However, these implications have not happened in a uniform way as different degrees of adoption and applications as well as outcomes are observed among farmers (Schewe and Stuart, 2015).

The use of advanced robotic technology in AMS has differentiated it from other dairy practices, although, many existing dairy farms use some form of milking machines (De Koning and Rodenburg, 2004). AMS allows cows to enter a milking machine voluntarily where a robotic system milks cows without direct human supervision (De

Koning and Rodenburg, 2004; Schewe and Stuart, 2015). As a result, AMS has reduced the reliance on labour involvement by 20-30% as farms start to use the technology. One robot unit can milk 60-70 cows and due to the increase in milking frequency, it may also increase the production of milk by 6-35% (De Koning and Rodenburg, 2004).

Adoption of AMS is the adoption of a completely new management system rather than merely a new milking system (Sauer and Zilberman, 2009). In order for the new system to be totally integrated into the farming system, installation of the robotic milking entails redesigning the complete dairy production system such as training new skilled labour and designing feeding and housing systems in accordance with the computer technologies being used in dairy operations management (De Koning, 2011; Meskens, et al., 2001). For instance, data captured from the cow identification chips and sensors can help farmers to track cow health, milk production, weight, frequency of visits to the robot, detection of infection, and insemination readiness (detection of cow movement and heat level) (De Koning, 2011; Meskens, et al., 2001; Schewe and Stuart, 2015). Therefore, the degree of adaptability of computer technologies and skills in a dairy production system can determine its productivity and performance (Schewe and Stuart, 2015).

Today different types of AMS have been designed by different companies such as Lely (Figure 3.6A) and DeLaval (Figure 3.6B) to meet the demands of different dairy farms depending on the number of cows that are milked, the frequency of milking in a day, the machinery costs, and farmer's personal preference. As a result, the changes in the equipment have also led to the changes in the way dairies are designed today (Allen, 2017).

From an economic perspective, the outcomes of economic feasibility analyses of milking systems show that in order for AMS to be more profitable in comparison to conventional systems, higher returns can be achieved for farm sizes larger than 60 cows, using multi-stall AMS (Dekoning, Vandervorst, and Meijering, 2002; Hyde and Engel, 2002). Besides economic benefits, AMS adoption has improved farmer lifestyle by decreasing labour management and costs using automation and sensor technologies, increased production level by increasing the frequency of milking and better input management, and improved animal welfare and health (Hogeveen et al., 2001; Meijering and Hogeveen, 2004; Stuart et al., 2013). These factors can enhance the competitiveness of the farm and could support smaller-scale farmers to remain competitive with larger-scale farmers (Engel and Hyde, 2003). It has also been reported that AMS has improved the health and life quality of farmers such as sleep improvement, psychic health, physical health, and spending more time with family and on hobbies (Mathijs, 2004; Stræte et al., 2017). Therefore, noneconomic factors are as important as economic factors in shaping the adoption decision of farmers (Hyde et al, 2007).

(A) **(B)**

Figure 3.6. Automatic Milking Systems: Lely (A) and DeLaval (B).
Sources: DeLaval. (n.d.) and Lely (n.d.)

3.3. Mechanisation and automation in fruit tree harvesting

Similar to the dairy industry, the primary driving force toward mechanisation and automation in fruit production has been linked to costs, productivity, and availability of labour along with other related factors such as world market pressures, quality and safety of production, environmental risks and regulation, risks from diseases and pests, and cultivar/varietal enhancement (Burks et al., 2013; Silwal et al., 2015). With this in mind, the next section discusses studies relevant to automation and robotic harvesting systems in tree fruit crops.

Harvesting is the most time-sensitive and labour-intensive task in fruit production (Burks et al., 2013; Karkee, 2017; Karkee et al., 2018; Zhang, 2018). During the past decades, the tree fruit industry has been aiming to cope with the costs associated with fruit handling and harvesting and reduce the pressure from labour shortages through mechanisation and automation of fruit production, in particular harvesting (Burks et al., 2013; Karkee, 2017; Karkee et al., 2018; van der Merwe, 2015). The combinations of three fundamental technologies namely automation, mechanisation, and precision agriculture have reshaped the future of fruit production; however, mechanisation and precision agriculture have been the driving force toward agricultural automation systems such as robotic harvesting of labour-intensive fruit (Baeten, 2007; Peterson, 2005; Zhang, 2018).

Precision agriculture was originally developed for field crop production, but it can be adapted in tree fruit production to improve fruit quality and yield (Zhang, 2018). However, due to different characteristics of field crop and tree fruit farming, some applications of precision agriculture in fruit production may be different from those usually performed in field crop production (Zhang, 2018). For instance, tree fruit management practices such as pruning, thinning, and tree training demand accurate information and data including physical position, size, and orientation of the targeted objects rather than temporal and spatial factors of soil and plants, which are conventionally used by precision agriculture in field crop farming (Schimmelpfennig, 2016; Zhang, 2018). As a result, commercial development of mechanisation and automation technologies in tree fruit crops especially for fresh market have been limited (Karkee et. al, 2018).

3.3.2. Mechanical and automated harvesting systems for tree fruit crops

Nearly all the studied mechanised and automated harvesting systems for tree fruit crops are developed using a shake-and-catch (mechanical mass harvesting) or pick-and-place (robotic harvesting) mechanism (Karkee et al., 2018). However, considering the limited progress in automation and mechanisation in tree fruit harvesting for product for the fresh market, labour assistance tools, such as mobile platforms have been more feasible options in performing orchard activities not only being utilised for harvesting fruit for fresh market but also tree training, pruning, and thinning (Calvin and Martin, 2010; van der Merwe, 2015). Mobile platforms offer ways to increase the productivity and efficiency of labour until commercial robotic harvesters are viable (Calvin and Martin, 2010; van der Merwe, 2015; Sazo et al., 2010; Sazo and Robinson, 2013).

Shake-and-catch harvester (mechanical mass harvesting)

Shake-and-catch mechanical mass harvesters can be very cost effective and labour efficient compared to manual harvesting, thus providing high harvesting productivity (Karkee et al., 2018). However, successful development and commercial adoption of these machines has mostly been limited to fruit that are harvested for processing markets such as cider apples, juicing citrus, canned olives, and hard-shelled crops such as nuts, where damage to the fruit by harvesting machine will have minimal impact on value (Huffman, 2012; Gallardo and Zilberman, 2018; Karkee et al., 2018; Silwal et al., 2015). Much of the research and development on mechanical mass harvesting of fruit goes back to late 1950s and early 1960s for the processing market, with trials of mass harvesters for different crops including olives and prunes in California, Florida citrus groves, and more recently for deciduous tree fruit such as apples, sweet cherries, and peaches (Karkee et al., 2018).

Most of the mass harvesters use some type of self-propelled shake-and-catch harvesting mechanism such as for oranges (Figure 3.7A) and apples (Figure 3.7B) by applying some type of mechanical vibratory force to the canopy, trunk, or a branch to detach the fruit, and collect the detached fruit using a catching mechanism (Karkee et al., 2018; Silwal et al., 2015). However, these systems are not suitable for harvesting fruit for the fresh market such as apples, pears, or sweet cherries, due to harvest-induced damage such as bruising or cuts (Karkee et al., 2018; Silwal et al., 2015).

(A) (B)

Figure 3.7. Self-propelled shake-and-catch mechanised fruit harvester: Orange (A) and apple (B) harvesters. Source: Huffman (2012).

Pick-and-place harvester (robotic harvesting)

The early prototype systems of robotic technologies for selective fruit harvesting were developed in the 1980s in France using a suction mechanism to detach apples, and in Florida using a hydraulic arm to remove citrus from the tree (Karkee et al., 2018). However, the harvesting efficiency – the percentage of fruit identified and harvested with harvestable quality (Zhang, 2018), for the early prototypes was around 75% due to poor fruit identification and the difficulty in managing natural obstacles inside the tree canopy, due to the limited degree of freedom of the robotic arm (Karkee et al., 2018). Robotic harvesters developed in the past have performed with different detection and harvest accuracies, with approximately 50 -75% fruit detection accuracy and a harvesting speed of one fruit every 3-10 seconds, due to different lighting conditions and orchard types with a large proportion of fruit downgraded because of harvest induced bruises and/or without the stem (Karkee et al., 2018).

Developing a robotic apple harvester requires solving complex technical problems, such as visually identifying fruit suitable for harvest and manipulating the robot to harvest the fruit without damaging or bruising, and safely auto-navigating itself in the orchard (Skerrett and McRae, 2019). Sensing technologies, i.e. tools used to measure on-farm agricultural variables without human intervention, are embedded in the harvesting robots as a core component of the precision fruit production (Zhang, 2018) to precisely capture, process, and measure multiple variables and parameters associated with tree fruit such as location, size, ripeness, and orientation, in order to make accurate decisions about whether to harvest the fruit from the tree, while at the same time making sure the harvested fruit will not be mechanically damaged (Calvin and Martin, 2010; Scheuller, 2013; Zhang, 2018).

Robotic apple harvesting system

There are trials currently undertaken by companies with different types of robotic harvesters. Abundant Robotics (Figure 3.8A) in the USA has been able to develop and commercially trial an apple harvesting robot based on a pick-and-place mechanism using a combination of precision and automation technologies such as sensory computer vision, artificial intelligence, and a vacuum mechanism to pick the fruit off of the trees to meet the challenge of harvesting ripe apples without damaging the fruit (Chumko, 2019; Zhang, 2018).

The first prototype of the robot was tested in 2015. It was trialled commercially in New Zealand in 2019 to harvest two apple varieties, Envy and Jazz (Chumko, 2019). However, no technical information from this trial is available at the time of writing. The robot uses computer vision to scan apples for ripeness and harvestability, then vacuum picks the fruit onto a conveyor belt, which moves the harvested fruit to a bin (Chumko, 2019). In-orchard harvesting trials have shown that the robot should ideally be able to locate over 95% of fruit on tree, remove around 80% of fruit with a harvesting speed of one fruit per second (Zhang, 2018).

Considering the current harvesting performance of the robot that is not harvesting 100% of fruit, it is unlikely that the technology would completely replace seasonal fruit harvesters (NZHerald, 2019), however, it can complement manual labour. The robot can be used to harvest the first pick, and manual labour undertake the second pick (Chumko, 2019; NZHerald, 2019). In addition, the robot can boost the productivity of manual labour by being able to harvest a large proportion of fruit grown at the upper levels of the trees, thus making it easier, quicker, and safer for manual pickers to harvest the remaining fruit with lower physical demand. It is hoped that the robot would eventually enable the orchard industry to allocate people from harvesting into permanent roles for doing other tasks in the orchard such as post-harvest operations (Chumko, 2019; NZHerald, 2019).

Another robotic harvester has been developed and trialled by FFRobotics (Figure 3.8B) in the US for fresh market apples using precision and robotic technologies such as image processing and analysis, advanced algorithm, and a “three-pronged gripper”, which mimics the human picking action for locating, detaching, and putting the picked fruit into designated place (Dininny, 2017; Youngman, 2016). In addition, the robot can adapt to the specific canopy structures or cultivar using its fruit identification algorithm learnt in each orchard (Dininny, 2017). Although, the robot is currently focused on harvesting apples, it is hoped it would eventually be able to harvest other tree fruit using different specialized grippers. However, the robot is still in the trial phase and no commercial launch date has been announced by the company; once fully developed, it could work 24/7 and is estimated to pick 10,000 fruit an hour (Youngman, 2016).

(A) **(B)**

Figure 3.8. Robotic apple harvester types: suction (A) and gripper (B) mechanisms. Sources: Dininny and Mullinax (2016) and Dininny (2017).

Despite recent progress achieved by robotic companies in developing different types of robotic harvest technology for fresh market fruit, adoption of the technology has still been limited due to various limiting factors (van der Merwe, 2015; Sarig, 2005). From a horticulture point of view, the adoption of the robotic harvesting technology depends on various factors such as tree density, canopy structure, fruit density, size, and growing pattern. From an economic point of view, the adoption of the technology can be affected by the costs incurred for labour, fruit loss, machine purchase, maintenance, and repair. From a technical point of view, a robot harvesting system has to have a harvesting speed with harvested fruit quality equal to or better than that of the manual harvest. Moreover, performance and operation of robots may be affected by light conditions, because with the current technology robot may only be able to operate in bright daylight (Burks et al., 2013, Karkee et al., 2018; Silwal et al., 2015; Zhang and Pierce, 2013).

Therefore, at the current development stage, most of robotic apple harvesters may not be reliable, fast, and fully viable and able to match the skills of workers in the foreseeable future (Calvin and Martin, 2010; van der Merwe, 2015). Thus, it is unlikely that apple growers can completely replace manual labour with machinery. Labour aids namely platform harvesting systems can offer ways to improve labour productivity and safety and may reduce the current dependencies on labour until robotic harvesters become commercially available (Calvin and Martin, 2010; Sinnett et al., 2018).

Platform harvesting systems

Given that robotic apple harvesters are still in commercial trials, platform harvesting systems could be used as an alternative solution for growers that is commercially available. Platforms have been used by growers around the world since the 1970s along with other harvesting tools such as ladders and power ladders depending on the suitability to their production system to assist with not only harvesting, but also tree training, pruning, and thinning tasks (Sinnett et al., 2018). Mobile platforms can improve the efficiency of orchard workers as these machines can be equipped with hydraulic ladders with auto-steering capability (Sinnett et al., 2018; Zhang, 2018).

The adoption of platform systems has not been uniformed geographically (van der Merwe, 2015). In European countries like Italy, platforms have been the most viable option in orchards, allowing manual labourers to harvest fruit quicker, easier, and more efficiently while ensuring their safety (van der Merwe, 2015; Sazo et al., 2010; Sazo and Robinson, 2013; Zhang, 2018). Despite increasing efficiency of pickers by replacing ladder and eliminating climbing inefficiencies, there are still limiting factors that can affect the adoption of platform harvesters for fresh market fruit. For example, in the USA, harvesting platforms are not widely adopted due to incompatibility of platforms and the existing non-uniform tree canopy systems. Moreover, working as a team, the picking speed of the workers can be influenced by the slowest worker on the platform, thus reducing the overall harvesting speed and efficiency (Brady and Gallardo, 2015; Elkins et al., 2011; Robinson et al., 2013).

Research on the benefits of using platforms is not definite on the labour savings from different methods of harvesting, punning, and thinning (Sinnett et al., 2018). It has been found that platforms can improve labour efficiency for tasks such as pruning, thinning, and tree training compared to using ladder for the same tasks (Baugher et al., 2009; Wells, 2017a). Other research suggests that the degree of labour efficiency achieved for these tasks using platforms depends on tree height and structure, but could potentially reduce the harvesting rate by 20% in harvesting hard to reach parts of tall trees (Elkins et al., 2011; van der Merwe, 2015). Results from platform harvesting trials have shown that 13-17% efficiency can be gained by pickers who had experience in working with platforms and in teams compared to no efficiency gains with pickers with very little experience using the machine (Wells et al., 2017a).

It has been found that platform harvesting can improve harvesting time by 10% and up to 49%, subject to the variety picked (Schupp et al., 2011) and picking efficiency by 10-15% due to less movement of workers to a bin and up a ladder (Hornblower, 2016). Trials have shown that platform harvesting with four apple pickers can increase the picking speed to fill a bin compared to using a ladder by 15-33% depending on the variety picked; however, bruising also increased by 2.7-7.9% depending on the variety picked (Schupp and Baugher, 2017). In terms of productivity gains (harvested weight per hour), the average labourer on a platform can pick 183-266 kg per hour depending on the number of picks and cultivar compared to 130-150 kg per hour using conventional ladder picking (Hansen, 2011; van der Merwe, 2015). Different types of platform systems have been developed over the past decades from basic tractor pulled to self-propelled to advanced pneumatic mobile platforms. These are explained in detail in the subsequent paragraphs.

Platform types

Self-propelled platforms

Single-level (Figure 3.9A) and multi-level (Figure 3.9B) self-propelled platforms designs range from built on truck chassis to platforms equipped with self-steering, hydraulically controlled auto-levelling, and independently adjustable levels in multi-level platforms. These platforms can essentially replace ladders, carrying 4 to 16 workers (van der Merwe, 2015). It has been shown that multi-level harvesting platforms can provide a less strenuous and safer working environment meeting the comfort of labourers given the position of each picker standing at a different height with the picking area from waist to eye level (Elkins et al., 2010). However, pickers on the ground level have to cope with excessive stressing on the back given the constant bending down to reach lower apples. Therefore, it is advised that pickers on the platform are rotated on a regular basis to cope with this issue (van der Merwe, 2015).

(A) **(B)** **(C)**

Figure 3.9. Orchard platform types: Self-propelled single-level (A) and multi-level (B), and tractor pulled (C). Sources: Sazo et al. (2010), Wells et al. (2017b), and Hydralada (2018).

Recently, T&G Global Limited in New Zealand, acquired self-propelled Italian-made Nblosi Quad Lift platforms to enable safe, fast, and efficient picking of apples and increase harvested yield while deal with labour shortages especially allowing new or less fit workers to pick 6 bins per day compared to 2-3 bins per day using ladders. The platform can accommodate four people at one time and is equipped with a conveyer belt attached to the platform to transfer picked apples to a collecting bin at the back – Figure 3.10 (T&G, 2021).

Figure 3.10. Nblosi Quad Lift platforms (Hydralada, n.d.; T&G, 2021)

Tractor pulled or tractor mounted platforms

Tractor-mounted or tractor-pulled platforms (Figure 3.9C) are cheaper than the self-propelled models, carrying 4 workers. However, not all tractors are suited for platform operation, in case of the absence of a driver, the tractor must be controlled from the platform, which is not always possible. Harvested crops are collected with a bin trailer attached to the tractor or a bin placed on the ground (van der Merwe, 2015).

Pneumatic-type harvesting systems

Pneumatic-type harvesting systems are the more advanced type of platforms, manufactured by two American companies, DBR Conveyor Concepts (Figure 3.11A) and Oxbo International Corporation (Figure 3.11B) (Lehnert, 2012; van der Merwe, 2015; Warner, 2012). Earlier models could only accommodate two pickers but later models allow four pickers to work on the machine (Schupp et al., 2011; Warner, 2012). Manually harvested apples are placed in flexible tubes with a vacuum mechanism that suck the apples through the tubes with a decelerator before a mechanical bin filler places apple in the bin. The efficiency of the machine depends on fruit size - determining the vacuum pressure inside the tubes and the speed at which the fruit pass through the tubes (van der Merwe, 2015).

(A) **(B)**

Figure 3.11. Pneumatic vacuum apple harvesters: DBR (A) and Oxbo (B)
Sources: Warner (2012) and Lehnert (2012).

DBR Conveyor Concepts harvesting system is designed in a way that can be used on different mechanical platforms, which allow future updates to be done separately thus making it more feasible economically (Schupp et al., 2011). The Oxbo International Corporation harvesting system's module design does not allow it to be used with different mechanical platforms thus may limit its use on the same platforms. However, it comes with a sorting system, which allows fruit to be sorted on-the-go, graded and transferred to a separate bin, using an on-board camera and computer to record the size, quality, and number of fruit for each picker (McFerson, 2010). Trial outcomes with DBR conveyor harvesting system showed an increase of 10-20% in harvesting Pink Lady and Golden Delicious apple varieties (Schupp et al., 2011).

3.3.3. Post-harvest automation for tree fruit crops

Post-harvest operations including storage, grading, sorting, and packaging are among the most mechanised and automated operations of fruit production, where the environment allows for better integration of mechanical, computer, and electrical components by using various technologies such as machine vision and sensing systems

(Gao et al., 2010; Kondo and Kawamura, 2013). For example, fruit grading by size and colour is among the advanced fruit handling technology in post-harvest operations using computer vision systems to gather fruit image information and then fruit are sorted based on colour, size, and blemishes on surface (Gao et al., 2010). New Zealand has been one of the key players in innovating post-harvest automation systems in the horticulture industry. Compac Sorting Equipment (Figure 3.12), originally a New Zealand company that was established in 1984 and currently is part of the Tomra Food Family has been developing systems for sorting fruit based on colour, size, ripeness, and blemishes (NZHerald, 2016). The technology can sort 6,000 apples per minute into 58 categories of colour and size (Wood, 2003). Robotic Āporo apple packer (Figure 3.13) is another post-harvest automation system that has been developed and was launched commercially in 2018 by Robotics Plus Ltd, a New Zealand agricultural robotics company. The apple packer can identify and place up to 120 fruit per minute in display trays incorporating a suite of technologies including machine vision, robotics and automation, machine learning and Artificial Intelligence (AI), and software and control systems (Taunton, 2018; Scoop News, 2020). The technology is already operating commercially in packhouses in the United States and New Zealand (Taunton, 2018).

Figure 3.12. Compac apple sorting technology
Sources: Paulin (2012) and Jones (2014)

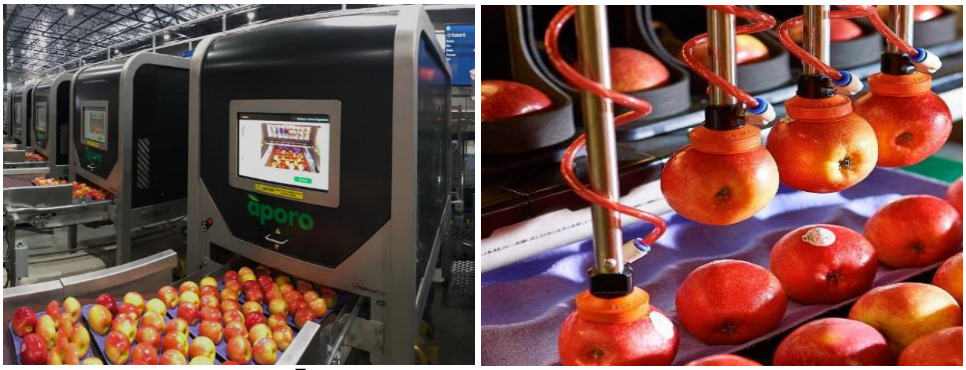

Figure 3.13. Robotic Āporo apple packer
Sources: Taunton (2018) and Robotics Plus Ltd (n.d.)

Notwithstanding, post-harvest handling is a major cost in fruit production especially in apple production (Mizushima and Lu, 2011; Zhang et al., 2017). For example, it has been reported that the post-harvest costs for Fuji variety can make up to 37.4% of the total apple production cost (Zhang et al., 2017). After apples are harvested, they are kept in cool storage with mixed quality grades until being transferred to packing operations for sorting and grading (Mizushima and Lu, 2011; Zhang et al., 2017). It should be noted that during the post-harvest operations, apples graded with a lower quality that are suitable for processing incur the same post-harvest handling costs as the higher-quality graded ones for fresh market. However, the lower graded apples are sold for a much lower price compared to fresh market ones (Zhang et al., 2017; Zhang et al., 2019). As a result, orchardist could lose profit from lower quality or processing apples. Therefore, orchardists would prefer to have the option of dumping lower graded apples in orchard and not having them transferred to the post-harvest operations (Zhang et al., 2017).

These issues have led the engineers to develop an in-orchard apple sorting technology with the capability of sorting high quality apples suitable for fresh market from low grade ones suitable for processing with the possibility of being integrated into a platform harvesting system (Zhang et al., 2019). In 2016, engineers from Michigan State University built the first prototype of the technology that was mounted to a self-propelled platform with horizontal and vertical level adjustments (Figure 3.14). The in-orchard sorting function can financially support growers by inhibiting the spread of microbial diseases and rot from defective fruit to high quality ones in the same bin during the post-harvest storage (Zhang et al., 2017; Zhang et al., 2019). The technology has not been fully commercialised and despite such benefits, it has not been widely accepted by apple growers due to the capital investment costs required in addition to acquiring the platform harvesting system (Zhang et al., 2019).

Figure 3.14. Platform mounted in-orchard sorting technology
Source: Milkovich (2020).

3.4. Orchard management systems

Considering that the orchard system is a critical consideration for the successful development and implementation of harvesting solutions, this section provides an overview of key horticultural factors and practices such as variety and rootstock choice, hedging, pruning and tree training, and tree spacing and population, that need to be taken into account by horticultural scientists and harvesting system developers to optimise the plant-machine system performance (Burks et al., 2018; Karkee et al., 2018). Moreover, given the importance of canopy systems in successful utilisation of mechanised or automated harvesting systems, the description and characteristics of the most commonly used tree canopy systems in New Zealand orchards will be discussed (Burks et al., 2018; Karkee et al., 2018).

From a horticultural perspective, an integrated orchard production automation system requires a systems approach rather than adopting a single tool (Gallardo and Zilberman, 2018; Sunding and Zilberman, 2001; Thompson and Blank, 2000; Rasmussen, 1968; Zhang, 2018). This is to ensure that in-orchard cultural practices including hedging and pruning (controlling tree size and shape), thinning (controlling fruit yield and size) (Burks et al., 2018), tree population and spacing, tree canopy system and shape (Zhang, 2018), and variety and rootstock choices are suitable for the crop variety and mechanised and automated operations considered (Burks et al., 2018; Zhang, 2018).

The decision to establish a new orchard is strategic as it is difficult to make any changes to key planting components such as cultivar, rootstocks, tree spacing, and training system, once trees are planted (Whiting, 2018). Current orchard systems are planted with size-controlling rootstocks, and new varieties are bred based on large fruit size, enhanced colouring, and consumer attraction (Whiting, 2018). Establishing a standardised orchard would mitigate horticultural limitations; such as tree density, tree canopy systems, or the uneven distribution and maturity of fruit on trees, and allow for easier adoption and optimal operation of machinery in orchard without the need for frequent customisation; which can improve yield and orchard profitability (Burks et al., 2013; Zhang, 2018). The ultimate goal of growers is to produce high quality fruit in high quantities in a sustainable and profitable approach (Whiting, 2018).

3.4.1. Variety and rootstock

Breeding new varieties can improve quality or characteristics by modifying crop characteristics suitable for mechanical harvesting, which could help with development and implementation of mechanical harvesting systems (Burks et al., 2018). When developing new varieties of fruit, plant breeders must take into consideration whether the market will accept the variety and how durable the variety will be under machine harvesting and handling (Burks et al., 2018). Fruit with long shelf-life and appealing appearance are well-accepted in the fresh market (Whiting, 2018). A variety must be resistant to harvesting and handling induced damage such as rupturing, cracking, and bruising, while it must be relatively easy to detach from the plant with the stem intact (Burks et al., 2018).

In combination with breeding new apple varieties, the advent and extensive adoption of size-controlling rootstocks (dwarfing rootstocks) has been the key development enabling the transition to more efficient orchard systems (Burks et al., 2018; Whiting, 2018). Dwarf trees are more compact and smaller than the standard apple trees, which make them suitable for high-density tree planting (Calvin and Martin, 2010; Gallardo and Brady, 2015). Dwarf rootstocks have led to improvements in canopy light interception, fruit quality, and production efficiency, mineral uptake, and enhancing resistance to environmental conditions and pests (Hooijdonk, 2009; Whiting, 2018).

For example, in New Zealand, apple orchards were traditionally planted with low density trees using semi-dwarf rootstocks with limited pruning or canopy management practices that consequently led to large canopies with poor light distribution (Hooijdonk, 2009). It required the use of tall ladders for harvesting, which made them unsuitable for mechanical harvesting (Hooijdonk, 2009; Whiting, 2018). The transition to dwarfing apple rootstocks has enabled New Zealand growers to reduce the final tree size, enabling them to switch to high planting density – modern fruiting wall orchard system (Hooijdonk, 2009). Furthermore, by utilising dwarfing apple rootstocks, the New Zealand orchard industry has boosted its capability to rapidly develop new apple varieties with high yield and improve marketable qualities including skin blush, total soluble solids, and in some cases, fruit size (Hooijdonk, 2009).

It is important to note that the choice of variety and rootstock not only affects production and competitiveness of the industry, but also can affect the labour supply and demand in the industry (Calvin and Martin, 2010). Even though the idea to use dwarf rootstocks was not exclusively derived from labour issues, but reduced labour costs, improved productivity, efficiency, and safety of workers are important benefits. Smaller trees allow workers to more easily find apples while reducing the use of ladders in the field, thus increasing safety and productivity (Calvin and Martin, 2010). Growers have been able to reduce the cost of pruning and fruit picking given the nature of dwarf rootstocks, once matured and properly managed (Hooijdonk, 2009).

However, developing a new orchard with dwarfing trees is expensive. This is because dwarf trees need structured support such as a canopy supports (trellis) to handle the weight of fruit (Calvin and Martin, 2010). In addition, and important in the context of the current research, dwarfing rootstocks pave the way for easier transition to mechanical harvesting (Calvin and Martin, 2010) by standardising the orchard with relatively uniform tree sizes and shapes, which can enhance the operation and efficiency of machines (Burks, et al, 2018; Cargill, 1983; Zocca, 1983). These orchard characteristics are further explained for the most commonly used canopy tree structures in New Zealand orchards in section 3.4.5.

3.4.2. Thinning and crop load

Managing crop load is one of the key components of orchard management that can determine not only the annual bearing, but also the profitability of orchard in the current and future seasons (Zhang and Chen, 2018). Crop load is used as a factor to measure orchard productivity according to the volume (number or weight) of fruit produced per branch or tree (Musacchi and Serra, 2018). Fruit trees set more fruit than is optimal in the context of fruit size or quality. An excess number of fruit compared to the overall plant growth could lead to smaller fruit size and inconsistent bearing in many perennial crops such as apple, pear, olive, citrus, and plum. Therefore, to ensure optimal fruit size and quality, it is important to manipulate the balance between the plant growth and fruit growth of a tree (Zhang and Chen, 2018).

There are many methods for the management of crop load such as fruit thinning and pruning (Zhang and Chen, 2018). Thinning is utilised as a practise to control crop load through adjustment of fruit: leaf ratio, by removing excess fruitlets from trees to improve fruit size, quality at harvest, colour, reduce biennial bearing, and increase return bloom (Musacchi and Serra, 2018). However, over-thinning could lead to extremely large fruit size or inferior quality such as reduced colours, flesh firmness, and post-harvest life in apples as larger sized fruit tend to bruise more severely and easily compared to smaller sized-fruit when there is fruit to fruit contact (Kupferman, 2006; var der Merwe, 2015). Therefore, managing crop load is about creating the right balance between adequately managing load for an optimal fruit size and sufficient return bloom without excessively reducing yield (Zhang and Chen, 2018). In addition, thinning can reduce occlusion and multiple fruit growing together, while ensuring fruit on each branch grow into an open space without leaning against the trunk, branch, or any other objects (Karkee et al., 2018). This can make fruit more visible and accessible, thus can increase the efficiency of harvesting solutions (Zhang and Chen, 2018).

There are three different thinning methods including hand thinning, mechanical thinning, and chemical thinning, which can be used together or separately. However, chemical thinning is considered as the most efficient method in terms of cost/result (Musacchi and Serra, 2018; Zhang and Chen, 2018). Growers can improve fruit quality by adjusting the fruit load using chemical thinners during and shortly after the bloom period (Calvin and Martin, 2010).

Technically, three crop management methods are implemented in a pre-determined order to adjust the crop load; starting with pruning without making any changes to the number of flower buds present on the tree, followed by chemical thinning to adjust the initial set of flower buds, and finally finished by hand thinning to adjust the load of flower buds to the desired fruit number. In addition, estimation and forecasting models are used to assist with decision making about efficient crop load management – taking into account a number of factors including variety, rootstock, tree age, and plant physiology and environment (Zhang and Chen, 2018). Note that assessing how total crop load or productive fruit weight changes according to the thinning strategy, whether increasing, decreasing, or staying the same, is beyond the scope of this research.

3.4.3. Pruning and tree training

Pruning is the first step to maintain tree growth balance in the next production season by reducing flower bud load (Zhang and Chen, 2018). Counting and reducing the number of flower buds per tree to a pre-defined number has become an important component of proper pruning with the introduction and widespread adoption of high planting density systems in apples (Zhang and Chen, 2018). Proper pruning and training (shaping young trees) when incorporated with thinning can create a uniform tree canopy shape and size requiring minimal labour work (Karkee et al., 2018). Moreover, tree hedgerows that are properly trained and shaped would create a fruiting wall, where fruit are grown on the outer side of tree canopy along the trellis wires (Zhang and Chen, 2018; Zhang, 2018). This can improve the accessibility and visibility of the canopy system, which would increase the efficiency and effectiveness of orchard operations such as harvesting, spraying, and thinning as well as improving the light interception into the canopy, resulting in better fruit quality (Zhang and Chen, 2018; Zhang, 2018).

A high accessibility and visibility level in the canopy system for a robotic harvesting system means that the robot could more easily locate, identify, and detach ripe fruit, thus taking less time harvesting and a smaller number of harvesting robots would be needed. In terms of labour use, most pruning and tree training activities require relatively skilled labour, happening during the winter when trees are dormant. Availability of labour has generally not been an issue because there is less demand for farm workers during winter and workers have a longer period to finish the task. Some employers hire workers year around for these activities. In addition, some growers may utilise platforms in an orchard with shorter trees, for labour to stand on while pruning trees and eliminating the need for ladders (Calvin and Martin, 2010).

3.4.4. Tree population and spacing

For efficiency and suitability of robot harvesting, orchards need to have relatively uniform and standardized tree sizes with predictable shapes to enhance the harvesting output and efficiency, and economic return (Cargill, 1983; Zocca, 1983). Standard tree size includes specific features such as tree height, thickness, shape, and spacing between and within rows to ensure the efficient operation of the harvesting machines with minimum idle time at harvesting when moving between trees (Burks, et al, 2018).

New orchards are established based on high planting density such as V-shaped canopies, in order to speed up fruiting by rapidly filling the inter- and intra-row space (Whiting, 2018). Inter-row spacing needs to accommodate machinery, which has restricted the distance between orchard rows to typically 1.2-3.0 m. With the introduction and adoption of vertical fruiting wall canopy systems, narrow row spacing (1.5-2.0 m) has become popular (Burks, et al, 2018; Whiting, 2018).

3.4.5. Tree canopy systems

Tree canopy refers to different canopy components such as branches and trunks in a conventional tree shape, grown and formed over time and through implementation of pruning and thinning practises (Karkee et al., 2018). Various types of tree canopy systems are used around the world for commercial growing of different fruit crops - taking into account horticultural and engineering aspects in parallel (Karkee et al., 2018). Essentially, the tree canopy structure and technology would drive the efficiency of future apple orchards (Finger, 2017). Effective tree canopy systems can also determine the success of new apple cultivars given the importance of high yield intensive plantings (Pollard, 2018; Wilton, 2018).

The canopy must be strong enough to bear the fruit load and even overhead netting for crop protection from sunburn and hail (Hughes, 2018a). Note that installation and maintenance costs of the tree canopy are some of the important factors that apple growers need to consider when selecting a tree support system. Higher costs and investment are needed for more structured canopy systems as well as more informed decision-making for implementing the right tree pruning and training practices (Finger, 2017; Hughes, 2018a; Karkee et al., 2018; Wilton, 2018).

This section provides a brief overview of the most commonly used canopy systems relevant to mechanisation and automation. Some of the canopy systems that are more commonly used in New Zealand include Slender Spindle (Figure 3.15), two-dimensional (2D) (Figure 3.16), V-shaped (Figure 3.17), and Future Orchard Production System (FOPS) (Figure 3.18) (McKay and Rogers, 2018).

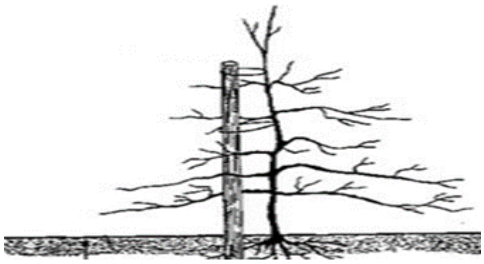

Figure 3.15. Slender Spindle canopy system Source: Gupta (2012)

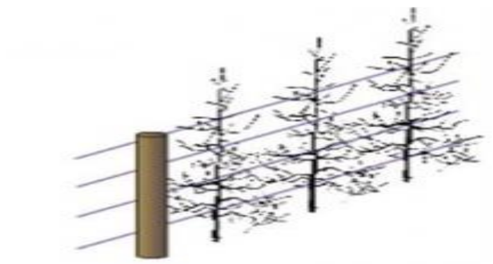

Figure 3.16. Two-dimensional (2D) canopy system Source: Lenhert (2010)

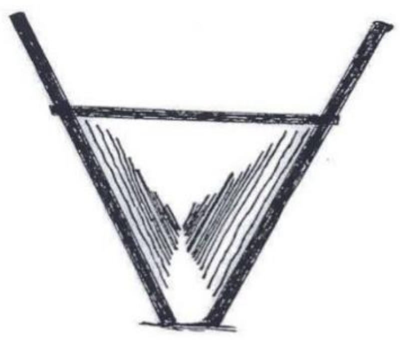

Figure 3.17. V-shaped canopy system Source: Apples and Pears Australia Ltd. (2012).

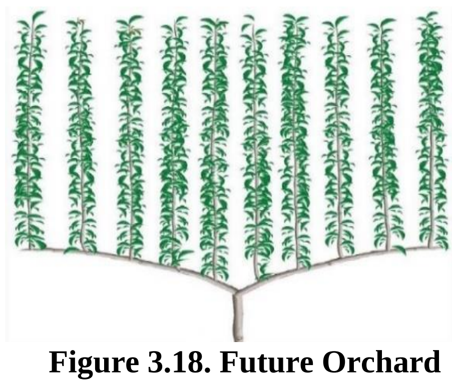

Figure 3.18. Future Orchard Production System (FOPS) canopy system Sources: Hughes (2018b) and van Hooijdonk and Tustin (2015).

Slender Spindle or three-dimensional (3D) canopy

Slender Spindle is one of the older variants of spindle or the vertical axis canopies with shorter canopy height (~ 2.5 m) compared to other spindle types as illustrated in Figure

3.15 (Karkee et al., 2018). It is one of the main growing canopies worldwide and in New Zealand (Hughes, 2018a; T&G, 2018). It is also known as a three-dimensional (3D) structure, referring to the dimensions of its depth, length, and width (Hughes, 2018a; Karkee et al., 2018). However, the depth dimension of the system has raised concerns about its adverse impacts on production efficiency and mechanisation potential (Karkee et al., 2018).

It would be unlikely to achieve a desirable level of robotic harvesting efficiency in an orchard with trees grown conventionally (3D) (Karkee et al., 2018). A 3D orchard system makes it more complex to develop a robot with the ability to navigate through the tree for fruit, thus leading to high acquisition and maintenance costs, and limiting its practical adoption (Karkee et al., 2018). Fruit size, quality, and difficult accessibility into the canopy for labour or even for a robotic harvester are among the disadvantages of the 3D system (Hughes, 2018). Lack of optimal light penetration in the small dwarf canopy's interior leads to a deterioration in production quality, and as the canopy ages, ease of access into the canopy will diminish (Hughes, 2018a).

The Slender Spindle canopy typically has a tree density of 2,400 trees per ha with between-row and in-row spacing of 3.5 and 1.25 meters, respectively (Table 3.7). Slender Spindle is among the cheapest canopy to establish. It costs around $20,600 per ha and trees cost $39,000 per hectare for two years capital investments to install the trellis (Table 3.7).

Table 3.7. Characteristics of different canopy systems in New Zealand apple orchards

Characteristics/Canopy type	Slender Spindle	2D	V-Shaped	FOPS
In-row spacing (metre/mm)	1.25	1.25	0.6	1.5-2
Between-row spacing (metre)	3.5	3.5	3.5	3
Density (trees/ha)	2,400	2,400	4,800	1,600-2,200
Trellis costs incl. labour costs ($/ha, for two years)	$20,600	$32,600	$40,700	$40,700
Tree costs	$39,000	$39,000	$47,000	$39,000

Sources: Barritt and Van Dalfsen (1992); McKay and Rogers (2018); T&G (2018).

In the table, the establishment costs for these canopies only refer to the trellis installation including the labour works and do not include other related costs for establishing and running the whole orchard system such as ground preparation, planting cost, and irrigation (T&G, 2018). In addition, labour costs and availability may also be considered a challenge, in particular for more advanced canopies such as 2D, V-trellis or FOPS. Labour needs to be trained and familiar with new approaches in pruning and training trees in order to improve the productivity of manual harvesting and robotic harvesting in future. Labour costs for installing trellis vary across varieties from $1,600 per ha for Slender Spindle, 2D, and FOPS trellis to $4,700 per ha for V-trellis systems (McKay and Rogers, 2018).

Two-dimensional (2D) canopy

The 2D canopy system was originally developed in Washington State and has enhanced the ergonomics and working environments for workers in orchards and is considered to be more suitable for mechanised or automated harvesting systems such as platforms or robotic harvesting – Figure 3.16 (Hughes, 2020; Karkee et al, 2018; Zhang, 2018). This is because fruit are visible from the row, which makes it easier and quicker for the robot to identify and pick them (Finger, 2017; Hughes, 2020; Karkee et al, 2018; Zhang, 2018).

Furthermore, 2D canopies can increase light interception into canopy, which can potentially lead to increased productivity and yield (Finger, 2017; Hughes, 2018a and 2018b; Pollard, 2018; T&G, 2018). As a highly structured canopy system with 2,400 trees per ha, 2D systems require substantial and constant tree training, which may not be acceptable to all growers (Hughes, 2018a). To install the trellis in New Zealand orchards, it costs around $32,600 per ha and trees cost $39,000 per hectare over two years capital investment (Table 3.7).

V-shaped canopy

V-shaped or angled canopy (Figure 3.17) also known as the Washington V is perhaps one of the most commercially adopted tree canopies and has the advantage of intercepting more light due to the angled shape of the canopy, which allows more light penetration in comparison to vertical canopies (Hughes, 2018a) as illustrated in Figure 3.17. However, difficulties in accessing the interior of the V canopy could be a disadvantage of this system (Hughes, 2018a), which could make it difficult for the robot to easily identify and pick fruit compared to 2D system.

In addition, the costs of canopy structure and training trees may be other disadvantages of using this canopy. The V-shaped canopy is the densest type of canopy with a density of 4,800 trees per hectare, mainly due to the smallest in-row spacing at 0.6 metre (Hughes, 2018a). However, the V-shaped canopy is among the most expensive canopies to establish. To install the trellis, it costs around $40,700 per ha and trees costs $47,000 per hectare over two years in capital investment plan (Table 3.7).

The Future Orchard Production System (FOPS)

The Future Orchard Production System (FOPS) or the vertical fruiting-wood system as illustrated in Figure 3.18 developed by Plant and Food Research New Zealand, has been a step change for tree design and orchard management (Hughes, 2018a & 2018b). FOPS is technically considered a new type of 2D growing system and "Cordon Planner" would be the better technical and descriptive name for it, even though this system has been known as FOPS, which is the name of the research program it was developed from (Hughes, 2020). The main objective of developing the FOPS has been to maximise the penetration and distribution of light by up to 90% while achieving high yields (Hughes, 2018a, 2018b).

The FOPS has a tree density of between 1,600 to 2,200 trees per hectare with an in-row spacing of 1.5-2 m (Table 3.7). However, the row width is one challenge for this system (3m) that may appear to hinder its adoption, as to whether it should be narrower for productivity purposes or wider for equipment movement (Hughes, 2018a, 2018b). Narrower rows may require using narrower or smaller bins and equipment, while wider rows for conventional equipment and bins may compromise productivity and yield levels (Hughes, 2018b, 2018a), which have to be taken into consideration by developers of the robotic harvester. In terms of establishment cost, similar to V-shaped canopy, the FOPS system is among the most expensive canopies costing around $40,700 per ha and trees cost $39,000 per hectare over two years of capital investment (Table 3.7).

3.5. Economic studies in perennial fruit systems

This section provides a brief overview of the most commonly used economic models that have been implemented to analyse different aspects of decision-making in perennial fruit crops that may not directly be applicable to the adoption of a new technology such as a robotic harvester, but the ideas and concepts used in these models can give insight as to what factors to take into account when developing models for analysing the economics of robot harvesting tree fruit.

The number of studies of the apple industry among perennial fruit is relatively limited, with the larger of the studied papers in recent years being econometric approaches (e.g. Tozer and Marsh, 2018) and simulation (e.g. Hester and Cacho, 2003) modelling of the industry among other approaches. Table 3.8 presents a summarised overview of these papers including the modelling approach, crop, and focus for each one.

Table 3.8. List of sampled published literatures on perennial fruit modelling

Author/s	Modelling appproaches[1]	Crop	Focus
Zhao et al. (2007)	EDM/DP	Apple	Impacts of shocks to industry
Busdieker-Jesse et al. (2016)	EDM	Apple	New technology and industry dynamics
Jiang et al. (2017)	EDM	Pear	Impacts of shocks to industry
Tozer and Marsh (2018)	EDM	Apple	Impacts of shocks to industry
Cassey et al. (2016)	EDM	Apple, peach	Labour management
French and Bressler (1962)	Econometric	Lemon	Industry dynamics
French and Matthews (1971)	Econometric	Peach	Elasticity and trade
Rae and Carman (1975)	Econometrics	Apple	New technology and decision-making
Baumes and Conway (1985)	Econometrics	Apple	Pesticide use and production
French et al. (1985)	Econometric	Peach	Tree removal/planting and Supply
Willett (1993)	Econometric	Apple	Elasticity and trade
Roosen (1999)	Econometrics	Apple	Impacts of pesticide removal
Devadoss and Luckstead (2010)	Econometrics	Apple, peach, cherry	Industry dynamics
Willis and Hanlonn (1976)	MP	Apple	Investment decision-making
Cittadini et al. (2008)	MP	Cherry	Production and labour management
Catalá, et al. (2013)	MP	Apple, pear	Investment decision-making
Catalá et al. (2016)	MP	Apple, pear	Resource management
Davis and Thiele (1981)	MP	Apple, pear	Thinning strategy and profitability
Childs et al. (1983)	MP	Apple	Orchard decision-making
Winter (1976 and 1986)	Simulation	Apple	Orchard decision-making
Scott and Rasmussen (1990)	Simulation	Peach	Orchard decision-making
Haley et al. (1990)	Simulation	Apple	Orchard decision-making
Thiele and Zhang (1992)	Simulation	Apple	Orchard decision-making
Groot (1999)	Simulation	Apple	Orchard decision-making
Cahn et al. (1997)	Simulation	Apple	Orchard decision-making
Whitaker and Middleton (1999)	Simulation	Apple	Orchard decision-making
Hester and Cacho (2003)	Simulation	Apple	Thinning strategy and profitability

[1] Mathematical programming = MP, Dynamic programming = DP, Equilibrium/displacement model = EM/EDM

The models in these studies consider economic and biological factors, helping with decision-making at different stages of production for deciduous perennial fruit crops including decisions about tree size, yield level, and the varietal mix at the planting stage (e.g. Hester and Cacho, 2003). As these decision variables are interlinked, they can also affect inputs and outputs such as profit and costs per hectare. Therefore, the profitability of an orchard substantially depends on biophysical and economic factors (Hester and

Cacho, 2003). In addition, these studies consider various objectives such as the impact of shocks to industry (Zhao et al., 2007, Jiang et al., 2017, Tozer and Marsh, 2018), industry dynamics, elasticity and trade (French and Bressler, 1962; Willett, 1993), or investment and orchard decision making (Willis and Hanlon, 1976; Hester and Cacho, 2003). The following sections provide a more detailed overview of each paper and categorises them according to the modelling approaches developed, keeping in view the gaps in the literatures that need filling to help with identifying the appropriate method for the current research.

3.5.1. Mathematical programming models

Linear programming (LP) or linear optimisation is a mathematical programming method to determine the optimal solutions with objectives such as profit maximisation or cost minimisation that includes inequalities or linear equations. Allocating resources to activities is the most common type of application of LP (Hillier and Lieberman, 2005; Jones et al., 2017). Most of the LP models developed focused on maximising the long term net present value (NPV) or the real value of the investment in present terms, depending on limited resources such as capacity of harvesting, investment funds, or availability of land (Zhang and Wilhelm, 2011). Willis and Hanlon (1976) developed a LP model to select an optimum mix of apple varieties for a Massachusetts farm under marketing and production conditions. The model considered an optimal mix of varieties (early-, mid-, and late-season) planted over time and a continuous period of harvest operations that maximises NPV with limitations on available resources such as capital, labour, land, and storage capacity.

Catalá et al. (2013) used a LP model to assess an investment decision about which trees to plant to maximise the NPV of the investment in an apple and pear production orchard in Argentina. Economic scenarios were compared over a period of twenty years for four different varieties of apples and five varieties of pears. From a variety perspective, the result showed that it is preferable to plant the most profitable varieties of apple and pear. The sensitivity analysis showed that a farm’s ultimate structure and profitability are influenced by the availability of labour.

Davis and Thiele (1981) formulated a dynamic model to assess the after-tax profit, optimal age of replacement, and stochastic variability due to hail or drought. The model examined the impact of replacement age on profit using two replacement systems including “self-replacement (270 trees/ha) and semi-intensive (715 trees/ha)” (p. 21).

The model showed an increase in profitability by using semi-intensive system and irrigation. It was concluded that price and yield influenced the timing of tree replacement, but not changes in cost levels.

Similar in methodology and objective, Childs et al. (1983) developed a dynamic model to select an optimum planting system and replacement time to analyse their impacts on maximum orchard profit using different assumptions and factors including after-tax cash flow, real discount rate, and expected yield. The results suggested that the discount rate, expected yield, and expected fruit quality are among the most important factors that can affect the optimal replacement timing of an orchard system. However, the developed model is limited by not taking into account components such as the decision for how much to replace, financial competency of growers for adopting the new replacement system, and disease issues from replanting.

More recently, Catalá et al. (2016) formulated a LP model to analyse two conflicting objectives namely profit maximisation and minimisation of product supply shortage due to quality losses, by integrating decisions on production, processing, distribution, and inventory for the pome fruit industry in Argentina. The model's scenarios included an increment in the capacities of a range of supply chain resources including refrigerated storage, packaging, and the transport systems. It was concluded that additional increases in these resources do not provide considerable enhancement due to the periodic nature of the supply system given the seasonality production of apple and pears.

Cittadini et al. (2008) applied a LP approach to assess options for on-farm strategic and tactical decision-making by maximising fruit production and optimising labour utilization. The model examines the effectiveness of current systems against sale price variations of cherries in Argentina. Sensitivity analysis on cherry prices showed that fruit producers should carefully consider effective land use planning while making contingency plans to avoid any probable crisis such as variations in sale price of fruit.

As can be observed from the reviewed studies, LP models are most appropriate when the main objective of the study is predicated on identifying the optimal solutions. However, it loses sight of the purpose in the context of the current research given the objectives of the current research are not based on finding the optimal solution but to assess the relative profitability and performance of utilising robotic apple harvester under various scenarios.

3.5.2. Econometric models

Econometric models have been developed to analyse demand and supply responses and estimate the expected responses of apple production to technological changes (Rae and Carman, 1975) or the expected industrial reactions to changes in domestic and export situations (Willett, 1993). Rae and Carman (1975) developed an apple supply model and its linkage to a technological change in the New Zealand apple production system resulting from significantly higher yields per ha using semi-intensive tree planting. Their models estimated the technological impacts on the yield expectations of producers and its consequent effects on decision making about new plantings, removals, yields, and the adoption of a new technology.

Willett (1993) developed an econometric model at the aggregated level of the US apple industry, to estimate supply and demand elasticities incorporating net imports, sub-models of yield and bearing area into the supply side as well as various apple demand functions including fresh or processed. Similarly, Baumes and Conway (1985) estimated the impact of the use of pesticide on production by modelling the U.S. apple industry at the aggregate level. Roosen (1999) developed a model at the regional level of the US apple industry to estimate the impacts of pesticide cancellations on national and regional welfare using elasticities for different supply and demand regions. The author acknowledged that production criteria and adjustments vary in different regions and this “heterogeneity” must be recognised when analysing welfare of technology shifts in the fruit industry.

French and Bressler (1962) developed a hypothesis using econometric modelling to analyse producer decision-making based on current and recent past prices, returns, and a possible correlation for acreage, production and lemon prices. The model estimated a lagged supply response equation and a set of demand equations for fresh and processed lemons. French et al. (1985) developed an econometric model using new plantings and removals functions adapted from French and Matthews (1971) to analyse supply response for Cling peaches. They considered new planting and historical removal patterns of cling peach trees to measure past returns, potential future production from existing acreage, risk, and change in bearing acreage. Devadoss and Luckstead (2010) developed an econometric estimation technique using the rational expectations approach to model the supply response of apple, cherry, and pear crops based on plantings removal and, revenue data.

The reviewed literature shows that the econometric models can incorporate elements important in analysing the outcomes of decision-making in particular for supply and demand responses. However, econometric models are not appropriate in the context of the investment decision-making in the current research. This is due to the complexity of apple production systems and sources of uncertainty that exist in operating a robotic harvester. As a result, if sources of uncertainty are taken into account in the model, it would make it difficult to disengage the impacts of them on the investment decision and consequently it could lose sight of the purpose in the context of the current research – assessing the relative profitability and performance of the technology by taking into account various decision elements such as the characteristics of apple variety and orchard size.

3.5.3. Bio-economic models

Various micro-economic models such as bio-economic models have been developed in combination with biological and biophysical models to simulate and assess different aspects of horticultural systems. Hester and Cacho (2003) used the outputs of a bio-economic model to assess the cost and revenues of changes in orchard management or fruit production. Bio-economic models can also be formulated to link farmers' decisions about the management of resources to existing and other production inputs to attain certain outputs and associated externalities (Hester and Cacho, 2003; Zhang and Wilhelm, 2011).

More specifically, these models are able to analyse crop growing practices such as thinning strategies and their impacts on orchard returns (Hester and Cacho, 2003), or make comparisons between the profitability of different orchard systems using various biophysical decision variables including planting density, variety, rootstock, and orchard size (Winter, 1976 and 1986), or the impacts of hail netting on apple orchard microclimate, productivity and tree growth with respect to the economic benefits (Whitaker and Middleton, 1999). Moreover, bio-economic models together with simulation models have been used to examine orchard profitability through identifying the effect of physiological production practices on optimal economic fruit load (Scott and Rasmussen, 1990).

In addition, these models have also been used as decision support tools to assist growers with tree fruit and financial management by incorporating interrelated factors such as yield, fruit quality and size distribution, revenue, and cost (Thiele and Zhang, 1992).

Groot (1999) constructed a simulation model to evaluate the impacts of orchard management decisions such as the reduction in chemical input application, on farm economics and environmental consequences. Haley et al. (1990) formulated a simulation model to provide an assessment of pest control using three major components including diagnose (identifying pests from their impacts on buds, fruit, bark or leaves), identify (designating the pests' names and their natural enemies existing in traps, on fruit or tree), and manage (evaluate the net profit of a pesticide application). Cahn et al. (1997) used a simulation model to predict the economic impacts of decisions about early cropping and tree spacing, labour hours, input usage on the model's outputs including net present value, cash flow, payback period, and internal rate of return.

Bio-economic models are versatile and widely applied among researchers given their ability to incorporate biological and biophysical factors to simulate and assess the impacts of various factors on the decision. However, bio-economic models studied aim to optimise an economic objective and therefore may be unsuitable in the context of the current research, as they are simplified to allow for the optimisation algorithm to identify a feasible solution set or optimal point. Therefore, they fail to acknowledge the complexities of the investment decision in the context of the present study. The present study aims to retain the complexity within the biophysical model in order to appropriately evaluate the relative profitability and performance of utilising the robotic apple harvester under various scenarios.

3.5.4. Equilibrium displacement models

Equilibrium displacement models (EDM) have been extensively applied to assess the effects of various external shocks such as pest and diseases (Jiang et al., 2017; Tozer and Marsh, 2018; Zhao et al., 2007) or adoption of genetically modified (GM) technology (Busdieker-Jesse et al., 2016) on various internal variables. Zhao et al. (2007) developed a partial dynamic EDM to examine the economic effects of apple maggot outbreak on international trade and grower welfare over short-, medium-, and long-term scenarios for several regions in the US with different production and pest outbreak characteristics. The model incorporated regions with or without pest outbreaks to assess the potential threat posed to fruit production. In addition, the developed model used two dynamic components including tree life cycle and pest spread. Hence, the model was able to measure the dynamic aspects of the impact such as trade flows, consumer surplus, producer benefit, and price equilibrium time path. Similarly, Jiang et al. (2017) designed a dynamic EDM for the US pear industry to assess the economic impacts of shocks such as disease or pest outbreaks, or restrictive export regulations, or foreign demand on intermediaries such as packers and processors. The model incorporated three different types of shocks including a negative supply shock such as a pest or disease outbreak, trade sanctions imposed by a foreign government, and a positive shock to foreign demand and an increase in trade cost.

Busdieker-Jesse et al. (2016) developed a partial EDM to evaluate GM technology adoption and its economic welfare effects to control fire blight on domestic (the US) and international apple markets over a thirty-five-year period. The model analysed and compared the costs and benefits of GM technology to traditional and other new approaches namely “microencapsulation of a bio-control agent” (p. 550). The authors suggested that growers can benefit greatly from the adoption of GM technology including a reduction in the costs of production and an increase in the production of vulnerable apple varieties such as Gala, Fuji, Jonathan, Pink Lady, Granny Smith, and Honeycrisp. The model provided a conceptual image of the overall scope of the technology and its adoption by growers once it is available.

Tozer and Marsh (2018) extended Jiang's et al. (2017) model and used a partial EDM of the US apple industry to examine the heterogeneity of supply responses and the effects of pest or disease shocks on production and consumption patterns in different regions. Four regions were incorporated into the model with various production practices, varietal options, and patterns of consumption. The model works according to a dynamic shift in regional bearing area equation due to existing lags in region-specific price and yield structures, leading to varying impacts of pest and disease shocks across regions as well as impacts on producer and consumer economic welfare. In contrast to pears, apple production is distributed throughout the US and this signifies the importance of developing a regionalized model to better study the local and regional shocks such as outbreaks and the impacts of an international trade sanction. Cassey et al., (2016) formulated an EDM to examine the economic impacts of a pre-harvest labour shortage on a number of post-harvest elements including employment and wages in the post-harvest labour market, and downstream commodity output markets of the US apple and pear industries.

As it can be learned from the reviewed studies, EDM are most appropriate when the main objective of the research is focused on examining the effect of various exogenous shocks on endogenous variables. However, this is not the focus of the current study – analysing the relative profitability and performance of the robotic harvesting technology under various decision factors. Therefore, using EDM will not serve the purpose of the context of the current research.

This section provided an overview of the most commonly used economic models that analysed the economic impacts of various perennial fruit crops by taking into account different variables. However, no studies have addressed the economic feasibility of adoption of robotic harvesting for fresh market fruit in particular apples, as is the context of this research. Therefore, the next section provides an overview of the economic research methods more appropriate for the purpose in the context of the current research namely net present value (NPV) and real option (RO) analysis. Advantages and disadvantages of each method is discussed, and which method is considered most appropriate for the current research.

3.6. Economic analysis of new technology adoptions

In studying the adoption of new technologies, the investment decision in capital assets such as agricultural technologies, breeding livestock, land, orchards, or buildings require different analysis approaches that are used to measure the investment in other operating inputs such as fertilizer, seed, and feed (Olson, 2011; Kay et al., 2016). This is because the associated returns and expenses occur at different time periods for each investment type. Investment in capital assets typically means that a large initial expense and resulting incomes associated with that asset occur over a number of future periods, whereas costs and incomes associated with investing in operating inputs usually occur within one production cycle in each period (Olson, 2011; Kay et al., 2016).

Furthermore, in contrast to operating assets, time is important when analysing capital assets; investment decisions about operating inputs can be changed annually, however capital assets investment are usually long-lived assets meaning that the investment decisions are made less frequently and are more difficult to change once an asset is constructed or purchased (Kay et al., 2016). Therefore, a capital investment analysis technique is required to evaluate whether an investment is profitable by taking into consideration multi-year budgeting, discounting of future expenses and incomes to estimate the present value of those future expenses and incomes, and comparing the net present value with the initial asset investment cost (Olson, 2011).

In addition to the profitability of an investment decision, it may be equally important to know whether the investment is financially feasible, generating sufficient cash flow at the appropriate time to cover any debt incurred to make the investment (Olson, 2011; Kay et al., 2016). Thus, the time value of money is an essential consideration particularly when a project involves cash flows, which extend over many years (Kay et al., 2016). An investment identified as economically profitable may not be financially feasible due to periods of negative cash flows (Olson, 2011; Kay et al., 2016). For example, planting new apple trees may not be considered profitable before trees start bearing fruit, thus may require outside financing during the development years (Olson, 2011).

The investment decision for robotic harvesting technology will likely be an important and complex decision considering the multi-dimensionality of the adoption decision for apple as a perennial crop together with the limitations in commercial development of the technology for fresh market fruit. Thus, a decision analysis method is needed to evaluate the multi-attribute nature of the investment decision taking into account economic, horticulture, and technical limitations involved in the adoption process.

In studying the factors involved in the adoption process of new technologies, the literature can be grouped into *ex ante* (evaluating the investment decision before the adoption decisions are made) and *ex post* (assessing adoption choices and factors that affect adoption after the investment decisions are made) (Gallardo and Zilberman, 2018). The current research specifically focuses on *ex-ante*, because the investment decision of a robotic harvest technology is evaluated before the adoption decision is made given the existing limitations in the adoption process.

Some of the most commonly used e*x ante* methodologies to analyse the investment adoption decision include net present value (NPV) – assuming that the investment decision is certain and reversible; or more sophisticated methods such as real options (RO) – taking into consideration the uncertainty and irreversibility factors of the adoption decision as well as the risk elements and optimal timing for the adoption (Gallardo and Zilberman, 2018). The present study expressly focuses upon the most commonly used methodologies, NPV and internal rate of return (IRR). However, other similar analytical methods such as benefit cost ratio or payback period will essentially provide a similar information but from different perspective. The main focus of the present research is on comparison of robot harvesting with platform or manual, while using other similar methods will not change the results, but merely provide more information. IRR provides more information that is not directly obtainable from NP method. It is the discount rate at which the future returns on investment to break-even or set equal to the required capital investment, i.e. NPV becomes zero. IRR greater than the discount rate warrants the profitability of the investment (Kay et al., 2016). However, IRR has some limitations. IRR ignores the size of the capital investment. This is important when a smaller investment with higher IRR may have a small NPV in absolute dollars when compared to alternative projects. It also assumes that the annual cash flow can be reinvested each period to return a profit equal to the IRR, however it may overestimate the actual rate of return if the IRR is very high (Kay et al., 2016).

3.6.1. Net present value versus Real option method

Assessing the net profit of a new technology and comparing it with the current alternatives is a common approach when an investment decision needs to be made for the adoption of new technologies (Gallardo and Zilberman, 2018). Net present value has become the most commonly applied indicator to calculate the costs and benefits of the investment decision – taking into account the time value of money and the size of net cash revenue over the life of the investment (Gallardo and Zilberman, 2017; Kay et al., 2008).

Net present value assumes certainty and reversibility are implicit in the analysis, i.e. it is possible to reverse the investment and recover the initial costs of the investment, and the future returns and costs are known with certainty (Tozer, 2009). However, this may not be true in most cases as even some unrecoverable sunk costs are incurred even with simple investments (Tozer, 2009). Investments with positive NPVs are considered worthy to consider and the investment is deemed to be profitable as the net benefits exceed costs. In other words, the investor can still afford to pay more for the investment and still get a rate of return equal to the discount rate used in calculating the NPV (Gallardo and Zilberman, 2017; Kay et al., 2008; Olson 2011).

Net present value has been criticised as only offering decision makers with two choices – to invest or not to invest; which can affect the decision without taking into consideration the ability to delay an irreversible and uncertain investment expenditures (Sporleder and Bailey, 2001). To address the irreversibility and uncertainty in the decision, RO is an alternative to NPV analysis, which enables a decision maker to take into account irreversibility, uncertainty, and have the choice to wait to make a decision and evaluate the impact of these factors on the profitability of the decision (Tozer, 2009). The option to wait to make a decision provides the investor with the choice to gather further information to reduce the irreversibility costs and uncertainty level (Tozer, 2009).

Despite the points made above, however, the use of RO is limited. There are reasons that RO may not be widely accepted and used in decision making of companies. First, lack of support from top management as top managers are hesitant to accept a methodology, they cannot follow step by step. Second, the preference to use proven methods such as discounted economic value – the NPV, is greatly favoured and applied in the literature. Third, RO is considered to be more difficult to comprehend thus it requires top managers to be mathematically more sophisticated with backgrounds in science and engineering. Fourth, RO can lead to excessive risk taking for decision makers, i.e. overstating the value of uncertain investments, encouraging decision makers to over-invest in such investments (Block, 2007). Moreover, there are stigma among managers to discontinue an investment once the decision is made based on the initial analysis. Discontinuation of an investment may be unlikely regardless of the approach applied for the initial investment analysis (the NPV or RO), as managers may have less interest to discontinue the investment at a later stage as they have been identified with it (Block, 2007).

Previous research has studied uncertainty and irreversibility aspects of the investment decision as the main objective using RO as a stand-alone method or an expanded component to the NPV. Evaluating the uncertainty and irreversibility factors in the adoption of new agricultural technologies has been a common theme in research such as the production risk and cost of investment in adoption of a free-stall dairy housing (Purvis et al., 1995); water markets supply and future prices, expected benefit of the technology, and investment tax credit in adoption of irrigation technology (Carey and Zilberman, 2002); future demand, discount rates, irreversibility of entry-exit option, and operations capacity choice in adoption of remote sensing technologies (Isik et al., 2003); and project value and funding availability in adoption of methane digester technology (Stokes et al., 2008; Anderson and Weersink, 2014).

Other researchers such as Engel and Hyde (2003) and Hyde et al. (2003) studied the impacts of various factors such as the lifetime of the current technology and the useful life of the new technology on the adoption decision to replace a milking parlor with an

Automatic Milking System (AMS) by comparing the outcomes from using the NPV and RO methods in the presence of uncertainty and irreversibility associated with purchasing an AMS. Tozer (2009) analysed the investment in precision agriculture taking into account factors affecting the decision such as price and yield variability to either acquire machinery suitable for performing controlled traffic precision agriculture or to purchase a conventional system under both certainty and uncertainty using the NPV and RO techniques, respectively, and compared the returns estimated from an application of each method. It was concluded that RO is the preferred approach for the analysis compared to the NPV, taking into account the value of waiting for new information to reduce the uncertainty of the cashflows generated by the investment (Tozer, 2009).

None of these studies have considered the economic assessment of adoption of a robotic harvest technology in perennial crops. Perennial crops such as apples are considered to be more difficult to model than annual crops due to the dynamic nature of their life cycles, as it may take several years for a perennial crop like apples to reach full production (Thiele and Zhang, 1992; Tozer and Marsh, 2018; Devadoss and Luckstead, 2010). Production cycles of perennial crops such as olives or apples are complex with a delay between initial planting and first yield, followed by a prolonged production period, then a reduction in production, and finally removal of trees after 20-30 years (Devadoss and Luckstead, 2010). These production cycles introduce issues related to the interactions of production in one year to the next as each stage is interconnected and dependent on the previous events and growing practices, which can impact yield, quality, and price of apples accordingly (Thiele and Zhang, 1992), which can become sources of uncertainty in the investment decision.

In addition, the production inputs such as canopies once established cannot be reversed or used for other purposes, thus may be considered a sunk cost (i.e. irreversible cost). Therefore, better management of inputs and knowing about the profitability of the investment decision in the early years of the investment can help growers make better decisions regarding the production of perennial crops and adoption of harvesting robot technology (Devadoss and Luckstead, 2010; Tozer and Stokes, 2009; Willis and Hanlon, 1976). From a technology perspective, the capital investment for a robotic harvester for apples involves significant up-front costs, and limited possibility to liquidate the investment capital quickly. This is mainly due to the particular use of the technology and the perennial nature of apple production, as it may take several years for the crop to reach the full production level. Hence, much of investment in the apple production and the adoption of a robotic harvester once made could be regarded as sunk costs (Isik, 2006; Thiele and Zhang, 1992; Tozer, 2009; Tozer and Stokes, 2009).

The investment decision of a robotic apple harvester can exhibit a high degree of uncertainty in variables such as the fruit price, yield, quality of fruit, and the costs to acquire and maintain the robot, which can affect the profitability of the investment decision. Moreover, in spite of the applications of RO approach, the objective of the current study is not to evaluate the input of uncertainty and irreversibility on the investment decision, but to analyse the economic feasibility of the technology.

Given the previous discussion, the shortcoming of NPV analysis stems from the improper use of it and it is not necessarily that NPV analysis is an inappropriate method to use (Block, 2007). The NPV analysis can correctly be used if all options such as invest, not to invest, or defer are known at the beginning of the investment such that they all can be assessed (Block, 2007). Furthermore, the NPV approach can be more valuable in the early years of the investment given the time value of money, whereas the RO approach is likely to have the greatest value in the later years of the investment, because flexibility in the investment may be at its most valuable phase and uncertainty at its highest level (Block, 2007).

As noted earlier, the RO method is constructed based on the NPV, if the rise of uncertainty and irreversibility is considered probable in the later phase of the investment (Block, 2007). However, in the current research, the condition of the investment decision does not meet with the current situation for implementing the decision, i.e. it is assumed that the investment decision is exercised in absence or controlled framework of uncertainty and irreversibility factors throughout the investment period such that they can be evaluated using the NPV approach. In addition, due to the dynamic nature of apples as a perennial crop, it may be more difficult to model it. Therefore, it requires the use of a method like NPV to simplify the complex nature of the investment decision by taking into account the multi-variate nature of apple production in combination with the limitations discussed earlier in commercial development of a robotic harvest technology for fresh market apples.

3.7. Conclusion

This chapter provided an overview of the literatures used in the context of the current research. The chapter discussed some of the issues around labour important to the apple industry including labour shortages, costs, and health and safety. The chapter also gathered and discussed the related literature on the key developments of the robotic systems in agriculture field specifically horticulture, animal agriculture, and more importantly tree fruit harvesting. Next, the chapter identified and explained the key horticultural factors that could affect the adoption of robotic harvesting technology in apple orchards such as thinning, pruning, tree training, tree population, and tree canopy systems. Lastly, the chapter provided an overview of the most related economic studies in tree fruit, taking into consideration the most commonly used methods and existing gaps that could help to identify the most appropriate analytical method for the current research.

Based on the reviewed economic studies, given that there are no examples of the experience and output of commercial orchards adopting the robotic harvester, no evidence or commercial information about robotic harvester performance and operating that represents best practice as well as no previous studies assessing the economic feasibility of the technology coupled with the complexity of apple production, NPV was selected as the most appropriate analytical method to more clearly evaluate and describe the variation of types across orchards such as varietal price and yield, and orchard sizes along with the uncertainty around ownership and operation of the robot. Thus, it can more easily disentangle the impacts of uncertainty and economics of investment when presenting the outcomes. Otherwise, it would have not been possible to analyse and present the outcomes of the analysis if more sophisticated analytical methods such as RO or other analytical approaches discussed in section 3.5 were used. Note that even though some of the methods used in the reviewed studies were comprehensive in their defined scopes, using such sophisticated approaches would make it difficult to disentangle the impacts of uncertainty and economics of investment in the context of the current research. This is because of the complex nature of the current research having variation across orchards such as varietal price and yield, and orchard sizes. As a result, the key aspect of the model – analysing the relative profitability and performance of the robotic harvester technology would have been lost when using a more complex analytical method.

In addition, considering the advanced and fast trend in developing robotic harvester systems in agriculture coupled with the uncertainties around availability of labour, investment in a robotic harvest technology may not be as much of a risk for growers but an opportunity to better manage their resources and reduce their reliance on harvest labour. However, there are still elements of uncertainty related to the investment decision and performance of robot that will be considered in the investment decision. From the viewpoint of the robot, there are many unknowns or uncertainties with the technology given it is not a proven technology and is still in commercial trial phase. Some of the uncertain elements that may affect the investment decision includes purchase cost and harvesting efficiency and speed of the robot. From the viewpoint of labour management, it involves coping with labour associated uncertainties such as labour wages, availability, and efficiency. Therefore, these elements will be taken into account in the analysis by conducting sensitivity analyses to assess the impacts they can have on the profitability of the investment decision.

Chapter 4. Conceptual model

In the context of this research, apple growers are assumed to have choices over using different harvesting systems – solely relying on manual labour or utilising mechanical harvesting systems such as platform or robot with the use of pickers. In this chapter, the conceptual framework for feasibility analysis of these three harvesting systems (manual, robot, and platform) will be explained. The developed models can be empirically applied to measure economic feasibility of each harvesting system, using the principle of NPV, and return prospective of the investment, using IRR of the investment. The remainder of this chapter will describe the successive stages of this process in detail.

4.1. Yield

In the current model, it is assumed that producers will have orchards planted with different tree structures and varieties, which can result in different yield levels. Initially, the biological yield (estimated yield before harvest begins) for variety *i* in *t* ($BY_{i,t}$, kg/ha) is the product of NT_i or the number of fruit bearing trees per hectare for variety *i*, $NA_{i,t}$ or the number of apples per tree for variety *i* in *t*, and ga_i or the average fruit weight of variety *i* in grams:

$$BY_{i,t} = NT_i * NA_{i,t} * ga_i \tag{4.1}$$

Yield for harvesting system *z* of variety *i* in *t* ($Y_{z,i,t}$, kg/ha) varies depending on whether fruit are harvested manually or mechanically. Therefore, yield for harvesting system *z* of variety *i* in *t* ($Y_{z,i,t}$, kg/ha) is calculated as:

$$Y_{z,i,t} = BY_{i,t} * \chi_z \tag{4.2}$$

Where χ_z (%) is the harvesting performance of picking fruit, which will be explained in more detail in section 4.5.1.

4.2. Revenue

Total revenue per hectare for system *z* of variety *i* in *t* ($TR_{z,i,t}$, \$/ha) is generated by apple sales, which are the product of the price of variety *i* for harvesting system *z* in *t* ($P_{z,i,t}$, \$/kg), yield for harvesting system *z* of variety *i* in *t* ($Y_{z,i,t}$, kg/ha), and salvage value for each robot or platform harvesting variety *i* in *t*, $\Phi_{z,i,t}$ (\$/machine):

$$TR_{z,i,t} = P_{z,i,t} * Y_{z,i,t} + \Phi_{z,i,t} \tag{4.3}$$

Conceptually, price will depend on the method of harvest and how much of the harvested fruit are of export quality; $P_{z,i,t}$ consists of two components: export price of variety *i* for harvesting system *z* in *t* ($Pe_{z,i,t}$, \$/kg) and domestic price of variety *i* for harvesting system *z* in *t* ($Pd_{z,i,t}$, \$/kg). $Pe_{z,i,t}$ is determined by the export market, whereas $Pd_{z,i,t}$ indicates apples sold mainly for local market as fresh or processed (juice or other products such as canned apples). In addition, $P_{z,i,t}$ is affected by the packout or the export recovery rate of variety *i* for harvesting system *z* in *t* ($\bar{e}_{z,i,t}$, %), i.e. the percentage of harvested apples that are graded as export quality after being harvested by system *z*. Therefore, $P_{z,i,t}$ is calculated as the weighted sum of $Pe_{z,i,t}$ multiplied by $\bar{e}_{z,i,t}$ and $Pd_{z,i,t}$ multiplied by the complement of packout rate (1- $\bar{e}_{z,i,t}$), where $0 \leq \bar{e}_{z,i,t} \leq 1$. Thus:

$$P_{z,i,t} = (Pe_{z,i,t} * \bar{e}_{z,i,t}) + (Pd_{z,i,t}) * (1 - \bar{e}_{z,i,t}) \tag{4.4}$$

Salvage value for each robot or platform harvesting variety *i* in *t*, $\Phi_{z,i,t}$ (\$/machine), is an estimated sales value of a machine that is expected to be received at the end of its useful life that can be considered as a recovery income for the orchard business (Edwards, 2015) and is the product of $TPC_{z,i,t}$ and the salvage rate (ϕ, %):

$$\Phi_{z,i,t} = TPC_{z,i,t} * \phi \tag{4.5}$$

4.3. Net revenue of orchard

Initially, R_t (\$/ha) or net revenue for the entire orchard is the difference between total revenue and cost in t (TU_t, \$/ha) and (TK_t, \$/ha), respectively:

$$R_t = TU_t - TK_t \tag{4.6}$$

The model assumes that producers will grow different apple varieties, *i* (where *i* = 1,…, I) and will have the options of utilising different harvesting systems, which are not mutually exclusive, *z* (where *z* = 1,…, Z) in their orchards. Therefore, TU_t and TK_t are calculated as the total revenue and cost for system *z* of variety *i* in *t*, $TR_{z,i,t}$ and $TC_{z,i,t}$, respectively:

$$TU_t = \sum_{z=1}^{Z} \sum_{i=1}^{I} TR_{z,i,t} \tag{4.7}$$

And

$$TK_t = \sum_{z=1}^{Z} \sum_{i=1}^{I} TC_{z,i,t} \tag{4.8}$$

4.4. Net Present Value

Net present value (NPV) of an investment assumes certainty and reversibility of the investment decision as implicit, i.e. future costs and returns are known with certainty and the initial costs of investment are recoverable (Tozer, 2009). Standard NPV (V)

analysis considers the investment valuable if sum of the discounted net returns from the investment (R) are greater than the initial recurrent costs of the investment (K):

$$V = R - K \tag{4.9}$$

And

$$V = \sum_{t=1}^{n} \frac{R_t}{(1+\rho)^{t}} - K \tag{4.10}$$

Where R_t (\$/ha) is the annual expected net revenue or net cash flows from the investment, ρ is the risk-adjusted discount rate or the opportunity costs of the capital, and t is the number of periods in the future. Note that IRR is calculated using Eq. (4.10), where the equation is solved for ρ, and NPV is set equal to zero (Kay et al., 2016). As shown in Figure 4.1, M is the point of indifference between investing or not investing under certainty, the investment decision will be triggered when $K < M$ (Tozer, 2009).

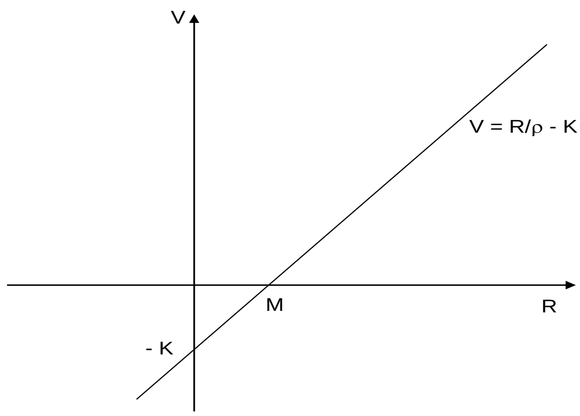

Figure 4.1. Optimal investment decision (Net Present Value)
Source: Tozer and Stokes (2009)

4.5. Harvesting systems

The economic feasibility of different harvesting systems, z, where z = 1,2,3 (1 = manual, 2 = robot, and 3 = platform) are explained using the concept of NPV. These systems are also referred as manual and mechanical harvestings (robot or platform) throughout the text. Given that robots are still in the developmental stage, platform harvesting is considered as an alternative solution, commercially available to assist labour not only with harvesting, but also selected pre-harvest tasks such as training, pruning, and thinning. Robot and platform models are constructed based on the same framework; different parameters and assumptions are used for each system, which will be discussed in this chapter.

4.5.1. Harvesting performance

Following Eq. (4.2), yield for each system or $Y_{z,i,t}$ depends on harvesting performance, χ_z , amongst other factors, which varies for each system given that each system uses different harvesting tools and technologies. χ_z accounts for the harvesting efficiency for system *z* (HF_z, %, $0 \leq HF_z \leq 1$) – the percentage of fruit identified with harvestable quality and harvested per seconds (Zhang, 2018; Sinnett et al., 2018), with 1 being fully efficient; and the operation efficiency for system *z* (OF_z, %, $0 \leq OF_z \leq 1$) – things that interrupt or reduce the normal harvesting operations such as technical failure, refuelling, turning blocks, or unloading harvested fruit, with 1 being fully efficient. Note that when harvesting systems are completely efficient i.e. HF_z= 1 and OF_z= 1, all fruit are harvested. Therefore, χ_z is calculated as:

$$\chi_z = HF_z * OF_z \tag{4.11}$$

Manual harvesting

It is assumed that manual harvest has an efficiency of χ_1, which can result in fruit not being harvested completely because of time-consuming activities such as moving, or climbing up or descending ladders (Zhang et al., 2019) coupled with physiological factors such as fruit not ready for harvest in the limited harvesting window. Otherwise, early harvested fruit may not be suitable for the fresh market or processing, and more importantly the shortage of manual labour could exacerbate the situation further – not having enough manual labour at the right time to perform the time-sensitive harvest operations and any fruit unharvested is wasted, thus reducing the profitability of the orchard (Ashton, 2018; Bartlett, 2018; Eddy, 2018; Zhang, 2018). As explained earlier $0 \leq OF_z \leq 1$, however for manual labour, OF_1 = 1 and it is assumed that any factors reducing the productivity of manual harvesting are considered in HF_1. Following Eqs. (4.2) and (4.11), manual yield for variety *i* in *t*, $Y_{1,i,t}$ is calculated as:

$$Y_{1,i,t} = BY_{i,t} * \chi_1 \tag{4.12}$$

Mechanical harvesting

It is assumed that robots harvest with the harvesting efficiency of HF_2, defined as the percentage of apples identified and harvested by robot per tree, which is derived from harvesting technologies embedded in the robot such as imaging and Artificial Intelligence systems to identify fruit on trees and harvest ones with harvestable quality (Zhang, 2018); and platform harvesting is performed with an efficiency of HF_3 or the percentage of fruit picked by manual pickers on the platform depending on how efficient each picker work on platform to locate and remove apples with harvestable quality – skill levels of individual pickers can slow down the overall picking efficiency of the picking team. Operation efficiency of robot or platform OF_z, which includes activities that decrease the working efficiency of robot or platform harvesting in orchard such as turning, refuelling, and technical failure. Orchard configuration (e.g. shape) and yield could also play a factor in OF_z e.g. orchards with shorter rows and higher volume of fruit for harvest at one time can result in longer than normal harvesting operation, requiring machines to turn more blocks and spend more time harvesting fruit in each block. Therefore, following Eqs. (4.2) and (4.11), mechanically harvested yield for robot or platform of variety *i* in *t*, $Y_{z,i,t}$ is calculated as:

$$Y_{z,i,t} = BY_{i,t} * HF_z * OF_z + \bar{Y}_{z,i,t} \tag{4.13}$$

Where $\bar{Y}_{z,i,t}$ (kg/ha) is the equivalent weight or yield of mechanically unharvested fruit of variety *i* in *t* that is assumed will be harvested by pickers, because of factors such as the efficiency of the harvesting machines, harvesting window (section 4.5.2), and harvesting speed (section 4.5.3).

4.5.2. Harvesting window of each variety

Considering the multi-varietal nature of the current model, in addition to the economic and operational aspects of using different harvesting systems, physiological aspects of apple production in particular harvesting window per variety (HW_i, days), among other factors, can impact the investment decision. HW_i refers to a narrow time-sensitive period in which apples are ready to be harvested based on the maturity parameters such as size, colour, brix, and quality and does not change regardless of the harvesting system employed. Note that HW_i is defined as an interval time-frame specific to planted varieties in an orchard. Thus, one or more varieties may have an overlapping harvesting window, which can affect the harvesting operation. To clarify this, assume three different varieties (V_{i_1}, V_{i_2}, and V_{i_3}) characterised with different harvesting windows (HW_{i_1}, HW_{i_2}, and HW_{i_3}) are to be planted in an orchard (Table 4.1). HW_{i_1}does not overlap with HW_{i_2} or HW_{i_3}, however HW_{i_2} overlaps with HW_{i_1} and HW_{i_3}.

This intersecting harvesting window will impact on the volume of fruit available to harvest at one time, and consequently the number of harvesting machines required to harvest and how they will be allocated across the orchard for each variety to make sure all fruit are harvested within their specific harvesting window, while the maximum harvest capacity of systems are met. This will be discussed further in section 4.5.4. As a side note, the harvesting periods mentioned in Table 4.1 are only for demonstration purposes and do not represent the harvesting periods of varieties used in the current research.

Table 4.1. Harvesting window and period for three apple varieties in an orchard in New Zealand

Harvesting window per variety (HW_i)	Harvesting period
HW_{i_1}	16 February - 8 March
HW_{i_2}	15 March - 7 April
HW_{i_3}	8 March - 10 April

Source: Created by the author for demonstration purpose.

4.5.3. Harvesting speed

Another component that captures the harvesting operation for each system in addition to OF_z and HF_z, is the harvesting speed – how fast each system harvests fruit taking into account the volume of fruit harvested in respect to the harvesting window and harvesting hours required.

Manual harvesting

Harvesting speed of a manual labourer per variety ($HS_{1,i}$) measured in harvested weight of fruit (kg) within the harvesting window (HW_i, days) involves harvesting apples based on colour and maturity and placing them into a harvesting bag that once full need to be dropped off to fill large wooden square containers called bins (NZPocketGuide. (n.d.)). Therefore, $HS_{1,i}$ is the product of MHN_b (bins/hour) or number of bins harvested manually per hour, g_b (kg) or weight of each bin that a manual labourer can harvest on average within HW_i:

$$HS_{1,i} = MHN_b * g_b * HW_i \tag{4.14}$$

Multiplying MHN_b by g_b returns weight (kg) of harvested apples within one day; and multiplying the result by HW_i will return the total weight of manually harvested apples within the harvesting window.

Robot harvesting

Harvesting speed of a robot per variety, $HS_{2,i}$ measured as the weight of apples harvested (kg) within HW_i (days), takes into account how fast robot harvests in terms of the number of apples per hour (RHN_a, fruit/hour) without any efficiency factors considered and is assumed to be the same across varieties, RD_i (hour) or daylight hours per variety for robot operation, ga_i (grams) or weight of each apple variety, and HW_i (days). Note that $HS_{2,i}$ varies per variety as each variety may be harvested in different months of year, which is characterised by different daylight hours given the assumption that robot can only operate in daylight at its current stage of development. Thus:

$$HS_{2,i} = RHN_a * RD_i * ga_i * HW_i \tag{4.15}$$

Multiplying RHN_a by RD_i and ga_i returns weight (kg) of apples harvested within one day; and multiplying the result by HW_i will return the total weight of apples harvested within the harvesting window. Important to note, $HS_{2,i}$ is determined by the harvesting technology embedded in the robot using a combination of precision and automation technologies such as sensory computer vision and Artificial Intelligence to locate and remove apples with harvestable quality (Zhang, 2018).

Platform harvesting

Harvesting speed of a platform per variety, $HS_{3,i}$ is measured as the weight of harvested apples (kg) within HW_i (days) accounting for PHN_b (bins/hour) or the number of bins harvested by platform (harvesting team) per hour, PD_i (hour) or daily working hours for platform operation per variety, g_b or weight of each bin (kg), and HW_i (days). Thus:

$$HS_{3,i} = PHN_b * PD_i * ga_i * HW_i \tag{4.16}$$

Multiplying PHN_b by PD_i and ga_i returns weight (kg) of harvested apples within one day; and multiplying the result by HW_i will return the total weight of apples harvested within the harvesting window. Note that $HS_{3,i}$ is determined by the harvesting speed of the slowest picker on the machine (the rate of harvesting is as fast as the slowest picker on the platform).

4.5.4. Number of harvesting units required

Number of harvesting units required per variety in *t* ($N_{z,i,t}$) is derived from $HS_{z,i}$ (kg/machine), $Y_{z,i,t}$ (kg/ha), and harvestable orchard area per variety (A_i, ha):

$$N_{z,i,t} = \frac{Y_{z,i,t} * A_i}{HS_{z,i}} \tag{4.17}$$

Where $N_{z,i,t}$ is applied when an orchard is planted with only one variety. However, as discussed in section 4.5.2 and illustrated conceptually in Figure 4.2 for an orchard planted with more than one variety (multi-varietal), where HW_i (days) for two planted varieties (V_{i_1} and V_{i_3}) does not overlap ($HW_{i_1} \not\cap HW_{i_3}$), then $TN_{z,t}$ or total number of harvesting units required in *t* are related to the maximum number of units required to harvest the maximum volume of fruit available at one time per variety in *t*, *Max* ($N_{z,i_1,t}$ and $N_{z,i_3,t}$).

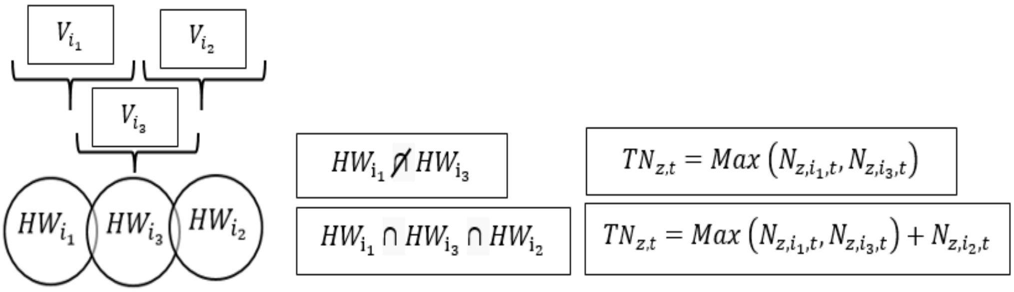

Figure 4.2. Harvesting window of three apple varieties and number of harvesting machines **(Source: Created by the author for demonstration purpose)**

Therefore, $TN_{z,t}$ is calculated as:

$$TN_{z,t} = Max\ (N_{z,i_1,t}, N_{z,i_3,t}) \quad (4.18)$$

Where $N_{z,i_1,t}$ and $N_{z,i_3,t}$ are calculated using Eq. (4.17). When a new variety, V_{i_2} is added to the orchard that has an overlapping harvesting window with other planted varieties ($HW_{i_1} \cap HW_{i_2} \cap HW_{i_3}$), then the maximum number of harvesting systems, for V_{i_1} and V_{i_3} as well as the additional number of harvesting systems will have to be utilised to harvest all varieties. Following Eq. (4.18), $TN_{z,t}$ is calculated as:

$$TN_{z,t} = Max\left(N_{z,i_1,t}, N_{z,i_3,t}\right) + N_{z,i_2,t} \quad (4.19)$$

Where $N_{z,i_2,t}$ is calculated using Eq. (4.17). Note that in this orchard with overlapping HW_i, $TN_{z,t}$ may not be equal to the number of harvesting units required per area, but with sufficient capacity to harvest all planted varieties. Theoretically, when mechanical harvesting is utilised, there may be excess harvest capacity for machines, however, in the multi-varietal orchard, it is assumed that extra number of harvesting machines will be purchased, enough to harvest all planted varieties. Nevertheless, harvesting machines may appear to have under-capacity in the first overlap i.e. $HW_{i_1} \cap HW_{i_2}$, due to a lower number of machines required to harvest both varieties and over-capacity in the second overlap i.e. $HW_{i_3} \cap HW_{i_2}$, where the second may be constraining the harvesting time period, because the maximum number of machines will have to be utilised to harvest both varieties. In addition, when mechanical harvesting (robots or platform) is utilised, it is assumed that machines are purchased in integer quantities, where $N_{z,i,t}$ = *int* (0,1,2,3,…), such that $BY_{i,t}$ (kg/ha) from Eq. (4.1) has to be greater than or equal to $Y_{z,i,t}$ (kg/ha):

$$BY_{i,t} \geq \sum_{z=1}^{Z} Y_{z,i,t} \quad (4.20)$$

To assess how $N_{z,i,t}$ are structured in orchard, it is assumed that producers will have harvesting machines of various ages in their orchards, which will harvest fruit in the current and next production seasons. Therefore, for each variety, number of machines for variety *i* in *t*, $N_{z,i,t}$ is a function of $N_{z,i,t-1}$ or the number of machines purchased per variety in the previous year, $PN_{z,i,t}$ or the number of machines purchased new per variety in the current year, and $RN_{z,i,t}$ or the number of machines replaced per variety in the current year due to reaching the end of their useful life (L_z, years) resulting from wear, tear, obsolescence, and age:

$$N_{z,i,t} = N_{z,i,t-1} + PN_{z,i,t} - RN_{z,i,t} \tag{4.21}$$

4.5.5. Number of pickers required

Number of pickers required per variety for robot or platform in *t*, $NM_{z,i,t}$ is derived from $\bar{Y}_{z,i,t}$ (kg/ha) that is assumed will be harvested by pickers for the orchard area of A_i (ha) over $HS_{1,i}$ (kg/manual picker):

$$NM_{z,i,t} = \frac{\bar{Y}_{z,i,t} * A_i}{HS_{1,i}} \tag{4.22}$$

Where $HS_{1,i}$ is estimated using Eq. (4.14), and $\bar{Y}_{z,i,t}$ (kg/ha) is calculated as:

$$\bar{Y}_{z,i,t} = \frac{\left(\frac{HS_{z,i} * N_{z,i,t}}{Y_{z,i,t}} * BY_{i,t} * F\right) + \left(A_i - \frac{HS_{z,i} * N_{z,i,t}}{Y_{z,i,t}} * BY_{i,t} * F^{-}\right)}{A_i} \tag{4.23}$$

Where the first term of the equation on the left-hand side captures the unharvested yield per variety resulted from HF_z and OF_z of operating robots or platforms, and the second term captures the unharvested yield for the area that were not covered by machines for each variety given the assumption that machines are purchased in integer numbers. In addition, it is assumed that the pickers to pick the unharvested yield due to HF_z and OF_z of operating robots or platforms picks unharvested fruit with an efficiency of F and pick the unharvested fruit from the area not harvested by robot or platform with a picking efficiency of F^{-}. Note that $\bar{Y}_{z,i,t}$ varies for robot and platform harvesting systems depending on how much fruit are unharvested by each machine that will have to be harvested by pickers.

4.5.6. Cost

Following Eq. (4.8), total cost for system *z* of variety *i* in *t* ($TC_{z,i,t}$, \$/ha) is calculated as:

$$TC_{z,i,t} = TFC_{z,i,t} + TVC_{z,i,t} \tag{4.24}$$

Where $TFC_{z,i,t}$ ($/ha) and $TVC_{z,i,t}$ ($/ha) are total fixed and variable costs for harvesting system *z* of variety *i* in *t*, respectively. Introducing robot or platform as an alternative to manual harvesting changes the cost structure, accordingly, because mechanical harvesters have a different set of costs compared to the manual harvesting system, which are explained in this section. In the current research, $TFC_{z,i,t}$ includes machine-related and orchard-related fixed costs. It is assumed that machine-related fixed cost includes the total purchase cost of harvesting machines required to harvest the orchard size of variety *i* in *t* ($TPC_{z,i,t}$, $/ha), which occurs regardless of machines use. Other machine-related fixed costs are interest ($\beta C_{z,i,t}$, as a proxy for the opportunity cost of the capital), and insurance and housing ($\tau C_{z,i,t}$), which are incurred whether machines operate or not. Orchard-related costs include orchard establishment and maintenance costs, classified as pre-harvest costs performed by system *z* in *t* ($\bar{P}HC_{z,t}$, $/ha). These are activities required to prepare and maintain the orchard before trees reach production and are ready for harvest such as tree planting, trellis, irrigation, training, pruning, and thinning. Note that some of pre-harvest activities such as training, pruning, and thinning occur after trees have reached bearing age and are performed as part of annual orchard maintenance. Thus, $TFC_{z,i,t}$ is calculated as:

$$TFC_{z,i,t} = TPC_{z,i,t} + \beta C_{z,i,t} + \tau C_{z,i,t} + \bar{P}HC_{z,t} \tag{4.25}$$

Total annual operating or variable costs for system *z* of variety *i* in *t* ($TVC_{z,i,t}$, $/ha) vary with the amount of machinery and facility use (Edwards, 2015). These costs are categorised as harvest variable cost for system *z* of variety *i* in *t* ($HC_{z,i,t}$, $/ha) and nonharvest variable or post-harvest cost for system *z* of variety *i* in *t* ($PHC_{z,i,t}$, $/ha) and will be explained in detail later in this chapter. Thus, $TVC_{z,i,t}$ is calculated as:

$$TVC_{z,i,t} = HC_{z,i,t} + PHC_{z,i,t} \tag{4.26}$$

Therefore

$$TC_{z,i,t} = TPC_{z,i,t} + \beta C_{z,i,t} + \tau C_{z,i,t} + \bar{P}HC_{z,t} + HC_{z,i,t} + PHC_{z,i,t} \tag{4.27}$$

Purchase cost of harvesting machines

When harvesting is performed manually, no harvesting machines (robot or platform) will be required, thus no costs will be incurred from purchasing and operating harvesting machines, i.e. $TPC_{1,i,t}$ = 0. When mechanical harvesting is utilised, from an investment decision-making perspective, it is necessary to know the total purchase cost for robots or platforms as it would provide an initial piece of the investment decision.

Total purchase cost of robots or platforms per variety in t ($TPC_{z,i,t}$, \$/ha), is a fixed cost derived from number of robots or platforms purchased new per variety in t, $PN_{z,i,t}$, and price for each machine (PC_z, \$/machine), spread over the whole orchard area per variety (A_i, ha) in the budget. Thus:

$$TPC_{z,i,t} = \frac{(PC_z * PN_{z,i,t})}{A_i} \tag{4.28}$$

Following the assumption that a platform will be used for harvest as well as selected pre-harvest tasks (tree training, pruning, and thinning), a platform, with a basic harvest functionality, does not require any extra components to be used for pre-harvest tasks, which means the price will not increase (Zhang et al., 2019).

Interest cost

Interest on the capital spent for purchasing robot or platform of variety i in t, $\beta C_{z,i,t}$ (\$/machine) is a cost either as a cash cost when money is borrowed, or an opportunity cost of capital when machine is bought with saved money (Edwards, 2015). In the current model, it is assumed that credit of any size can be taken by any farmers or potential investors at an annual interest rate of r (%), which represents the average annual effective interest rate of local bank loans to source capitals for an investment. Thus, $\beta C_{z,i,t}$ is calculated as:

$$\beta C_{z,i,t} = \left(\frac{TPC_{z,i,t} + \Phi_{z,i,t}}{2}\right) * r \tag{4.29}$$

Where the second term on the right-hand side captures the annual average value of the machine over its ownership period or its value at mid-life, as the value of the machine declines over time (Edwards, 2015).

Insurance and housing cost

Insurance and housing cost for robot or platform of variety i in t, $\tau C_{z,i,t}$ (\$/machine) accounts for the damages to the machine from fire, collision, hail, wind, or theft, and for any liability coverage (Edwards, 2015) and is the product of the insurance and housing rate (ω, %) and real value of the machine (Gallardo and Brady, 2015):

$$\tau C_{z,i,t} = \left(TPC_{z,i,t} - \Phi_{z,i,t}\right) * \omega \tag{4.30}$$

Pre-harvest costs

In the current model, manual pre-harvest costs in t ($\bar{P}HC_{1,t}$, \$/ha) are given, thus no calculations are needed to derive related cost elements. When robot harvest is utilised, it is assumed that pre-harvest activities are operated manually, and associated costs are calculated similar to the manual harvest model, thus $\bar{P}HC_{2,t}$ = $\bar{P}HC_{1,t}$. For platform harvesting, given that platforms will also be utilised for selected pre-harvest tasks including tree training, pruning, and thinning, and the remaining pre-harvest tasks will be performed manually and calculated similar to the manual harvest model. Therefore, pre-harvest cost for platform in *t*, $\bar{P}HC_{3,t}$ ($/ha) is calculated as the sum of the costs associated with utilising platform for selected pre-harvest tasks in *t* ($\overline{SP}HC_{3,t}$, $/ha) and the costs for performing the remaining pre-harvest tasks manually in *t* ($\bar{P}HC_{1,t}$, $/ha):

$$\bar{P}HC_{3,t} = \overline{SP}HC_{3,t} + \bar{P}HC_{1,t} \tag{4.31}$$

Where $\overline{SP}HC_{3,t}$ is estimated based on the total operation hours required by platform per task in *t*, $h_{3,\vartheta,t}$ (hour/hectare) where ϑ = 1,2,3 (1 = tree training, 2 = pruning, 3 = thinning). $h_{3,\vartheta,t}$ for each task is given and assumed it varies across orchard establishment years and remains constant across varieties. Thus, $\overline{SP}HC_{3,t}$ is calculated as:

$$\overline{SP}HC_{3,t} = \sum_{\vartheta=1}^{3} h_{3,\vartheta,t} * h_w * \Psi * N_l \tag{4.32}$$

Where h_w ($/hour) is the hourly labour wage, N_l is the number of workers on a platform, and Ψ (%) accounts for the actual hours of labour – actual labour hours utilising machines usually exceed field machine, due to factors such as technical failure, refuelling, turning blocks, lubricating and servicing machines; to take this into account, h_w is multiplied by Ψ (Edwards, 2015). The remaining pre-harvest tasks are assumed to be performed manually and estimated similar to the manual harvest model.

Post-harvest costs

Post-harvest costs across harvesting systems and varieties in *t* ($PHC_{z,i,t}$, $/ha) is the product of $Y_{z,i,t}$ (kg/ha) and post-harvest wage (PH_w, $/kg):

$$PHC_{z,i,t} = Y_{z,i,t} * PH_w \tag{4.33}$$

Harvest costs

Harvest cost using manual labour to harvest variety *i* in *t* ($HC_{1,i,t}$, $/ha) is the product of $Y_{1,i,t}$ (kg/ha) and the manual labour wage (MH_w, $/kg):

$$HC_{1,i,t} = Y_{1,i,t} * MH_w \tag{4.34}$$

When robots or platforms are utilised to harvest variety *i* in *t* ($HC_{z,i,t}$, $/ha), harvest costs include the total machine-related operating or variable costs for variety *i* in *t* ($TMVC_{z,i,t}$, $/ha) and the cost incurred from employing picker to harvest unharvested variety *i* by system *z* in *t* ($\overline{MHC}_{z,i,t}$, $/ha):

$$HC_{z,i,t} = \overline{MHC}_{z,i,t} + TMVC_{z,i,t} \tag{4.35}$$

Where $\overline{MHC}_{z,i,t}$ is the product of $\bar{Y}_{z,i,t}$ (kg/ha) and MH_w ($/kg):

$$\overline{MHC}_{z,i,t} = \bar{Y}_{z,i,t} * MH_w \tag{4.36}$$

And $TMVC_{z,i,t}$ ($/ha) is calculated as the product of total number of machines required in *t*, $TN_{z,t}$, and machine-related variable or operating costs for system *z* of variety *i* in *t*, $MVC_{z,i,t}$ ($/machine) over A_i (ha):

$$TMVC_{z,i,t} = \frac{TN_{z,t} * MVC_{z,i,t}}{A_i} \tag{4.37}$$

Where $TN_{z,t}$ is calculated depending on the varietal harvesting window following Eqs. (4.18) and (4.19). $MVC_{z,i,t}$ includes repair ($\gamma C_{z,i,t}$), fuel ($\varphi C_{z,i,t}$), oil and lubrication ($\delta C_{z,i,t}$), and robot operator or platform labour ($\varrho C_{z,i,t}$) costs for variety *i* in *t*. Thus:

$$MVC_{z,i,t} = \gamma C_{z,i,t} + \varphi C_{z,i,t} + \delta C_{z,i,t} + \varrho C_{z,i,t} \tag{4.38}$$

Repair cost

Repair costs for robot or platform of variety *i* in *t*, $\gamma C_{z,i,t}$ ($/machine) account for wear, tear, accidents, and routine maintenance, which vary with age, use, machine type, preventive maintenance programs, and other factors (Edwards, 2015). $\gamma C_{z,i,t}$ is the product of $TPC_{z,i,t}$ and the repair rate (κ, %):

$$\gamma C_{z,i,t} = TPC_{z,i,t} * \kappa \tag{4.39}$$

Fuel cost

Fuel cost for robot or platform of variety *i* in *t*, $\varphi C_{z,i,t}$ ($/machine) is the product of the fuel price (fp, $/litre), the average fuel consumption of diesel (fc_z, litres/hr), and total operation hours of the machine per variety in *t* ($h_{z,i,t}$, hr):

$$\varphi C_{2,i,t} = fp * fc_z * h_{z,i,t} \tag{4.40}$$

Where $h_{z,i,t}$ is calculated differently for robot and platform, given the assumption that robot is only utilised for harvest, whereas platform is utilised for harvest as well as selected pre-harvest tasks, thus total operation hours for each system will vary accordingly. Each variety is characterised by different harvesting periods and thus harvested in different months of the year, which follows a different monthly daylight hours accordingly that will determine the daily working hours for robot given the assumption that robot can only operate in daylight at the current development stage. Thus, $h_{2,i,t}$ (hour/machine) or total operation hours required by robot to harvest each variety in *t*, is the product of $N_{2,i,t}$, RD_i or daylight hours that a robot will operate per variety and HW_i (days):

$$h_{2,i,t} = RD_i * HW_i * N_{2,i,t} \quad (4.41)$$

And $h_{3,i,t}$ (hour/machine) is the sum of the total operation hours that a platform will be utilised for harvest and selected pre-harvest tasks. In the current research, total hours required for pre-harvest and harvest operations by platform are calculated based on different measurements – pre-harvest operation hours per task are estimated based on hour per hectare, whereas harvest operation hours are measured as the number of hours platforms operated in orchard, which changes based on orchard area and variety. It is assumed that total pre-harvest operation hours required will remain the same across varieties. Thus, $h_{3,i,t}$ is calculated as:

$$h_{3,i,t} = \sum_{\vartheta=1}^{3} h_{3,\vartheta,t} * A_i + (PD_i * HW_i * N_{3,i,t}) \quad (4.42)$$

The first term of the equations on the right-hand side captures the total harvest operation hours by taking into account the number of platform harvesters required for variety *i* in *t*, $N_{3,i,t}$ (using Eqs. (4.17) and (4.21)), HW_i (days), and PD_i or daily working hours; and the second term captures the total operation hours required for selected pre-harvest tasks in *t*, $h_{3,\vartheta,t}$ (ϑ=1,2,3) based on A_i, which are given in the current model.

Oil and lubrication costs

Oil and lubrication costs for robot or platform of variety *i* in *t*, $\delta C_{z,i,t}$ (\$/machine) is estimated as a percentage (q) of fuel cost for machines, $\varphi C_{z,i,t}$ (Edwards, 2015):

$$\delta C_{z,i,t} = \varphi C_{z,i,t} * q \quad (4.43)$$

Labour costs

The labour cost associated with utilising each machine varies between robot and platform. It is assumed that robot is operated in orchard by an operator, which is a variable-harvest cost and varies based on the total operation hours of the robot. Thus, robot operator cost per variety in *t*, $\varrho C_{2,i,t}$ (\$/machine) is the product of the robot's operator wage (R_w, \$/hour) and $h_{2,i,t}$ (hr/machines):

$$\varrho C_{2,i,t} = R_w * \Psi * h_{2,i,t} \quad (4.44)$$

Platforms are used by pickers working on them to perform pre-harvest and harvest operations, calculated as the labour cost per variety in *t*, $\varrho C_{3,i,t}$ (\$/machine):

$$\varrho C_{3,i,t} = h_w * \Psi * h_{3,t} * N_l \quad (4.45)$$

Multiplying R_w and h_w by Ψ return the actual hourly wage of a robot operator and platform labour, respectively, accounting for the actual working hours, as explained for Eq. (4.32).

4.6. Conclusion

This chapter developed a conceptual model to examine the investment decision in the robotic harvest technology as well as other alternatives including platform and manual harvesting systems - taking into account various elements important in the investment decision such as varietal characteristics e.g. harvesting window, fruit weight, fruit value, and yield, and the purchase and operating costs of the robot.

Chapter 5. Empirical model

This chapter provides a description of the application and data required to extend the conceptual framework developed in chapter 4 to an empirical model to investigate the decision of investing in the robotic harvest technology compared to manual and platform harvesting systems. The decision is examined taking into consideration key factors such as orchard type (single-, bi-, and multi-varietal), size, tree structure, and apple variety.

5.1. Varietal data

This section explains the varietal data, which have been used in the model. Varieties used are Envy, Jazz, and Royal Gala. The data includes price, packout rate, and yield. Three apple varieties were the minimum to justify the model and show that the concept is generalisable to orchards with more than three varieties. Two premium apple varieties (i.e. Envy and Jazz) (usapple, 2018; Jazzapple, 2018; T&G, 2020) and one that accounts for 26% of total national planted area (i.e. Royal Gala) (NZAPI, 2018 & 2019) were selected to represent the apples grown in New Zealand and cover the harvesting window, which makes the model generalisable and the concept testable, but any number of apples could be considered in the model with different values and yields. It is also assumed that the orchard is constructed with a 2-dimensional tree structure suitable for harvesting either manually, robotically, or by platform (Chumko, 2019; Wiltshire, 2019a).

5.1.1. Price, packout rate, and yield per variety

As shown in Eq. (4.4), P_i ($/kg) or price of variety *i* where *i* = 1, 2, 3 (1 = Envy, 2 = Jazz, 3 = Royal Gala) ($/kg) is measured as the weighted sum price of apples in the export, Pe_i ($/kg) and domestic markets, Pd_i ($/kg) and the packout or recovery rates, $\bar{e}_i$ (%) of apples going into each of the two markets. Data on Pe_i, Pd_i, and $\bar{e}_i$ were derived from the Orchard Monitoring Report for Hawke's Bay (2011-2018) (MPI, 2012 and 2018). The weighted sum of P_i and $\bar{e}_i$ was calculated from the historical price and packout rate data in that report. Prices are adjusted for inflation using the Reserve Bank of New Zealand Consumer Price Index (RBNZ, 2019). Summary data for P_i and $\bar{e}_i$ for the apple varieties included in the model that are grown in the Hawke's Bay region are listed in Table 5.1.

Table 5.1. Estimated export and domestic real prices, export packout rates, and average weight for three apple varieties included in the model

Variety	Pe_i, Export price ($/kg)	Pd_i, Domestic price ($/kg)	$\bar{e}_i$, Export packout rate (%)	Weight (grams)
Envy	$2.35	$0.04	75	260
Jazz	$1.56	$0.08	80	226
Royal Gala	$1.53	$0.21	80	181

Sources: Orchard Monitoring Report for Hawke's Bay (2011-2018) (MPI, 2012 and 2018); Fern Ridge Fresh NZ Packing guide (2016)

As was shown in Eq. (4.1), biological yield, $BY_{z,i,t}$ (kg/ha), is the product of NT_i, number of trees per hectare, $NA_{i,t}$, number of apples per tree, and ga_i, average fruit weight per apple (grams). As shown in Table 5.2, $NA_{i,t}$ varies per variety and production year depending on the variety. It is assumed that trees start bearing fruit from year three after orchard establishment and will reach full production in year six. Note that $NA_{i,t}$ from year three to six is an estimate based on the full production levels from the apple orchards of T&G Global Ltd. in Hawke's Bay (McKay. L., personal communication, 2018) and do not represent the actual figures across orchards in Hawke's Bay. In terms of NT_i, it is assumed that newly established orchards are structured in 2D with 2,400 trees per hectare (Table 5.2) (Harding, 2018; McKay and Rogers, 2018). Average fruit weight per apple, ga_i for the apple varieties included in the model are shown in Table 5.2 (Fern Ridge Fresh, 2016).

Table 5.2. Number of trees per ha and fruit per tree for three apple varieties included in the model in 2D tree structure

Variety	Trees per ha	Fruit per tree			
		Year 3	Year 4	Year 5	Year 6 (full production)
Envy	2400	45	80	120	170
Jazz	2400	60	120	180	245
Royal Gala	2400	70	135	205	280

Source: Apple orchard of T&G Global Ltd. in Hawke's Bay (McKay. L., personal communication, 2018).

5.1.2. Harvesting period, harvesting window, and daylight hours

As each variety is harvested in different months of the year, daylight hours from dawn until dark vary for each month accordingly. This can affect the harvesting operation hours for robot harvesting given the assumption that the robot at the current stage of development can only operate in daylight. Table 5.3 shows the information for the varieties included in the model.

Table 5.3. Harvesting period, harvesting window, and average daylight hours during harvesting period for three apple varieties included in the model

Variety	Harvesting period	Harvesting window (days)	Assumed harvesting window (days)	Average daylight hours (hr/day)
Royal Gala	20 February - 30 March	16 - 18	18	13.00
Jazz	10 March - 10 April	18 - 21	18	11.40
Envy	1 April - May 1	18 - 21	18	10.30

Source: McKay. L (2019, personal communication) and calculated data from timeanddate.com.

Note that these dates do not represent the exact dates across orchards in Hawke's Bay or even New Zealand. For the simplicity of calculations, it is assumed that all varieties have a harvesting window of 18 days. Average daylight hours for the Hawke's Bay region from February to May were derived from the Hawke's Bay daylight database (Time and Date, 2019) and are shown in Table 5.3.

Harvesting period refers to an extended period throughout the growing season that a crop becomes available for harvest (Alder, 2019). Harvesting window per variety, HW_i (days) is the period in which apples are considered ready to be harvested based on the maturity parameters such as size, colour, and brix that varies across varieties (Blanpied and Silsby, 1992). Harvesting window, HW_i and harvesting period for the varieties included in the model are shown in Table 5.3. From the table, it is possible to see that harvesting period and harvesting window vary for each variety. Planting these varieties together in an orchard can extend the harvesting period from February for Royal Gala to May for Envy. Therefore, there could be overlapping harvesting periods and harvesting windows across these varieties (Table 5.3).

5.2. Harvesting system data

5.2.1. Harvesting performance per harvesting window

As was shown in Eq. (4.11), harvesting performance consists of harvesting efficiency, HF_z and operation efficiency, OF_z rates (%) for each system. Harvesting performance can affect harvested yield, $Y_{z,i,t}$, the number of pickers required for mechanical harvesting systems, $NM_{z,i,t}$, and consequently the revenue of the orchard, $TR_{z,i,t}$ ($/ha).

Manual harvesting

As shown in Eq. (4.12), manual yield, $Y_{1,i,t}$ (kg/ha) is dependent on HF_1 or the percentage of apples that can be harvested by each picker. The data for HF_1 was unavailable, thus an estimated harvesting efficiency for a robotic harvester was used as a reference, i.e. 80% (Zhang, 2018) and adjusted by 10% given the assumption that manual labour harvests more efficiently than a robot at its current stage of development. Therefore, a manual picker can harvest with an efficiency of 90%, which also takes into consideration the operational factors in the orchard such as moving, or climbing up or descending ladders (Zhang et al., 2019) that can reduce the harvesting efficiency of manual labour. In addition, this rate accounts for the second pick given that not all fruit may be ready to be picked in the first pick.

Robot harvesting

Following Eq. (4.13), it is assumed that a robot harvests with an efficiency, HF_2, of 80%. This is derived from the harvesting technology embedded in the robot such as imaging and Artificial Intelligence systems (Zhang, 2018). Due to the novelty of robot, data for its operation efficiency, OF_2 was unavailable, thus that of a similar harvesting technology i.e. platform, 12%, was instead used (Gallardo and Zilberman, 2016). It includes factors that decrease the harvesting efficiency of a robot in orchard such as turning, refuelling, technical failure, or shape, length, and slope of the orchard.

Platform harvesting

The assumed platform utilised in the model is a self-propelled single-level model that allows four people to work on it. As was shown in Eq. (4.13), harvesting efficiency for a platform, HF_3, is determined by the skill level of each picker on platform i.e. beginner or experienced, which can affect the overall harvesting efficiency of the picking team. It is assumed that utilising platforms increases the manual harvesting efficiency (Zhang and Heinemann, 2017). Thus, the harvesting efficiency of a manual picker was used as a reference and adjusted up by 5% to reflect the improvement attained in harvesting efficiency from utilising a platform. Therefore, a platform picker can harvest with an efficiency of 95%. In addition, it is assumed that operating a platform presents a similar set of operational limitations to those of robot harvesting. Thus, an operational efficiency (OF_3) of 12% is used for a platform (Gallardo and Zilberman, 2016).

Pickers complementing robots and platforms

When platform or robot harvesting system is utilised, there are two types of unharvested fruit: one from the remaining area due to purchasing machines in integer values and the other being remaining fruit due to harvesting inefficiency of machines. It is assumed that the pickers used to pick unharvested fruit left over by robots from remaining area picks with the efficiency of 90% compared with the lower efficiency of 85% for pickers to pick unharvested fruit left over by robots. Pickers pick unharvested area faster because trees are full with fruit thus, pickers can more easily find and pick them, whereas in the case of unharvested fruit, there are fewer fruit on tree comparatively and fruits are not spread consistently in all trees, thus it requires pickers to search all over tree and climb and descend the ladders more often to pick more fruit, which can make the picking process take longer and reducing their efficiency.

5.2.2. Harvesting speed

Another component in the harvesting operation is captured by the harvesting speed, $HS_{z,i}$ (kg/days), which varies across harvesting systems.

Manual harvesting

Following Eq. (4.14), manual harvesting speed, $HS_{1,i}$ (kg/days) is a function of the number of bins harvested per day (MHN_b, bins/hour), weight of each bin (g_b, kg), and the harvesting window (HW_i, days). It is assumed that an average picker, can harvest five bins per eight hours of daily work (McKay, 2019; personal communication) and each bin weights 400 kg (Palmer, 2008). As explained in section 5.1.2, for the simplicity of calculations, HW_i is assumed to be a constant 18 days across varieties. The hours of work are based on the availability of harvesting work, up to 40 hours per week and between eight to ten hours per day, with work over no more than six days per week, Monday to Sunday inclusive. The spread of hours can be changed by agreement between an employer and labourers (HortNZ, 2019; GA, n.d.). In the model, labour is considered as FTE, which is working up to 40 hours per week but in theory one labour unit can work more than 40 hours as long as are agreed with employers and paid with the right wage. Therefore, the number of workers maybe different to the number of FTEs.

Robot harvesting

As was shown in Eq. (4.15), harvesting speed of a robot per variety, $HS_{2,i}$ (kg/days) is measured in terms of the number of apples harvested per hour (RHN_a, fruit/hour), taking into consideration the weight of each apple, ga_i (grams), robot working hours per day, RD_i (hours/day), and HW_i. It is assumed that a robot can harvest one apple per second or 3,600 apples per hour (Zhang, 2018), and GA_i is shown in Table 5.3. Robot working hours, RD_i is shown as the average daylight hours in Table 5.3 for each variety, which is the maximum daily working hours for a robot, given the assumption that robot can only operate in daylight.

Platform harvesting

Following Eq. (4.16), platform harvesting speed per variety, $HS_{3,i}$ (kg/days) is measured based on how fast the platform (harvesting team) picks in terms of the number of bins filled within the designated picking window. As noted in section 5.2.1, platforms are assumed to increase the overall harvesting efficiency of pickers and number of bins harvested per day compared to manual harvesting (Zhang et. al., 2019). It is assumed that each platform can accommodate four workers (Sinnett et al., 2018) and a manual picker on a platform on average can fill six bins per day and work an average of eight hours per day (Sinnett et al., 2018), which equates to 24 bins per day or 9,600 kg/day per platform. Similar to manual harvesting, operation hours required to finish harvesting by platform could follow the agreed working hours of workers and the employers to finish the work. It is assumed that harvesting team on the platform work on average up to 40 hours per week (HortNZ, 2019; GA, n.d.).

Furthermore, following the assumption of utilising platforms to perform selected pre-harvest tasks, limited information is reported on the pre-harvest performance of a platform. In terms of the orchard area coverage, based on the reported data by Sinnett et al., 2018, it is assumed that one platform with four workers working can cover up to 24 ha of orchard to perform selected pre-harvest tasks (training, thinning, and pruning). In terms of the operation hours required to perform each of the selected pre-harvest tasks, the data reported in the work of Robinson et al. (2013) were derived and adjusted for the context of the current research. Table 5.4 summarises this information. Note that these operation hours do not represent the exact number of operation hours required and may vary based on working team and orchard as it could also follow the agreed working hours of workers and the employers to finish the work. It is assumed that pre-harvest and harvest activities are performed in different months of the year, platforms are utilised during the non-harvest months to maintain trees for the next production season.

Table 5.4. Platform operation hours per ha required for pre-harvest tasks per year

Production year	Pruning and tree training	Thinning
1-2	90	0
3-5	90	64
6-25	100	72

Source: Adapted from Robinson et al. (2013).

5.2.3. Number of harvesting units

Following the discussions in sections 4.5.2. and 4.5.4, and as shown in Table 5.3, it is assumed that the harvesting period and harvesting windows of the studied varieties in the current research overlap, i = 1,2,3 ($HW_1 \cap HW_2 \cap HW_3$), meaning that if the orchard is planted with only one of these varieties (single-varietal orchard), the number of harvesting units required, $N_{z,i,t}$, is calculated using Eq. (4.17) and will not be purchased in excess capacity. However, when these varieties are planted together as a bi-varietal orchard and multi-varietal orchard, given the overlapping harvesting windows, the total number of harvesting units, $TN_{z,t}$, is calculated using Eqs. (4.18) and (4.19), respectively, where $TN_{z,t}$ are purchased to ensure all fruit of all varieties will be harvested within their specific harvesting window.

5.2.4. Useful life of harvesting machines

Platforms are assumed to have a useful life of ten years (Sinnett et al., 2018). As robots are still in commercial trial phase, there is no information available on their useful life. Therefore, the useful life of an Automatic Milking System (AMS) (Hyde et al., 2003), a precision agriculture system (Tozer, 2009), and a platform (Sinnett et al., 2018) were used and adjusted for robots accordingly. It was therefore assumed robots have a useful life of six years.

5.3. Discount rate, investment period, and salvage value

Discount or interest rate is used to take into consideration the opportunity cost of capital or the time value of money. It represents the cost of capital used to finance the investment and accounts for the risk of the investment to determine whether an investment is financially feasible (Feuz and Larsen, 2020; German, 2015; Kay et al., 2016). In the context of the current research, only one discount rate is considered to mainly evaluate the costs of capital used for the investment in robots or platform harvesting system, as the single capital investment, but if growers would consider investing in something entirely different in addition to robots or platforms in their orchards, then a second discount rate could be considered. It would help to better realise the time value of capital investment in a mechanical harvester by being able to benchmark it against other prospective investment options outside of the orchard.

Depending on how orchardists source the capital to finance the investment, discount rate is determined accordingly. This could be from debt, equity, or both (Kay et al., 2016; Moss, 2013). If growers borrowed the capital from a bank i.e. debt, to purchase the robot or platform, the borrowing rate (interest rate) will determine the discount rate. However, if apple orchardists used their own capital i.e. equity, the discount rate would be determined by the opportunity cost of the capital that could be invested elsewhere in the orchard business. If it is from a combination of equity and debt, then the weighted average cost of capital (WACC) is used to determine the discount rate (Feuz and Larsen, 2020; Kay et al., 2016; Moss, 2013; Zhang and Heinemann, 2017).

A fixed real interest rate of 5% was considered for all analyses that is assumed to remain the same for the entire length of the investment and at the time of conducting this study was consistent with the real pre-tax discount rate from New Zealand Treasury (NZ Treasury, 2020). The real interest rate is adjusted by subtracting the expected inflation rate to reflect the real cost of investing capital in farm machinery, whereas nominal interest rate refers to the rate before taking into account inflation rate (Edwards, 2015).

The orchard investment period was assumed to be 25 years, as the expected age of an orchard planted with dwarf or semi-dwarf trees, before being removed (Barden and Neilsen, 2003; Tustin, 1998; Webster and Wertheim, 2003). Harvesting robot, platform, and equipment and building infrastructure were depreciated over 6, 10, and 25 year, respectively.

As mentioned in Eq. (4.5), $\Phi_{z,i,t}(\$/\text{machine})$, accounts for the salvage value or the expected sales value of machines to be received at the end of useful life. Salvage rate (ϕ) is used to calculate $\Phi_{z,i,t}$; ϕ for AMS (Hyde et al., 2003) and platforms (Zhang et. al., 2019) were used as reference and adjusted for robot and platform in the context of the current research, ϕ = 5%.

5.4. Cost data

5.4.1. Pre-harvest cost

In the current research, it is assumed that pre-harvest tasks are completely performed manually when manual and robot harvesting systems are utilised. When platform harvesting system is utilised, it is assumed that selected pre-harvest tasks (tree training, pruning, and thinning) are performed by platform, and the remaining tasks are performed manually, and related costs are calculated separately for each.

Manual and robot

The estimated data for pre-harvest costs ($/ha) performed manually are derived from the Orchard Block Information in Hawke's Bay of T&G Global Ltd. (McKay. L., personal communication, 2018) and the Orchard Monitoring Report of the New Zealand Ministry for Primary Industries (MPI, 2018). The data are adjusted for inflation as for apple prices. This data is used to calculate the pre-harvest costs for manual and robot harvestings, which include ground preparation, trees purchasing and planting, training, pruning, thinning, pollination, canopy structures (trellis), irrigation system, wind machines, fertiliser, weed and pest control, and machinery repair and maintenance.

Platform

When platform harvesting is utilised, pre-harvest costs consist of costs related to the manually performed tasks based on the data from the Orchard Block Information in Hawke's Bay of T&G Global Ltd. (McKay. L., personal communication, 2018) and the Orchard Monitoring Report of the New Zealand Ministry for Primary Industries (MPI, 2018); and costs incurred from utilising platform for selected pre-harvest tasks (tree training, pruning, and thinning) calculated using Eq. (4.31) and the data in Table 5.4. It is assumed that labourers in Hawke's Bay are paid an hourly wage (h_w) of $27.60 per person to perform these pre-harvesting tasks (Wiltshire, 2019b). Note that these wage rates account for the actual hours of labour that exceed field machine time by 10 to 20%, due to turning blocks, technical failure, lubrication, or refuelling. This is taken into consideration by multiplying the default hourly wage rate by $\Psi = 1.2$ (Edwards, 2015).

5.4.2. Harvest costs

With manual harvesting system, it is assumed that the harvest operation is performed manually using ladders with no mechanical harvesters involved. Therefore, related harvest costs are calculated differently compared to those of mechanical harvesting including costs incurred from purchasing and operating machines.

Manual harvesting

When fruit are harvested manually, harvest costs are calculated using Eq. (4.34), where the manual labour wage (MH_w, $/kg) is $0.12 per kilogram, derived from the Orchard Monitoring Report of the New Zealand Ministry for Primary Industries (MPI, 2018) and adjusted for inflation. It is assumed the wage rate includes penalty rates.

Mechanical harvesting

As shown in Eq. (4.35), mechanical harvesting costs include the costs associated with harvesting fruit with machines and pickers. Costs associated with mechanical harvesting include the ownership and operating costs of machines. Pickers costs is calculated using Eq. (4.36).

5.4.3. Purchase cost of machine

Purchase or ownership cost of machines is a fixed cost and calculated using Eq. (4.28). When fruit are harvested manually no costs will be incurred for machines. Hence, the ownership costs of robot and platform harvesting are only discussed when fruit are harvested mechanically.

Robot

Given that apple-harvesting robots are still in commercial trial stage, data on their purchase costs are unavailable. To address the lack of this data, price of an AMS, $150,000 (Hyde et al., 2003) and different types of platform harvesting systems, $70,000 to $180,000 (Sinnett et al., 2018; Zhang et al., 2019; Zhang and Heinemann, 2017) were used as reference and adjusted to calculate the base price for a robotic harvester, $500,000. In the absence of real data this may be considered a conservative high value for robot. This value accounts for more hydraulic and mechanical components there are built into the robot compared to AMS and platforms, cost of shedding space, and unforeseen maintenance costs. However breakeven prices for robots for three varieties across orchard sizes are calculated to test the feasible range of prices.

Platform

A range of purchase prices (i.e. $70,000 to $180,000) are reported in the works of Sinnett et al (2018), Zhang et al. (2019), and Zhang and Heinemann (2017). These prices were used as reference and adjusted accordingly. Therefore, the price of a platform was assumed to be $120,000. In addition, it was further assumed this cost will not increase if platform is used for pre-harvest tasks because it will not require any extra components to perform these tasks (Zhang et al., 2019).

5.4.4. Other machine-related fixed costs

Other machine-related fixed costs are interest ($\beta C_{z,i,t}$), and insurance and housing ($\tau C_{z,i,t}$), which are incurred whether machines operate or not. Note that in the current research it is assumed that $\alpha C_{z,i,t}$, $\beta C_{z,i,t}$, and $\tau C_{z,i,t}$ are tax deductible.

Interest cost

Interest ($\beta C_{z,i,t}$, \$/machines) is calculated following Eq. (4.29) using a real interest rate (r) of 5%, as noted in section 5.3.

Insurance and housing cost

Insurance ($\tau C_{z,i,t}$, \$/machines) is calculated as shown in Eq. (4.30), the insurance rates (ω) for a platform and a robot were assumed to be 1% (Sinnett et al., 2018) of the depreciated value of each machine over its ownership period.

5.4.5. Operating costs of machines

Following Eq. (4.38), machine-related variable or operating cost, $MVC_{z,i,t}$ (\$/ha) includes repair ($\gamma C_{z,i,t}$), fuel ($\varphi C_{z,i,t}$), oil and lubrication ($\delta C_{z,i,t}$), and robot operator or platform labour ($\varrho C_{z,i,t}$) costs for variety i in t.

Repair cost

Repair cost ($\gamma C_{z,i,t}$, \$/machine) is calculated following Eq. (4.39), which is predicated on the repair rate, κ, and machine costs. It is assumed that platforms have κ = 1% (Sinnett et al., 2018; Gallardo and Brady, 2015; Zhang et al., 2019). However, the data for κ was unavailable for robots, thus, the data for a platform was instead used and adjusted for a robot such that κ = 3%. The increase is due to the robot having more mechanical and hydraulic components built in, which may require repair and maintenance at a higher rate compared to a platform.

Fuel and Oil and lubrication costs

As shown in Eq. (4.40), fuel costs ($\varphi C_{z,i,t}$, \$/machine) is the product of the fuel price of diesel (fp, \$/litre), the average fuel consumption of diesel (fc_z, litres/hr), and total operation hours of the machine per variety in t ($h_{z,i,t}$, hr). In the model, fp of \$1.30/litre for robot and platform is assumed (Globalpetrolprice, 2020) and fc_3 for platform is assumed to be one litre per hour (Sinnett et al., 2018; Gallardo and Brady, 2015). Data for fc_2 of robot was unavailable, thus information for a platform (Sinnett et al., 2018) was used as reference and adjusted for robot such that fc_2 = 4 litres per hour. This is considered based on the assumption that robot could weigh more with more mechanical and moving components built into it, thus consumes more fuel to move and operate compared to a platform.

The operation hours are calculated differently for robots and platforms. Given a robot is only utilised for harvest, and a platform is used for harvest as well as the selected pre-harvest tasks, thus total operation hours for each system will vary accordingly. For a robot, $h_{2,i,t}$ is calculated using Eq. (4.41), where operation hours is changed according to the daylight hours for each variety given each variety is harvested in different months of the year specified by different daylight hours, as presented in Table 5.3. For platforms, $h_{3,i,t}$ is calculated using Eq. (4.42), as the platform is used to perform harvest and selected pre-harvest tasks. Following Eq. (4.43), oil and lubrication costs for robot or platform, $\delta C_{z,i,t}$ ($/machine) is calculated as 15% of $\varphi C_{z,i,t}$ (Edwards, 2015).

Robot operator and platform labour cost

Labour costs associated with utilising each machine varies between robots and platforms. Robot operator cost ($\varrho C_{2,i,t}$, $/machine) is the product of the robot's operator wage (R_w, $/hour) and $h_{2,i,t}$ (hr/machine) following Eq. (4.44). Data for $R_w$was unavailable, thus the hourly wage for a skilled tractor operator of $36 per hour was used instead (PayScale, 2020). Platform labour cost ($\varrho C_{3,i,t}$, $/machine) is the cost for labour team (four workers, Sinnett et al., 2018) working on a platform to perform harvest operation with an hourly wage (h_w) of $27.60 per person (Wiltshire, 2019b) and calculated using Eq. (4.45). Note that R_w and h_w account for the actual hours of labour as explained in section 5.4.1, multiplying the default hourly wage rate by Ψ = 1.2 (Edwards, 2015).

5.4.6. Post-harvest cost

As shown in Eq. (4.33), post-harvest cost for each system is the product of yield (kg/ha) for each system and manual post-harvest costs ($/kg). It is assumed that the post-harvest operations are performed at a cost of $0.42 per kg, which includes packing, packaging, cool storage (incl. freight from cool store to port), freight (orchard to packhouse), and levies & compliance. The required data were derived from the Orchard Monitoring Report for Hawke's Bay (2011-2018) (MPI, 2012 and 2018) and adjusted for inflation.

5.5. Factors included in system scenarios

There are different factors that can affect the investment decision including the choice of harvesting system (manual, robot, or platform), orchard type and size (single-, bi-, and multi-varietal), canopy structure, and apple variety. These factors are examined under different system scenarios as summarised in Table 5.5. The first set of scenarios (i.e. single-, bi-, and multi-varietal orchard models) examine the profitability of newly established orchard with 2D tree structure in terms of the number of harvesting machines (robots or platforms) required with respect to the orchard type, orchard size, and apple variety. The second set of scenarios (i.e. orchard system transition model) considers replacing an orchard planted with an older variety structured in 3D canopy with a premium variety in a 2D canopy structure to make it possible to utilise platforms as an available alternative until robots become commercially available.

Table 5.5. Summary of factors used in the system scenarios

Scenarios	Details
Harvesting system	Manual, number of robots/platforms purchased in different production year
Orchard size	9,10, 15, 20, 30, 40, 50, 100, 200
Orchard type	Single-, bi-, and multi-varietal
Variety	Envy, Jazz, Royal Gala, Braeburn

5.5.1. Harvesting system scenarios for single-varietal orchard

For a single-varietal orchard (i.e. orchard planted with only one variety in 2D structure), the number of robots or platforms required is calculated using Eq. (4.17). It is assumed that machines are purchased in integer numbers with no excess capacity allowed. The base models for manual, robot, and platform harvesting systems are constructed for a single-varietal orchard. Seven orchard sizes were tested; 10, 20, 30, 40, 50, 100, and 200 ha for each of the three varieties (1 = Envy, 2 = Jazz, 3 = Royal Gala). These seven orchard sizes were selected to examine whether there is a scale effect as orchard size increases per variety for each harvesting system.

It is assumed that platforms are purchased from year one of the orchard establishment that platforms are utilised for selected pre-harvest tasks in additional to harvesting starting from year three of orchard establishment. In addition, machines are purchased in integer values.

5.5.2. Harvesting system scenarios for bi- and multi-varietal orchards

The bi- and multi-varietal orchards (i.e. orchards planted with more than one variety and structured in 2D), are designed to analyse how different varietal mixes could affect the investment decision utilising robot or platform harvesting. To simplify the analysis, orchards planted with two varieties i = 2,3 are grouped as bi-varietal orchard, and those planted with three varieties, i = 1,2,3 as multi-varietal. Each orchard type is allocated with equal sizes of 9 or 15 ha, which are the representative orchard sizes in the Hawke's Bay region of New Zealand (NZAPI, 2018).

Note that Jazz and Royal Gala are selected as the planted varieties in a bi-varietal orchard to test whether having these two varieties planted together in an orchard may be profitable for robot and platform harvesting. This is performed following the results from the preliminary analysis for these two varieties in single-varietal orchards, returning very little profit for robot harvesting and relatively lower profit compared to Envy when harvested with platform.

As shown in Table 5.6 and Table 5.7, the number of scenarios for two orchard sizes (9 and 15 ha) across bi- and multi-varietal orchards are defined based on the number of machines purchased at different intervals to harvest all fruit within the harvesting window and examine the impact on the profitability of orchard. The platform and robot harvesting models are constructed based on a similar framework. However, for platforms, $TN_{3,t}$ includes the number of platforms purchased in the first year to perform pre-harvest tasks to save labour compared to if these tasks were going to be performed conventionally using ladders.

Table 5.6. Scenarios to be simulated for robot harvesting bi- (RB) and multi- (RM) varietal orchards

Scenario	Harvesting system	Orchard type	Production year1 and purchased number of harvesting machines						Orchard size (ha)
			1	2	3	4	5	6	
RB000003	Robot	Bi-varietal						3	9
RB000012	Robot	Bi-varietal					1	2	9
RB000120	Robot	Bi-varietal				1	2		9
RB000111	Robot	Bi-varietal				1	1	1	9
RB000005	Robot	Bi-varietal						5	15
RB000014	Robot	Bi-varietal					1	4	15
RB000140	Robot	Bi-varietal				1	4		15
RB000113	Robot	Bi-varietal				1	1	3	15
RB001112	Robot	Bi-varietal			1	1	1	2	15
RM000002	Robot	Multi-varietal						2	9
RM000011	Robot	Multi-varietal					1	1	9
RM000110	Robot	Multi-varietal				1	1		9
RM000003	Robot	Multi-varietal						3	15
RM000012	Robot	Multi-varietal					1	2	15
RM000120	Robot	Multi-varietal				1	2		15
RM000111	Robot	Multi-varietal				1	1	1	15

Production begins from year three and full production is reached in year six. Platform purchases begin from year one.

Note that even though solving labour shortages is the premise of the current research, the focus is mainly on harvesting rather than pre-harvest operation. Using platforms for pre-harvest task can free up labour that could be used to perform other tasks on orchard or even in post-harvest operations. However, they cannot be immediately used for harvest given the time lapse exists between pre-harvest tasks to prepare and maintain trees for the next production season and harvesting fruit. Platforms purchased in the first year will also be utilised for harvesting along with any additional number of platforms purchased when fruit production begins in year three. In addition, the harvesting capacity of machines are better utilised when fruit bearing trees are near to or in full production. Therefore, it may be more economically feasible to purchase the maximum number of machines when trees are closer to or already in full production level in year six and beyond.

Robot harvesting bi- and multi-varietal orchards

As shown in Table 5.6, robot harvesting a bi-varietal orchard is abbreviated with ‘RB’ and for multi-varietal with ‘RM’. The abbreviations are followed by six digits, which denote the number of robots or platforms purchased in year one to six of orchard establishment. For example, RB001112 is read as bi-varietal robot harvesting system where one robot is purchased in years three, four, and five, and two robots are purchased in year six.

The nine scenarios utilising robots for bi-varietal orchard (RB000003-RB001112) assume a maximum number of three or five robots to harvest a 9 or 15 ha orchard, respectively. Similarly, the seven scenarios utilising robots in a multi-varietal orchard (RM000002- RM000111) assume a maximum number of two or three robots to harvest a 9 or 15 ha orchard, respectively. Scenarios RB000003, RB000005, RM000002, and RM000003 examine how the profitability of the orchard and harvest capacity of robots will be affected if robot purchases are delayed until year six, when robots can be used at their full harvesting capacity as trees are in full production. Scenarios RB000012-RB000111, RB000014-RB000113, RM000011-RM000110, and RM000012-RM000120 examine how the profitability of the orchard and harvest capacity of robots will be affected if robots are purchased in different intervals starting from year four and five where orchard has sufficient fruit on trees for the robot to operate at its full or near full harvesting capacity. Scenario RB001112 examines the possibility of purchasing robots starting from year three, when there may not be sufficient fruit on trees for the robot to be utilised at its full capacity and how the profitability of orchard could be affected.

Platform harvesting – bi- and multi-varietal orchard

As shown in Table 5.7, platform harvesting bi-varietal orchard is abbreviated with ‘PB’ and multi-varietal with ‘PM’. As noted earlier, six digits after abbreviations denote the number of platforms purchased from year one to six of orchard establishment. For example, PB100002 is read as bi-varietal platform harvesting system where one platform is purchased in year one and two platforms are purchased in year six.

Table 5.7. Scenarios to be simulated for platform harvesting bi-(PB) and multi-(RM) varietal orchards

Scenario	Harvesting system	Orchard type	Production year[1] and purchased number of harvesting machines						Orchard size (ha)
			1	2	3	4	5	6	
PB100002	Platform	Bi-varietal	1					2	9
PB100020	Platform	Bi-varietal	1				2		9
PB100110	Platform	Bi-varietal	1			1	1		9
PB100011	Platform	Bi-varietal	1				1	1	9
PB100003	Platform	Bi-varietal	1					3	15
PB100030	Platform	Bi-varietal	1				3		15
PB100012	Platform	Bi-varietal	1				1	2	15
PB100021	Platform	Bi-varietal	1				2	1	15
PB100111	Platform	Bi-varietal	1			1	1	1	15
PM100001	Platform	Multi-varietal	1					1	9
PM100010	Platform	Multi-varietal	1				1		9
PM100002	Platform	Multi-varietal	1					2	15
PM100011	Platform	Multi-varietal	1				1	1	15
PM100101	Platform	Multi-varietal	1			1		1	15
PM100110	Platform	Multi-varietal	1			1	1		15
PM100020	Platform	Multi-varietal	1				2		15

Production begins from year three and full production is reached in year six. Platform purchases begin from year one.

For multi- and bi-varietal orchards, platform purchases start from year one (PB100002-PM100020), where platforms will be utilised to perform pre-harvest operation starting from year one and harvest from year three and beyond. No platform purchase is considered for year three for multi- and bi-varietal orchard, because it is assumed that platforms purchased in year one can be utilised in year three when trees start bearing fruit. Purchasing any additional number of platforms in year three is considered too early and not feasible economically, as there is insufficient production level to utilise platform harvesting up to its full capacity. Therefore, it is better to postpone purchases until year four, five, or preferably year six, as sufficient or full production level is reached.

The nine bi-varietal scenarios (PB100002-PB100111) assume a maximum number of three or five platforms in operations in a 9 or 15 ha bi-varietal orchard, respectively. In a multi-varietal orchard, the seven scenarios (PM100001-PM100020) assume a maximum number of two or three platforms to operate in a 9 or 15 ha orchard, respectively. These seven scenarios examine the profitability of the orchards and harvest capacity of platforms when additional numbers of platforms (in addition to the one purchased in year one) are purchased in different intervals in year four, five, and six.

Scenarios PB100002, PB100003, PM100001, and PM100002 examine how the profitability of the orchard will be affected if platforms purchased in year of production is utilised until reaching full production (year six) before any additional platforms are purchased. This also examines how the harvesting capacity of additional purchased machines in year six will be utilised given trees are in full production level, and whether this would generate more profit. Scenarios PB100020-PB100011, PB100030-PB100021, and PM100010, PM100011-PM100020 examine how the profitability of orchard and harvest capacity of platforms will be affected if machines are purchased at different intervals starting from year four and five, where trees have sufficient fruit for platforms to operate at their full or near full harvesting capacity.

5.6. Break-even analysis of robot price

The purchase cost of robot is considered as the most expensive element in the investment decision that could affect the profitability of robot harvesting in particular harvesting lower value or lower yield variety. For researchers and engineers developing robotic technologies, it is important to know how much they need to invest in the development of different components necessary for the implementation of the robotic harvesting technology (Shockley et al., 2019) without having a significant impact on the NPV of the investment. However, robot is not commercially available and no data is available for the price of the robot. Therefore, the break-even prices, or the price at which the NPV is zero, are identified for a robotic harvester in a single-varietal orchard for the studied apple varieties across orchard areas. The break-even price will be an important indicator to identify the minimum price for the robotic harvester that will prevent losses (Kay et al., 2016; Berry, 1972; Gutierrez and Dalsted, 2012), which will be an important piece of information for developers and investors of the technology.

5.7. Sensitivity analysis

The aim of the current research is to show the comparison between investing in robot harvesting systems with platform or manual, and why it would be better to invest in robots. However, given that the robot is in commercial trial phase, there are uncertainties in terms of its operation compared to available alternatives, i.e. manual picker or platform. Therefore, operators of the robot may not know yet what would be the ideal performance for a robot in relation to NPV and labour. As such, a series of sensitivity analyses were constructed based on a 10 ha of Envy orchard in year six of production, to test how outcomes of the robot harvesting are affected according to the changes made on the inputs of the model.

Envy is selected as the only variety for the sensitivity analyses following the outcomes of the preliminary analyses for the single-varietal orchard, where relatively higher returns are generated for Envy across orchard sizes compared to Jazz or Royal Gala. This could make it more appealing for growers to consider utilising robotic harvesters for Envy compared to other two varieties. Therefore, it is assumed that the sensitivity analyses for Jazz and Royal Gala will not make a practical sense as lower returns are generated compared to Envy regardless of the changes made to the inputs of the model. Envy orchard was analysed in year six to account for the full production level and replicate the long-term sensitivity analysis for the orchard establishment period.

Considering the interdependency among the inputs in the model, two main components of the robot harvesting operation, the harvesting speed (HS_2) and harvesting efficiency (HF_2) of a robot are tested in the analysis. Other inputs important in determining the profitability of the investment decision were also tested in the model including the purchase price of a robot, labour availability, labour efficiency, and labour wages.

5.7.1. Decreasing the purchase price of robot

Growers will only invest in robots when they can generate an income equivalent or close to those for manual or platform harvesting. In addition, apple producers may want to know how flexible their budgets have to be when purchasing a robotic harvester to justify their investment for harvesting their orchards by the robot with respect to other alternatives, i.e. manual or platform harvesting system. Given the overall technology trend, it is assumed that the robotic harvester becomes more affordable as the technology advances. This has been evident with the development of AMS, where the technology has improved and become more affordable over the years, thus leading to widespread adoption (Woodford et al., 2015).

Sensitivity analyses for the purchase cost of the robot were conducted based on 10 ha of Envy orchard to examine the price thresholds, at which the investment in the technology will generate profit equivalent or close to that of manual or platform harvesting. To put the analysis in perspective, the break-even purchase price of robot for 10 ha of Envy was used as the gauge for the maximum price at which a grower may become indifferent between operating with the robotic harvester versus alternatives such as manual or platform harvesting system (Shockley et al., 2019).

5.7.2. Harvesting speed and efficiency

Harvesting speed of robot, HS_2 – how fast the robot harvests each apple per unit of time (seconds); and harvesting efficiency of robot, HF_2 – the percentage of apples identified and harvested by the robot per tree, are two key components of the robot's harvesting performance in the model. Therefore, three sensitivity analyses were conducted to test how increases in HS_2 and HF_2 could affect the outputs of the model such as the number of pickers and robots required, and the NPV.

Increasing harvesting speed

The harvesting speed of robot, HS_2 was increased by 0.5 seconds per apple from the default value of one second per apple, while HF_2 was kept constant at its default value, 80%. Note that the outcomes of the model did not show significant changes to values below 0.5 seconds per apple.

Increasing harvesting efficiency

The harvesting efficiency of robot or the percentage of fruit per tree picked by robot, HF_2 was increased by 5% from its default efficiency rate of 80%, while HS_2 was kept constant at its default value of one second per apple. Note that the outcomes of the model did not show significant changes to values below 5%.

Increasing harvesting speed and efficiency simultaneously

The ultimate goal in harvesting apples by robot is to ensure that the robot performs to its optimal capacity. However, this may not mean that a robot should operate with the highest HS_2 and HF_2. In the current model, the optimal operation of the robot is defined with respect to the labour substitution and capital requirement that could determine the profitability of the orchard. For example, operating the robot more efficiently will make it slower as it will spend more time scanning and harvesting apples per tree. As a result, it will leave more area unharvested, which may require using more pickers or more robots to be harvested, which in turn could affect the NPV. Thus, it may not be practical to derive the operation of robot solely on HF_2. Therefore, a series of sensitivity analyses were performed based on increasing both the HS_2 and HF_2 by a mix of increments to identify the best combination of HS_2 and HF_2 that will provide the balance of labour to capital ratio and generate profit.

5.7.3. Labour uncertainty

Skilled labour required to operate the robot and complementing labour to pick unharvested fruit by robot, is essential when investing in the robotic harvester. To determine the impact of labour in the analysis, three sensitivity analyses were conducted for 10 ha of Envy to study how sensitive the NPV of the investment in a robotic harvester is to the changes associated with the labour uncertainties including labour wages, labour availability, and labour efficiency.

Increasing labour wages

In the current research wage rates are assumed constant over the period of orchard establishment, whereas in reality, rates could change annually due to various factors such as changes in the contracts, inflation rates, minimum wage policy, and standard of fairness (Dickens et al., 2007). In addition to annual inflation, a future potential scarcity of on-orchard labour may result in increased labour costs. From a grower's perspective, when the pool of labour becomes limited, they may decide to increase wage rates to attract locals interested in working in orchards, but this may not happen in normal circumstances.

To account for this, the historical data for annual changes in harvesting labour wages were derived from the Orchard Monitoring Report of the New Zealand Ministry for Primary Industries (MPI, 2018), which reflected an annual wage increase of 1% in average from 2011-2018. However, the NPV of the model did not show a considerable sensitivity to this increase of wages. To examine the impacts of changes in the labour wages from the labour availability perspective, the work of Cassey et al. (2016) was also considered, which reported that a 7% reduction in labour availability can increase the wages for pre-harvest labour and post-harvest labour operations by 6.7% and 3.5%, respectively. Therefore, to simulate the impact of changes in labour wages on the NPV of the orchard, the wages for all labour-related operations including robot operator, picker, and post-harvest labour were increased by 5% per year and their impacts on the profitability of a 10 ha Envy orchard were analysed.

Even though labour wages are one of the major expenditures in apple production, in reality they do not change at a relatively fast rate, however, the unskilled labour rate may not increase at the same rate as the skilled labour rate. Increases in wages for robot operators may be higher as it requires skilled workers to operate the robot compared to manual harvest and post-harvest operations and if the wage rates are not high enough, producers might not be able to source labour to operate the robot when these workers can earn a similar rate in other roles. In addition, as robot technology advances it may become more complex to operate, thus skilled operators may require higher wage rates. Therefore, an increase of 50% in wages for robot operators and 5% for manual pickers and post-harvest were considered in the model. Note that in the current analysis, the wages are increased while labour availability and efficiency were kept constant in their default values in the model.

Reduction in labour availability

It is assumed that any changes in the availability of labour to complement robot harvesting is reflected in the manually harvested yield. To reflect this, harvested yield by pickers is reduced in the model to simulate labour shortages for growers in the industry. In this analysis, it is assumed that reductions in the availability of labour will not have any impact on the efficiency of the available pickers. This is because growers are assumed to still have access to a pool of experienced pickers or will be able to train new pickers with no picking experience.

Given the focus of the current research is on the harvesting operation, changes in the labour shortages for harvest and expected impacts on the NPV are unknown. Cassey et al. (2016) found that the labour shortages impact pre-harvest operations more than post-harvest operations, reducing labour availability for pre-harvest by 30% and post-harvest by 4.4%. With this information in mind, it is assumed that labour availability for harvest also decreases by 30 and 50% to simulate labour shortages in the industry in the most optimistic and pessimistic way, respectively. Under the base scenario, labour availability is assumed to be at 100%. Note that any unharvested fruit due to reduction in labour availability are considered wasted and an income loss for growers.

Reduction in labour availability and efficiency

When labour availability is limited, the efficiency of labour decreases (Cassey et al., 2016) and this is no different for pickers. When labour is available, access to a pool of experienced pickers is higher, however when a labour shortage becomes an issue then growers have no choice but to have anyone pick apples with no prior experience or training, which means that they harvest fruit with a lower efficiency compared to experienced pickers. This may affect the yield and quality of harvested apples. However, it is assumed that growers can train manual labour and slightly improve their picking efficiency in the limited time available to pick fruit. As a result, growers may be able to reduce the impacts of labour shortages on the efficiency despite the training cost and time required. To reflect this, it is assumed that growers will experience slight reductions of 5% in the harvesting efficiency of labour when only 30 and 50% of labour are available – taking into account the training of pickers before starting the harvest. For the default case, it is assumed that with 100% labour availability, pickers pick unharvested fruit left over by robots from remaining area with the efficiency of 90% compared with the lower efficiency of 85% for picking unharvested fruit left over by robots.

5.8. Orchard system transition

The orchard system transition model combines some of the concepts discussed earlier such as orchard type, apple varieties, canopy structure, and harvesting system into one model to examine the economic feasibility of converting a section of an established orchard from 3D to 2D in preparation for platform or ultimately robot harvesting (Table 5.8). The model could provide a more realistic approach toward the investment decision in a robotic harvester given that the technology is still in commercial trial stage. It is assumed that the new orchard will be harvested by platform, even though it is designed to be harvested but not necessarily will be harvested by robot as the technology is not presently commercially available.

Table 5.8. Factors considered in the orchard system transition

Factors	Details
Tree canopy structure	3D → 2D
Transition speed	5 ha in year one or 1 ha per year over five years.
Apple variety	Braeburn → Envy
Harvesting system	Manual → Platform

There are many apple growers operating an established orchard planted with trees in a 3D structure and want to adopt robot harvesting. However, a robot is designed to work in an orchard with a suitable tree structure, i.e. 2D. The 2D canopy structure allows growers to utilise available harvesting system, i.e. platform and alternatively robot in future. This will also allow them to gradually adapt with the new production strategies suitable for platform and robot harvesting such as tree maintenance practices (e.g. pruning). Therefore, when robotic harvest technology becomes commercially available, growers can have an easier and smoother transition to complete automation.

The orchard to be converted is a 5 ha section of a 20 ha orchard (i.e. Baseline orchard model) structured in 3D and planted with three varieties (2 = Jazz, 3 = Royal Gala, 4 = Braeburn), and each variety is allocated with 5, 10, and 5 ha sizes, respectively. The allocation of these orchard sizes to each variety is representative of the orchard size of each variety in the Hawke's Bay region (NZAPI, 2018). The 3D area of Braeburn is replaced with a 2D canopy structure orchard of Envy, which is harvested by platform. The reason Braeburn is replaced with Envy is derived from the annual changes in the planted area allocated for each variety in Hawke's Bay region. According to the area distribution of varieties grown in Hawke's Bay for a 40 ha orchard between 2013-2018 (MPI, 2018), the area planted to Braeburn has reduced by around 10% annually, whereas Envy-planted area has increased by around 10% annually, and Jazz and Royal Gala have relatively remained stable. In addition, Envy is a premium variety with higher export value ($2.35 per kg) than Braeburn ($1.31 per kg) (MPI, 2012 and 2018), thus has the potential to return higher profit for growers.

Given the multi-variate nature of the orchard system transition model, to examine the economic feasibility for variety replacement and canopy structure conversion, two system scenarios are simulated to assess the impact of the transition speed, i.e. replantation timeframe, on the net returns of the entire orchard, while taking into account the cash flow from the current orchard (Table 5.8). Scenario one considers replanting 5 ha of Braeburn with Envy in year one of orchard establishment; and scenario two considers replanting 5 ha of Braeburn with 1 ha of Envy per year over the period of five years. The outcomes of the analysis will help growers with their decision-making whether to implement scenario one or two, depending on the financial situation of the orchard. Implementing scenario one requires a large investment and it might be considered a financial burden for growers with financial debt as no income will be generated until trees begin bearing fruit from year three. The benefit of implementing scenario two is that it can provide an income stream for growers during the replantation period and provide them with a transition time to gradually level up their tree management practices to better manage and maintain the replanted tree with 2D canopy structures.

Three separate models are constructed to calculate the cash flow for the baseline orchard model, scenario one, and scenario two. The cash flow from the baseline orchard model is summed up with the cash flow for each of the scenarios one and two to calculate the profitability of the entire 20 ha orchard for each scenario. It is assumed that the baseline orchard model is already in full production and will produce fruit, while the 5 ha of Braeburn is being replanted with Envy. The orchard system transition model is basically a single-varietal orchard to be harvested by platform, where replantation begins with the orchard establishment, and production begins from year three. Given that not all fruit can be harvested mechanically, use of pickers are considered in both scenarios. The baseline orchard (i.e. 15 ha) is only harvested manually given it is structured in 3D, thus platforms cannot be used. Key financial measures for this orchard are estimated similar to the single-varietal orchard model. In addition, platforms are assumed will be utilised to perform harvest and selected pre-harvest tasks.

5.9. Twenty-four hours robot operation

At the time of conceptualising the model, the parameters and assumptions used in the model regarding the operation of the robot reflected the assumed information – robot operation in daylight. But the robot has advanced, and new information reveals that the robot may be capable of operating 24 hours a day (MIT, 2019). This has been incorporated into model to test how it will impact the performance and profitability of robot harvesting single-varietal orchard. This demonstrates the application and adaptability of the model to changing dynamics and incorporate new parameters and assumption based on changes and advancements of robot technology. It is assumed that the robot operates for 24 hours a day for six days a week. Operators are assumed paid per hour. It is assumed that robots are operated in excess capacity. Note that administrative implications such as varied payment rates for operators in day and night are not considered in the model. The analysis is performed based on a 10 ha of the single-varietal orchard for each of Envy, Jazz, and Royal Gala.

5.10. Conclusion

This chapter presented and discussed the empirical model with respect to the research design, data collection, and data analysis. The estimated data and assumptions for various elements in the model were described that are required to extend the conceptual framework into an empirical model to assess the investment decision in the robotic harvester technology. To put the analysis in perspective, utilisation of available harvesting systems such as manual and platform were considered in the analysis. The empirical model incorporated various factors essential in the investment decision, such as orchard size, orchard type, canopy structure, and apple variety with respect to utilising different harvesting system (manual, robot, or platform). The break-even price analysis for the robotic harvester provides the minimum price ranges across varieties and sizes that the investment in the technology will prevent losses. Sensitivity analyses will be conducted to take into account the uncertain decision factors including the purchase price of the robot, harvesting speed and harvesting efficiency, labour wages, labour availability, and labour efficiency. Under two scenarios, the orchard system transition model examines the economic feasibility for variety replacement and canopy structure conversion, and utilising platforms, which could provide a more realistic approach toward the investment decision in a robotic harvester given that the technology is still in commercial trial stage. The twenty-four hours robot operation model incorporates the latest development of the robot with regard to its operation hours, which could affect the profitability of the investment. The outcomes for the application of these data into the model are presented and discussed in the next chapter.

Chapter 6. Results and discussion

This chapter presents the results and subsequent discussion for the conceptualised model of Chapter 4 and the data and systems described in Chapter 5. The results and discussion are focused on analysing the investment decision of adopting a robotic harvester compared to platform or manual harvesting system for single-varietal, bi-varietal, and multi-varietal orchards of various orchard sizes – taking into account varietal characteristics such as yield, value, harvesting window, purchasing and operating costs for robots, and the cost of establishing an orchard with tree canopy structure suitable for robot harvesting.

As outlined in the empirical chapter the results of the analysis are presented and discussed in terms of various elements essential for the investment decisions including number of harvesting units required, number of full time equivalent (FTE) pickers required, and the net present values (NPV) and internal rate of return (IRR) of the investment. All NPVs are calculated over a 25-year period. Uncertainties around the key parameters, which can influence the investment decisions are captured through sensitivity analysis. These parameters include changes in purchase cost, harvesting speed, or efficiency of the robot, labour wages, labour efficiency, and labour availability, which are conducted for the analysis to examine the conditions that make a robotic harvester investment feasible and to determine what variables have the largest impact on feasibility.

Initially the break-even purchase cost of a robotic harvester for three apple varieties across different orchard sizes in a single-varietal orchard are calculated. Given that a robotic apple harvester is still in commercial trial phase, no studies have analysed its feasibility and profitability. Therefore, in order to provide a comparative discussion, previous studies evaluating similar agricultural technologies such as Automatic Milking System (AMS) and platform harvesting system are considered, even though they may not represent similar systems.

6.1. Harvesting systems

In the model, harvesting costs consisted of using either robot, platform, or manual harvesting. Given the harvesting speed and efficiency of each harvesting system, and the limited harvesting window, not all fruit could be harvested by robot or platform and thus, the use of pickers for areas unharvested by robots or platform was also taken into account. The results of the analysis for the single-varietal orchard planted with different apple varieties (Envy, Jazz, or Royal Gala) across seven orchard sizes (10, 20, 30, 40, 50, 100, and 200 ha) are shown in Table 6.1 (manual), Table 6.2 (robot), and Table 6.3 (platform). The results presented in the tables below are for the full production level – year six. Note that the analysis for the single-varietal orchard is only performed to check whether there is a scale effect as scaling up orchard sizes and it is not considered from a realistic perspective, because no growers will have single-varietal orchard.

6.2. Manual harvesting – Single-varietal orchard

Manually harvesting the three varieties followed a linear increase in orchard size from the smallest (10 ha) to the largest (200 ha) orchard size (Table 6.1). Results for 20 to 200 ha orchards are provided in Appendix 1. Manually harvesting 10 ha of a single-varietal orchard planted with Envy employed 26.52 FTEs, produced a yield of 1,007,760 kg, and generated a NPV of $8.0 million with an IRR of 26.44%; Jazz employed 24.40 FTEs, produced a yield of 927,276 kg, and generated a NPV of $1.5 million with an IRR of 10.82%; and Royal Gala employed 25.03 FTEs, produced a yield of 951,216 kg, and generated a NPV of $1.7 million with an IRR of 11.40%, over a 25-year period. There was no scale-effect, and yield and NPV increased linearly as orchard size increased (Appendix 1).

Table 6.1. Manual harvesting single-varietal orchard for 10 ha of three apple varieties in full production

Variety	Size (ha)	Manual yield (kg)	Pickers (FTE)	NPV ($)	IRR (%)
Envy	10	1,007,760	26.52	8,032,924	26.44
Jazz	10	927,276	24.40	1,573,084	10.82
Royal Gala	10	951,216	25.03	1,756,173	11.40

6.3. Mechanical harvesting – Single-varietal orchard

Results in Table 6.2 and Table 6.3 indicate that price and yield determine which variety harvested by robot or platform generated the highest profit. In a single-varietal orchard, Jazz and Royal Gala are relatively more expensive to harvest as they are relatively lower value and lower yield varieties compared to Envy.

Increasing orchard size, increased machine to labour substitution. For example, comparing changes from 10 ha to 200 ha of Envy, the number of robots increased from 0.40 robots per ha to 0.43 robots per ha with robot harvested yield increasing from 69 t/ha to 74 t/ha, while the number of pickers decreased from 0.88 to 0.74 FTEs per ha with manually harvested yield decreasing from 27 t/ha to 23 t/ha; NPV increased from $727,087 per ha to $779,955 per ha with an average IRR of 25.62% across orchard sizes. Similarly, when harvesting Envy by platform, increasing orchard size from 10 ha to 200 ha increased the number of platforms from 0.50 per ha to 0.51 per ha with platform harvested yield increased from 86 t/ha to 88 t/h. The number of pickers decreased from 0.47 to 0.42 FTEs per ha with manually harvested yield decreasing from 14 t/ha to 13 t/ha, and NPV increased from $749,012 per ha to $769,422 per ha with an average IRR of 25.88% across orchard sizes. A similar trend is also observed for Jazz and Royal Gala. The relationship between the outcomes of the analysis will be discussed in detail across orchard sizes and varieties in the subsequent sections.

Table 6.2. Robot harvesting single-varietal orchard for three apple varieties across seven orchard sizes in full production

Size (ha)	Harvested yield (kg) Robot	Harvested yield (kg) Manual	No. of robots1	Pickers (FTE)	NPV ($)	IRR (%)
			Envy			
10	694,138	268,093	4	8.76	7,270,874	24.73
20	1,388,275	536,186	8	17.52	15,000,648	25.36
30	2,082,413	804,279	12	26.28	22,730,495	25.57
40	2,950,085	936,517	17	30.61	30,739,357	25.78
50	3,644,222	1,204,610	21	39.37	38,474,529	25.82
100	7,461,979	2,273,365	43	74.29	77,749,725	26.01
200	14,923,958	4,546,731	86	148.59	155,991,032	26.08
			Jazz			
10	613,138	266,695	5	8.72	341,898	6.41
20	1,348,903	437,388	11	14.29	1,150,219	7.34
30	1,962,040	704,082	16	23.01	2,068,120	7.78
40	2,697,805	874,776	22	28.59	2,920,906	7.94
50	3,433,571	1,045,469	28	34.17	3,774,359	8.03
100	6,867,141	2,090,938	56	68.33	8,172,091	8.27
200	13,734,282	4,181,876	112	136.66	21,367,252	9.44
			Royal Gala			
10	627,588	274,660	5	8.98	479,766	6.63
20	1,380,694	451,056	11	14.74	866,663	6.95
30	2,008,282	725,716	16	23.72	2,478,633	8.28
40	2,761,387	902,111	22	29.48	3,416,155	8.39
50	3,514,493	1,078,507	28	35.25	4,435,529	8.52
100	7,028,986	2,157,015	56	70.49	9,500,771	8.75
200	14,057,971	4,314,030	112	140.98	19,643,113	8.87

[1]One operator will be required per robot.

Number of harvesting machines

The number of robots and platforms required differ across varieties due to differences in fruit size and number, as the Envy apple is larger, fewer robots and platforms were required for harvest in contrast to the smaller Jazz and Royal Gala apples. Harvesting 10 ha of Envy, Jazz, and Royal Gala required four, five, and five robots, respectively (Table 6.2); and five, four, and four platforms, respectively (Table 6.3).

Table 6.3. Platform harvesting single-varietal orchard for three apple varieties across seven orchard sizes in full production

Size (ha)	Harvested yield (kg)		No. of platforms	Platforms (FTE)	Pickers (FTE)	NPV ($)	IRR (%)
	Platform	Manual					
			Envy				
10	864,000	143,349	5	20	4.68	7,488,894	25.32
20	1,728,000	286,697	10	40	9.37	15,123,573	25.65
30	2,592,000	430,046	15	60	14.05	22,799,570	25.86
40	3,456,000	573,394	20	80	18.74	30,531,066	26.10
50	4,320,000	716,743	25	100	23.42	38,120,269	25.96
100	8,812,800	1,299,853	51	204	42.48	76,866,679	26.12
200	17,625,600	2,599,706	102	408	84.96	153,874,593	26.14
			Jazz				
10	691,154	212,170	4	16	6.93	846,794	8.42
20	1,555,301	290,708	9	36	9.50	2,061,923	9.09
30	2,419,449	369,246	14	56	12.07	3,292,308	9.23
40	3,110,400	581,416	18	72	19.00	4,256,814	9.32
50	3,974,400	659,954	23	92	21.57	5,501,069	9.35
100	8,121,600	1,186,276	47	188	38.77	11,422,664	9.50
200	16,243,200	2,372,551	94	376	77.53	22,985,584	9.54
			Royal Gala				
10	691,420	231,448	4	16	7.56	1,070,562	9.22
20	1,555,276	329,264	9	36	10.76	2,181,185	9.31
30	2,419,133	427,080	14	56	13.96	3,992,615	10.14
40	3,283,200	524,896	19	76	17.15	5,463,690	10.26
50	4,147,200	622,711	24	96	20.35	6,936,663	10.34
100	8,294,400	1,245,423	48	192	40.70	14,014,049	10.40
200	16,588,800	2,490,846	96	384	81.40	28,121,000	10.41

As orchard size increased there was a marginal scale-effect, resulting in a non-linear increase in the number of robots and platforms across varieties. For example, the number of robots and operators required to harvest Envy increased by one extra when the orchard size increased from 30 ha to 40 ha, i.e. from 12 to 17 rather than 16 as was the case with increases in the size, from 50 ha to 100 ha for Envy; and from 20 ha to 30 ha for Jazz and Royal Gala (Table 6.2). Similarly, the number of platforms required to harvest Envy increased by one extra platform when orchard size increased from 50 ha to 100 ha, i.e. from 25 to 51 rather than 50. In the case of Jazz and Royal Gala, other than 10 ha, the increases are linear (Table 6.3).

Number of Full Time Equivalent (FTE) pickers

Robot harvesting required a robot operator and platform harvesting can accommodate four pickers, while both systems required pickers to pick unharvested fruit left by the robot or platform due to harvesting speed and efficiency as well as the limited harvesting window. The number of robot operators or platform workers were directly correlated with the number of robots and platforms utilised, respectively, and increased in a non-linear way identical to the robot or platform increases reported previously. For example, the number of robot operators for Envy orchard increased by one extra when the orchard size increased from 30 ha to 40 ha and 50 ha to 100 ha, i.e. from 12 to 17 and 21 to 43 FTEs, respectively, rather than 16 and 42, respectively. When using platforms, the number of platform workers increased by four extras when harvesting Envy orchard when increasing orchard size from 50 ha to 100 ha, i.e. 100 to 204 rather than 200 FTEs. Similar effects are observed for Jazz and Royal similar to what was discussed for the number of robots and platforms required.

The number of pickers required to harvest unharvested fruit left by robots or platforms was in direct substitution with the number of robots or platforms utilised, adding or dropping one robot or platform reduced or increased the labour requirements directly. As a result, there was a marginal scale-effect and non-linear change in the number of pickers as orchard size increased. For example, increasing orchard size from 30 ha to 40 ha for Envy increased the number of pickers non-linearly, from 26.28 to 30.61 rather than 35.04 FTEs. This resulted from the changes in robot numbers from 12 to 17 discussed above

For Jazz and Royal Gala, similar effects were observed when orchard size increased from 20 ha to 30 ha, with the number of pickers increased from 14.29 to 23.01 FTEs for Jazz and 14.74 to 23.72 FTEs for Royal Gala, whereas if it was a linear increase it would have been 19.86 and 20.50 FTEs, respectively.

In the short to medium term, it is unlikely that robots would completely replace pickers as they cannot harvest all fruit at the current harvesting efficiency and speed (NZHerald, 2019), but pickers can aid robotic harvesting (Wiltshire, 2019b). Robots may improve the productivity of pickers by being able to harvest fruit grown at the upper levels of trees, thus making it easier and quicker for pickers to harvest the remaining fruit with less physical stress (Skerrett and McRae, 2019). This is based on the assumption that robots harvest fruit based on colour (Tao and Zou, 2017) and top grown fruit can ripen and develop colour faster due to being more exposed to sunlight (Bursac, 2013).

It is assumed that there are two types of unharvested fruit: unharvested fruit from an unharvested area as machines are purchased in integer numbers, and the other is left-over fruit due to the harvesting efficiency and speed of the robot. Growers may not care about picking left-over fruit in the second pick when utilising harvesting robots especially if the availability of manual labour is uncertain. Further, harvesting remaining fruit may not be economical, as it takes more time and effort to pick the same volume as fruit are sparse. Returns may not justify the piece rate paid for the effort. Therefore, the marginal cost of harvesting in the second pick could be higher than the marginal value of fruit. This would allow growers to utilise the robot for high value apples then manual labour for other lower value varieties such as Jazz or Royal Gala that would not make economic sense to be harvested by robot.

In the long term, similar to an AMS, which replaced milking labour (Engel and Hyde, 2003; Hyde et al., 2003; Shortall et al., 2016), it is expected that robots would replace pickers as harvesting efficiency and speed improve, this may also occur as relative wages increase. As a result, robots will be able to harvest all fruit without relying on pickers, but it would require an operator to be with it while operating (Briscoe, 2019). In addition, it is likely that robots would enable the orchard industry to allocate people from harvesting into permanent roles doing other tasks such as post-harvest operations (Chumko, 2019; NZHerald, 2019). This has been evident from utilising AMS, which freed-up milking labour into higher-valued activities such as managerial functions in smaller farms, monitoring other farm labour, and researching marketing options (Hyde et al., 2003).

Use of platforms is more rational when labour shortages are not acute as platforms, given they are commercially available, can enhance pickers efficiency and safety (Sinnet et al, 2018). It has been reported that health and safety of workers can cost growers. For example, picking apples using ladders is physically more demanding and puts pickers at risk of occupational injuries, whereas platforms can improve the workers' safety and health, e.g. reducing time spent in awkward postures and incidents of ladder falls (Earle-Richardson et al., 2006; Gallardo and Brady, 2015; Isaacs and Bean, 1995; Lewis, 2015). Thus, utilising platforms can create a different demographic of labour as less fit or new workers with no picking experience to work more efficiently and make it physically less demanding, taking into account health and safety measures, and still generate a net return comparable to the case of using a manual harvesting system.

Yield

As defined in chapter 4, yield for each harvesting system takes into account the number of fruit bearing trees per hectare, the number of fruit per tree, the average fruit weight, and the harvesting efficiency of the harvesting unit. As shown in the tables, the total yield for robot and platform harvesting included machine harvested yield (results from utilising a number of machines) and manually harvested yield (or harvested yield by pickers derived from the unharvested area and left-over fruit).

As can be observed from the results, increases in orchard size increased the yield harvested by robot or platform in a non-linear manner. This is related to the non-linear changes observed in the number of robots and platforms as well as the pickers, as discussed earlier. For example, increasing the orchard size of Envy from 30 ha to 40 ha increased the harvested yield by robot from 2,082,413 kg to 2,950,085 kg and manually harvested yield from 804,279 kg to 936,517 kg, where if it was a linear change it would have been 2,776,551 kg and 1,072,372 kg, respectively.

Comparing the total harvested yield for each harvesting system across varieties and orchard sizes, manual harvesting generated the highest yield compared to robot and platform across all varieties and orchard sizes. For example, for 10 ha of Envy, the highest total yields were from manual harvesting system with 1,007,760 kg followed by platform with 1,007,349 kg, and robot with 962,231 kg. Note that manual harvested yield also accounts for the second pick by manual pickers for the fruit that were missed or not ready-to-pick in the first pick. Similarly, robot and platform harvested yield include yield from the second pick by pickers. Robot harvested yield was the lowest because the aggregate harvesting efficiency of robot plus the efficiency of pickers were lower than the aggregate efficiency of platform (picking team) and the efficiency of the pickers.

It is expected that the performance of robot, i.e. harvesting efficiency and harvesting speed, will improve in future that could possibly be comparable with the performance of a picker. This could mean that robot will be able to harvest fruit identified with harvestable quality within the harvesting window without the need of pickers. This has been a similar trend with the adoption of AMS, where farmers had considered utilising AMS on their farms for a decade but had decided to wait for the technology to improve and become more affordable to adopt (Woodford et al., 2015).

Net present value

As orchard area and number of robots increases in a non-linear fashion, NPV changes similarly. Using Envy as an example, the NPV for 10 ha is $7.3 million, if the NPV increased in a linear manner, the NPV for 20 ha would be approximately $14.6 million, but the estimated NPV from the model is $15.0 million. Similarly, for a 100 ha orchard, if linear, the NPV would be $73.0 million, but the model estimates the NPV at $77.7 million (Table 6.2). When harvesting Envy by platform, the NPV for 10 ha orchard is $7.5 million, if it was a linear increase the NPV for 100 ha would be approximately $75 million, but the estimated NPV from the model is $76.9 million. The reason for the non-linear increase is related to the change in the substitution effects between robots and pickers. When an orchard is harvested by robots or platforms, growers will significantly generate lower net returns harvesting Jazz and Royal Gala compared to Envy (Table 6.2 and Table 6.3) due to the trade-off between relative cost and return where the costs incurred for robot or platform harvesting these two varieties outweigh returns.

Either system of harvesting, i.e. robot or platform, will generate lower returns compared to manual harvesting. If labour is available, then growers can generate more profit at the current wage rate by manually harvesting their orchards. When moving to orchard sizes above 40 ha for Envy, harvesting by robots generate more profit compared to platform due to a trade-off between relative costs and returns, where the returns of the investment outweigh the costs incurred from using robots.

6.4. Variety – Single-varietal orchard

The relationship between results from a varietal perspective is examined considering three varieties based on a 10 ha orchard given the linear increase observed from the smallest to the largest orchard sizes for three harvesting systems (Table 6.1, Table 6.2, and Table 6.3). Studied elements for each variety are compared including yield, number of harvesting units and pickers required when fruit are harvested mechanically, the NPV, and IRR. The outcomes of the analysis will be discussed in detail in the subsequent sections.

6.4.1. Envy

Manually harvesting 10 ha of single-varietal orchard planted with Envy used 26.52 FTE pickers, produced a total yield of 1,007,760 kg, and generated a NPV of $8 million and an IRR of 26.44% over a 25-year period (Table 6.1). To harvest the same orchard using robots and pickers – taking into account fruit yield, size, harvesting speed and efficiency - required four robots, produced a total yield of 962,231 kg, and generated a NPV of $7.3 million and an IRR of 24.73% (Table 6.2); and harvesting the orchard using platform and pickers required five platforms, produced a total yield of 1,007,349 kg, and generated a NPV of $7.5 million and an IRR of 25.32% (Table 6.3). As can be observed from the tables, harvesting the orchard by robot and platform reduced pickers compared to manual harvesting by 52% (26.52 to 12.76 FTEs) and 7% (26.52 to 24.68 FTEs), respectively. Note that the pickers required by robot or platform included pickers to pick unharvested fruit by robot or platform as well as robots' operators or platforms workers.

6.4.2. Jazz

To harvest 10 ha of single-varietal orchard planted with Jazz manually required 24.40 FTEs, produced a total yield of 927,276 kg, and generated a NPV of $1.5 million and an IRR of 10.82% (Table 6.1). Harvesting the same orchard using robots and pickers required five robots, produced a total yield of 879,833 kg, and generated a NPV of $341,898 million and an IRR of 6.41% (Table 6.2); and harvesting the orchard using platform and pickers four platforms, produced a total yield of 903,324 kg, and generated a NPV of $846,794 and an IRR of 8.42% (Table 6.3). Harvesting the orchard by robot and platform reduced pickers required compared to manual harvesting by 44% (24.40 to 13.72 FTEs) and 6% (24.40 to 22.93 FTEs), respectively.

6.4.3. Royal Gala

Manually harvesting 10 ha of single-varietal orchard planted with Royal Gala required 25.03 FTEs, produced a total yield of 951,216 kg, and generated a NPV of $1.7 million and an IRR of 11.40% (Table 6.1). To harvest the same orchard by robots and pickers five robots, produced a total yield of 902,248 kg and generated a NPV of $479,766 million and an IRR of 6.63% (Table 6.2), while harvesting the orchard using platform and pickers four platforms, produced a total yield of 922,868 kg, and generated a NPV of $1,070,562 and an IRR of 9.22% (Table 6.3). Harvesting the orchard by robot and platform reduced labour requirement compared to manual harvesting by 44% (25.03 to 13.98 FTEs) and 6% (25.03 to 23.56 FTEs), respectively.

When comparing the varieties from the NPV and IRR perspective, the lower NPV and IRR for each of Jazz and Royal Gala for manual, robot, and platform harvesting were because of the relatively lower price and yield of these two varieties compared to those of Envy. For relatively lower value and lower yield varieties such as Jazz or Royal Gala, robot harvesting is less profitable in a single-varietal orchard, however given their high IRR ranges – generated returns exceeded the assumed discount rate of 5% in the model that make the investment for harvesting these varieties by robot or platform attractive. Therefore, growers are better off harvesting these two varieties manually than by robot, because they can generate higher returns. However, this very much depends on having sufficient labour available for harvest, otherwise, it will be a risk to growers to mainly rely on manual labour.

Even though adoption of the robotic harvester can significantly reduce labour requirements, it also increases the capital requirements given the purchase cost of the robot as the major cost in the investment and its profitability. Thus, this may be the case that growers will generate lower returns by adopting robots compared to using manual harvesting across all varieties. This could be considered a demotivating factor for those growers who are in debt and not financially stable, in this case they would avoid adopting the robot harvester until it becomes more affordable.

On the other hand, for those growers who have trouble sourcing enough labour for harvesting, adoption of a robotic harvester could be appealing. Previously published work has found a similar trend in adoption of AMS, in that some farmers had considered utilising AMS on their farms for a decade but had decided to wait for the technology to improve and become more affordable to adopt (Woodford et al., 2015). Dijkhuizen et al. (1997) found that generally the adoption of AMS varies among farmers depending on the financial situation of the farm and how easy it is to acquire milking labour.

It is assumed that operating the robot faster and more efficiently could make it profitable to harvest Jazz and Royal Gala, but this may not be possible at the current development stage of the robot. Moreover, when compared to Envy, harvesting these two varieties by robots will generate lower returns comparatively, thus it could be the case that growers may consider utilising robots only for Envy. Therefore, some of the strategies that growers could consider instead to make robotic harvesting of Jazz and Royal Gala economically feasible are discussed in the subsequent paragraphs.

One of the strategies that growers could implement to make Jazz and Royal Gala economically feasible for robot harvesting is to change their tree management practices such as thinning. As discussed in chapter 3, growers can use thinning strategically to manage fruit load and size (Musacchi and Serra, 2018; Whitfield et al., 2016; Zhang and Chen, 2018). When tree is thinned as only a small number of fruits are left on the tree, average price increases (Hester and Cacho, 2003). Hester and Cacho (2003) reported that the highest price per kilogram for apples are received when thinning leaves between

20 to 25% of fruit on the tree. The authors noted that thinning beyond this level put the fruit in lower-valued count sizes and decrease the fruit price in line with lower fruit size.

For example, fruit size (i.e. weight) is one of the reasons that Envy is generating higher income as the bigger apple variety (260 grams), worth more per kilogram ($2.35 per kg) compared to Jazz (226 grams and $1.53 per kg) and Royal Gala (181 grams and $1.56 per kg). Even though implementing strategic thinning could increase the cost of production, growers could generate more income when fruit size is increased strategically, because largest sized apples do not receive the highest price per kilogram (Hester and Cacho, 2003). Therefore, it is important that growers thin Jazz or Royal Gala trees strategically to achieve a size (weight) in line with that of Envy. This could increase the demand and prices for these two varieties in the fresh market.

More importantly, achieving larger sized fruit for Jazz and Royal Gala can increase the robot adoptability potential by making them more profitable. Bigger fruit means less fruit per tree and from a grower's point of view, lower number of fruit per tree could impact the number of robots required. This is because each robot can perform faster while harvesting efficiency and speed remains the same for the robot. Robots do not operate more efficient necessarily, but it can harvest more area as there will be less fruit per tree to be harvested, thus the robot moves faster over the area it harvests, which means more labour substitution without having to purchase more robots. This is evident from the results of the sensitivity analysis on increasing harvesting speed of the robot, which will be discussed in detail in section 6.7.2.

Therefore, growers could get the same level of robot output for Jazz or Royal Gala by investing in strategic thinning instead of buying another robot or without having the robot operate faster or more efficient, thus, the adoptability of the robot is not only about the robot management and tree structure, but also related to the input and fruit management. Another alternative that growers could consider is to plant these two varieties together with Envy as a multi-varietal orchard, which is discussed in section 6.5.

Another strategy is that adopters and developers of the robot could consider incorporating an in-orchard sorting function into the robot. Previous research has studied the feasibility of including an in-orchard sorting function for platform in the apple industry (Baugher et al., 2009; Mizushima and Lu, 2011; Zhang et al., 2017;

Zhang et al., 2019). The in-orchard sorting function allows growers to save costs on post-harvest storage and packing apples as it pre-sorts apples in-orchard before finally being sorted and graded in the post-harvest operation (Mizushima and Lu, 2017; Zhang et al., 2019; Zhang et al., 2017). It has been reported that even though adding in-orchard sorting function increased the investment costs, the benefits gained from in-orchard sorting exceeded those from increased harvest productivity of utilising platforms without the in-orchard sorting function (Mizushima and Lu, 2017; Zhang et al., 2019; Zhang et al., 2017).

In addition, it was found that the integration of in-orchard sorting and harvest-assist functions is more beneficial for growers as the investment in the platform system generated positive NPV only with the addition of the in-orchard sorting function (Mizushima and Lu, 2017; Zhang et al., 2019; Zhang et al., 2017). Furthermore, pre-sorting apples in-orchard is considered to be more consistent in terms of fruit quality, which allows packing-houses to better manage the packing and storage in post-harvest operations to meet market demands and standards (Mizushima and Lu, 2017). In the context of this research, incorporating an in-orchard sorting function into the robotic harvester may compensate for the costs incurred harvesting Jazz and Royal Gala with robots by saving on the post-harvest sorting and grading costs. This requires further investigations in future research.

Another component that can affect the profitability of the orchard is packout rate – the percentage of harvested apples that are graded as export quality after being harvested. This is important when apples are harvested for the export fresh market, because a higher percentage of export quality apples are reflected in their packout rates (Lee-Jones, 2019). This is more important for high value and demanded varieties such as Envy. Harvested apples not graded for the export market are priced as non-export apples depending on the local consumption of any apple variety (MPI, 2019; see section 5.1.1). For example, Jazz and Envy may not be as popular or as much consumed compared to Royal Gala in New Zealand considering the local price for each variety. Therefore, they may be more suitable for juicing, hence have low non-export market values of $0.04 and $0.08 per kg, respectively (Table 5.1). Whereas, Royal Gala, despite having a similar export packout rate (80%) to those of Jazz (80%) and Envy (75%), has a higher price for non-export market ($0.21 per kg), because of the local demand.

In the case of Envy, higher harvesting effort in terms of multiple passes to fetch fruit at the right maturity is justified as far as marginal costs are lower than marginal benefits due to high value and weight of fruit (Calvin and Martin, 2010). When labour cost or availability is an issue, it is better to deploy robots to pick higher value and higher weight fruit, thus increase the packout rate. Further, robots can enhance the fruit value by minimising damage, thus increasing packout rates (Briscoe, 2019).

6.5. Mechanical harvesting – Bi-varietal and multi-varietal orchards

Following the NPV outcomes for robot and platform harvesting single-varietal orchards, it was less profitable to harvest Jazz or Royal Gala by robots or platforms compared to Envy. Therefore, bi- (Jazz and Royal Gala) and multi- (Envy, Jazz, and Royal Gala) varietal orchards in a 2D structure were modelled to analyse how varietal mix could affect the investment decision.

Table 6.4. Results of the simulated scenarios for robot harvesting bi- (RB) and multi- (RM) varietal orchards in full production of two orchard sizes (9 and 15 ha)

Scenario[1]	Size (ha)	Harvested yield (kg)		No. of robots[2]	Pickers FTE	NPV ($)	IRR (%)
		Robot	Manual				
RB000003	9	626,428	190,295	3	6.22	606,170	7.68
RB000012	9	626,428	190,295	3	6.22	616,640	7.72
RB000120	9	626,428	190,295	3	6.22	583,224	7.54
RB000111	9	626,428	190,295	3	6.22	629,410	7.77
RB000005	15	1,044,046	317,159	5	10.36	1,246,958	8.25
RB000014	15	1,044,046	317,159	5	10.36	1,259,795	8.28
RB000140	15	1,044,046	317,159	5	10.36	1,215,889	8.14
RB000113	15	1,044,046	317,159	5	10.36	1,285,834	8.36
RB001112	15	1,044,046	317,159	5	10.36	1,325,735	8.47
RM000002	9	641,659	194,922	2	6.37	3,052,084	15.65
RM000011	9	641,659	194,922	2	6.37	3,106,260	15.90
RM000110	9	641,659	194,922	2	6.37	3,156,591	16.17
RM000003	15	1,069,432	324,870	3	10.62	5,458,999	16.24
RM000012	15	1,069,432	324,870	3	10.62	5,520,444	16.42
RM000120	15	1,069,432	324,870	3	10.62	5,620,695	16.75
RM000111	15	1,069,432	324,870	3	10.62	5,667,943	16.91

[1]RB: Robot Bi-varietal (Jazz and Royal Gala); RM: Robot Multi-varietal (Jazz, Royal Gala, and Envy).
[1]Production begins in year three and full production is reached in year six. Robot purchases begin from year three.
[2]One operator per robot will be required.

Net present value

It is more profitable to grow a bi-varietal than single-varietal orchard planted with either Jazz or Royal Gala (Table 6.2, Table 6.3, Table 6.4, and Table 6.5). The average per ha NPV across orchard sizes in the single-varietal orchard harvested by robots increased from $71,101 per ha for Jazz, and $76,324 per ha for Royal Gala to $76,987 per ha in the bi-varietal orchard (RB000003 to RB001112); when platform harvesting system is utilised, the increase was from $106,159 per ha for Jazz and $129,325 per ha for Royal Gala to $129,995 per ha for the bi-varietal orchard (PB100002 to PB100111). However, these increases are still significantly lower than a single-varietal Envy orchard with an NPV of $761,461 per ha for robot harvesting (Table 6.2) and $666,367 per ha for platform harvesting (Table 6.3).

Table 6.5. Results of the simulated scenarios for platform harvesting bi- (PB) and multi- (PM) varietal orchards in full production of two orchard sizes (9 and 15 ha)

Scenario[1]	Size (ha)	Harvested yield (kg)		Platforms FTE[2]	Pickers FTE	NPV ($)	IRR (%)
		Platform	Manual				
PB100002	9	743,883	105,434	12	3.45	1,027,228	9.86
PB100020	9	743,883	105,434	12	3.45	1,006,021	9.75
PB100110	9	743,883	105,434	12	3.45	976,493	9.57
PB100011	9	743,883	105,434	12	3.45	1,040,022	9.94
PB100003	15	1,239,805	175,723	16	5.74	2,109,812	10.78
PB100030	15	1,239,805	175,723	16	5.74	2,145,686	10.91
PB100012	15	1,239,805	175,723	16	5.74	2,158,672	10.95
PB100021	15	1,239,805	175,723	16	5.74	2,177,697	11.02
PB100111	15	1,239,805	175,723	16	5.74	2,207,814	11.13
PM100001	9	761,971	114,350	8	3.53	3,101,873	17.14
PM100010	9	761,971	114,350	8	3.53	3,062,595	16.91
PM100002	15	1,269,951	190,584	12	5.88	5,384,197	17.58
PM100011	15	1,269,951	190,584	12	5.88	5,432,388	17.76
PM100101	15	1,269,951	190,584	12	5.88	5,408,273	17.66
PM100110	15	1,269,951	190,584	12	5.88	5,363,006	17.49
PM100020	15	1,269,951	190,584	12	5.88	5,387,121	17.59

[1]PB: Platform Bi-varietal (Jazz and Royal Gala); PM: Platform Multi-varietal (Jazz, Royal Gala, and Envy).
[1]Production begins in year three. Full production is reached in year six. Platform purchases begin from year one.
[2]Four pickers will be required per platform.

Robot and platform harvesting are more profitable in a multi-varietal orchard compared to a bi-varietal orchard (RM000002 to RM000111, PM100001 to PM100020). The average per ha NPV across orchard sizes for robot harvesting the bi-varietal orchard increased from $76,987 per ha to $359,933 per ha for the multi-varietal orchard, and for platform harvesting from $129,995 per ha to $354,753 per ha. Considering the IRR rates, when utilising robots, growing a multi-varietal orchard provides a better prospective on the profitability of the investment with an average IRR of 16.29% compared to 8.02% of bi-varietal or single-varietal orchard planted with Jazz (7.89%) or Royal Gala (8.06%); and for platform harvesting with an average IRR of 17.45% compared to 10.44% for bi-varietal or single-varietal orchard planted with Jazz (9.21%) or Royal Gala (10.01%).

The resultant higher relative returns and IRR from multi-varietal orchards are attributed to the harvest capacity utilisation of robots and platforms as a result of expanding the orchard harvesting window with the addition of Envy and positive attributes of Envy discussed earlier. Therefore, it could be the case that growers producing relatively high value and or yielding varieties are more likely to invest in robot or platform harvesting. Otherwise, potential adopters may prefer to use manual harvesting rather than going straight to robot or platform harvesting.

The average robot-harvested yield per ha for the single-varietal orchard increases from 66 t/ha for Jazz and 68 t/ha for Royal Gala to 69 t/ha in the bi-varietal, and 71 t/ha in the multi-varietal orchard, and for platform harvesting from 78 t/ha for Jazz and 80 t/ha for Royal Gala to 83 t/ha in the bi-varietal and 85 t/ha in the multi-varietal orchard. Growers could generate more returns when machines purchases were equally spread over production years with fruit bearing trees close to full production – starting from year four (e.g. scenarios RB000111, RB001112, RM000111, PB100011, PB100111, and PM100011). The costs incurred from purchasing machines in the initial years of production or orchard establishment is higher as the full harvesting capacity of machines cannot be utilised due to lower fruit volumes on trees. This will result in lower yield and revenue, and consequently lower profit for the orchard.

In the bi-varietal orchard, growers will generate less returns robot harvesting the orchard than using platforms. This is because the costs incurred for robot harvesting these two varieties outweigh their returns taking into account the higher capital cost required to invest in robots compared to platforms. Note that in the model, it was assumed that platforms were purchased from year one of orchard establishment to perform selected pre-harvest tasks, whereas robots were purchased when production started from year three. However, purchasing platforms from year one did not affect the return of the investment despite the fact that platforms may be underutilised in year one and two or even three because their full or near full operating capacity cannot be utilised until near full (year four and five) or full production level (year six) is reached. In the multi-varietal orchard, a relatively similar level of income is generated in every case for both robot and platform harvesting system. This is because the addition of Envy can compensate for the costs incurred harvesting other two varieties, thus it balances out the trade-off between harvesting cost and return from planted varieties.

Although, it is assumed that platforms are purchased from year one of the orchard establishment, some growers may decide not to purchase platforms until year two or three when trees are more grown and start fruiting and they can prune trees manually in year one. As a result, they can save up the costs of purchasing and operating platforms in year one and they can better utilise the platforms in year two or three by substituting labour more strategically as trees require more labour work and maintenance as they grow. As a result, growers could better balance out the labour to capital ratio this way.

Number of full time equivalent (FTE) pickers and harvesting machines

Installing a bi- or multi-varietal orchard did not necessarily reduce the dependencies associated with pickers compared to a single-varietal orchard (Table 6.4 and Table 6.5). Because of the assumed harvesting efficiency and speed, there are unharvested fruit left-over by robots or platforms that have to be picked by pickers regardless of the orchard type, in addition, growers will still need an operator for each robot and four workers on each platform.

Adding Envy to the bi-varietal orchard marginally increased the pickers required. Even though more pickers have to be recruited to harvest all three varieties, each hectare of Envy can be harvested faster than other two varieties because of the size and weight of Envy and its lower fruit density per tree. For example, completing harvest of Envy quickly allows growers to allocate the remaining pickers to harvest Jazz within the limited harvesting window given the assumption that orchard area is allocated equally across varieties.

Adding Envy extends the overlapping harvesting windows between the planted varieties. As a result, more pickers have to be hired to harvest all varieties within their limited harvesting window, the harvesting period now runs from the second week of February through the first week of May – 13 weeks, compared with 12 weeks of the bi-varietal orchard planted with Jazz and Royal Gala. This provides growers with more flexibility in allocating labour especially when labour availability is uncertain, as some growers may hire more labour than they need for the early harvesting season, considering the longer overlapping window between Jazz and Royal Gala as well as ensuring that they will have enough labour for the Envy harvest (Table 6.4). This could make it more difficult for smaller growers to compete for labour with larger growers with multi-varietal orchards during the limited harvesting window (Calvin and Martin, 2010).

In terms of the number of robots and platforms required, harvesting bi-varietal orchards required a greater number of robots and platforms compared to a multi-varietal orchard. In per ha terms, harvesting bi-varietal orchards required on average 0.33 robots or 1.19

platforms per ha compared to 0.22 robots per ha or 0.89 platforms per ha for multi-varietal orchard. This is because of the fruit size and fruit density per tree in the bi-varietal orchard planted with Jazz and Royal Gala compared to the multi-varietal orchard with the addition of Envy, characterised by larger fruit size and lower number of fruit per tree. This allows maximum utilisation of robots' and platforms' harvesting capacities and spread of capacity over more area.

In addition, for the multi-varietal orchard, there is twenty days of overlapping harvesting period between Royal Gala and Jazz as well as ten days overlap for Jazz and Envy. This means that there is a longer overlapping harvesting window in the first overlap than the second one meaning that growers will have to allocate more harvesting units in the first overlap compared to the second one. Even though this may impose more costs for growers as they need to purchase more robots or platforms in the first overlap, however when compared to the bi-varietal orchard, growers are able to better utilise robots or platforms to harvest varieties complementarily as the addition of Envy increases the harvesting span for another month meaning purchased robots or platforms could still be utilised in the second overlap to substitute more labour and harvest fruit.

6.6. Robot's break-even price

The break-even prices for a robot, or the price at which the NPV is zero in the single-varietal orchard are influenced by orchard size and varietal composition (Table 6.6). Across all orchard sizes examined for each variety (10 ha - 200 ha), the break-even price for a robot averaged $2,924,421 for Envy, $674,895 for Jazz, and $689,608 for Royal Gala. For all three varieties, the break-even price exceeded the assumed value of the robot (i.e. $500,000). For example, for 10 ha orchard size, this means that the price of robot can increase by approximately 80% for Envy, 13% for Jazz, and 17% for Royal Gala, and be economically feasible to invest in the technology for all varieties.

The break-even results indicated that the capital investment and operating costs over the useful life of a robotic harvester cannot be compared with available alternatives namely platform harvesting system. However, this comparison is based on the assumptions of the analysis such as the useful life of the robot, apple variety yield and value, and labour costs for harvest. For example, the break-even level of an investment for a robotic harvester for 10 ha of Envy is $2,486,650, which is $1,986,650 higher than the assumed base price for robot and $2,366,650 higher than the assumed price for a platform. Similarly, this has been found previously in the break-even analysis of AMS with the investment and operating costs over the life of an AMS when compared to those of traditional milking systems based on the assumptions of the analysis, such as the life of the equipment, herd milk production, and milking labour costs (Dijkhuizen et al., 1997; Hyde and Engel, 2002; Shockley et al., 2019). In a similar vein, Shockley et al., (2019) analysed the break-even investment for autonomous field machinery in grain crop production, indicating that the break-even investment price varies based on the economic benefits resulting from the adoption of autonomous machinery such as grain prices and farm size.

Table 6.6. Summary of robot's break-even purchase prices for three apple varieties in the single-varietal orchard in full production for different orchard sizes.

Orchard size (ha)	Break-even price ($)		
	Envy	Jazz	Royal Gala
10	2,486,650	575,290	605,650
20	2,843,250	632,000	599,475
30	2,986,000	669,640	703,300
40	2,950,000	679,970	710,200
50	3,018,560	685,830	717,446
100	3,067,930	706,850	739,787
200	3,118,560	774,684	751,400

Any prices for a robotic harvester above $2,486,650 will make harvesting 10 ha of Envy non-profitable, whereas for 10 ha of each of Jazz and Royal Gala, the break-even price of the robot has to be lower than $575,290 and $605,650, respectively, to make it economically advantageous to invest in the technology for harvesting these two varieties. On the other hand, if cost was higher, then growers could consider investment in alternatives such as platform harvesting system, to justify their investment and ultimately switch to robot harvesting when it becomes financially feasible. This is evident from the adoption of AMS in New Zealand, where most farmers had considered utilising the robotic milkers in their farms but waited for the technology to improve and become more affordable, while utilising their current milking systems (Woodford et al., 2015).

6.7. Sensitivity analysis

This section provides the results for the impacts on the NPV of the investment in robot harvesting 10 ha of Envy orchard based on the changes made on key factors affecting the investment in the harvesting robots including robot's purchase price, and harvesting speed and efficiency as well as labour's availability, efficiency, and wages. Envy is selected as the only variety for the sensitivity analyses given its relatively higher returns compared to Jazz or Royal Gala, which could make it more appealing for growers to consider utilising robotic harvester for compared to other two varieties.

6.7.1. Decrease in purchase price of robot

Robot price is of particular interest in this research given it makes up a significant portion of fixed cost of the investment. Potential adopters of a robotic harvester may consider robot price as a key decision-making criterion that will further justify their investment to reduce their reliance on pickers by having equal or close enough returns to that of platform or manual harvesting system. Sensitivity analysis on the robot price identified the equivalent levels of investment to make the robotic harvester as profitable as the available alternatives, i.e. platform and manual harvesting system (Table 6.7).

Based on the results, to make robot harvesting of 10 ha of Envy orchard as profitable as those of manual and platform harvesting system, a price of $291,783 and $440,093 per robot would be required, respectively. These prices could replicate the decreasing price trend of the robotic harvester in the long-term as the technology advances and becomes more affordable for potential adopters, as it has been the case with AMS (Woodford et al., 2015). The robot at its assumed base price of $500,000 may be too expensive for small growers and may be affordable only by large orchardists.

Comparing these prices to those of harvest-assist machines, e.g. platforms that are commercially available but at prices ranging from $70,000 to $180,000 (Zhang and Heinemann, 2017; Sinnett et al., 2018; Zhang et al., 2019), it is expected that the robotic harvest technology can replace platform harvesting system in future when it becomes more affordable and its harvesting efficiency improves matching that of platform or even pickers, then it would become more appealing for growers or potential adopters to invest in the technology. For example, potential adopters of AMS waited for several years for the technology to advance and become more affordable and accessible before making the investment decision (Woodford et al., 2015).

Table 6.7. Impact of changes in the purchase cost of a robotic harvester on the NPV (10 ha of Envy orchard in full production)

	Robot purchase cost ($)	NPV ($)
Assumed	500,000	7,270,874
Break-even	2,486,650	Zero
Platform harvesting’s equivalent level of profit	440,093	7,490,126
Manual harvesting’s equivalent level of profit	291,783	8,032,921

Note that the purchase cost of the robot should not be the only factor to consider when making the investment decision. Inclusion of robots changes the labour to capital ratio by an average of 48% to 54% across varieties and orchard sizes compared to manual harvesting system. This will be important for growers who have trouble sourcing labour for harvesting or feeling that their current labour cannot meet their expectations.

6.7.2. Increasing harvesting speed

Changing the speed of harvesting, i.e. reducing the time robots take to remove an apple, while maintaining efficiency at 80%, increased the NPV in the Envy orchard linearly (Table 6.8). A 5% reduction in time from one second to 0.95 second lifted the NPV by 2% ($7.3 to $7.4 million, Table 6.2 and Table 6.8) and the IRR by 16%, but maintained the same number of robots at four, robots spend less time harvesting each tree thus covering more area of the orchard or harvesting more trees per hectare, thus reducing the number of pickers to harvest the same area.

Table 6.8. Summary of sensitivity analysis for increasing robot's harvesting speed (10 ha Envy orchard in full production, per 18 days harvesting window)

Harvesting		Pickers (FTE)	No. of robots	NPV ($)	IRR (%)
Speed (second/apple)	Efficiency (%)				
1.00	80	8.76	4	7,270,874	24.73
0.95	80	7.83	4	7,390,621	24.89
0.90	80	11.72	3	7,289,582	24.86
0.85	80	10.85	3	7,408,844	24.99
0.80	80	9.87	3	7,573,119	25.29
0.75	80	8.76	3	7,759,399	25.63
0.70	80	7.49	3	7,972,314	26.01

When the harvesting speed of the robot was 0.90 second per apple, the number of robots dropped from four to three as robots could not operate with excess capacity, but it increased pickers required, by 2.96 FTEs compared to the scenario with a speed of one second per apple, even though more area could now be covered by each robot. However, the NPV still increased because the operating and fixed costs of robots and overall costs of the investment were reduced due to using a lower number of robots, even though more pickers were hired – a trade-off between labour costs and robot costs. Increasing the speed of robots further, even though the number of robots did not change, the number of pickers fell as each robot harvested faster thus covering more area and substituting labour.

Running the robot at the speed of 0.70 second per apple was the best harvesting speed compared to the default speed of 1.0 second per apple, as the number of pickers dropped by 14% (from 8.76 to 7.49 FTEs), while using less robots and pickers, and harvesting more of the orchard with an increase of 8% in NPV (from $7.27 to $7.97 million) and 5% in IRR (from 24.73% to 26.01%). The increase in the NPV and IRR is due to the reduction in the costs incurred from using a lower number of robots and pickers.

6.7.3. Increasing harvesting efficiency

Increasing harvesting efficiency, or the percentage of fruit per tree picked by robot, increases the NPV and IRR for the Envy orchard (Table 6.9). Increasing harvesting efficiency slows down robots as it takes longer to harvest each tree but increases robot-harvested yield, which substitutes more pickers. For example, if a robot harvests a tree with 100 apples at 80% efficiency and one second per fruit, the robot will take 80 seconds per tree, if the efficiency increases to 85%, then the robot will take 5 seconds longer. Assuming a tree density of 2,400 per ha, this increases harvesting time per ha by 3.33 hours.

Table 6.9. Summary of sensitivity analysis for increasing robot's harvesting efficiency (10 ha Envy orchard in full production, per 18 days harvesting window)

Harvesting		Pickers (FTE)	No. of robots	NPV ($)	IRR (%)
Speed (second/apple)	Efficiency (%)				
1.00	80	8.76	4	7,270,874	24.73
1.00	85	8.84	4	7,305,681	24.80
1.00	90	8.91	4	7,336,878	24.86
1.00	95	4.59	5	7,584,735	25.18
1.00	100	4.66	5	7,615,241	25.24

When the harvesting efficiency of the robot was 95%, the number of robots increased from four to five as operate slower, but it decreased pickers required, by over 50% compared to scenario with 80% efficiency. However, the NPV still increased despite adding one extra robot, this is because of increased yield as harvesting efficiency increases. Running the robots more efficiently increases the unharvested area while decreasing the unharvested yield from harvesting efficiency of the robots. It is assumed that pickers pick fruit from the area unharvested by robots with a higher efficiency than the unharvested fruit left by robots. Therefore, as harvesting efficiency increases the harvested yield by pickers from the unharvested area increases, while the harvested yield due to harvesting efficiency of the robots decreases. As a result, the overall harvested yield increases at an increasing rate as harvesting efficiency of the robot increases, resulting in a higher NPV, IRR, and labour substitution. The key point is there is no need to hire more labour as the efficiency rate increases.

Robots can be operated at a range of efficiency rates and where the highest NPV and IRR are generated can be a defining factor in identifying the most efficient rate, which is running the robot at its full efficiency rate of 100%, which can significantly alter the labour to capital ratio by eliminating the need for pickers by 47% (from 8.76 to 4.66 FTEs) while harvesting all fruit from trees using robots and pickers, and increasing NPV by 5% with the highest IRR of 25.24%, compared to the default case. However, in reality it may not be possible for the robot to harvest 100% of the identified apples on trees.

It must be remembered that running the robot more efficiently may not be the most ideal strategy, even though robots can harvest more apples per tree, however it slows down the overall harvesting speed of robots that has to be compensated with buying more robots. It can work well on the block that robots harvest but because of the time constraint it would be problematic as fruit have to be harvested within the limited harvesting window, otherwise late harvested or unharvested fruit may not be suitable for the export market or otherwise considered waste.

6.7.4. Increasing harvesting speed and efficiency simultaneously

As shown in Table 6.10, the first two entries are the base situation and the maximum efficiency from Table 6.9. Each one of the combinations in the table may be considered as the best combination at its own merit – taking into account the trade-off between speed and efficiency in relation to the NPV and IRR, and labour substitution and complementarity with robots. For example, at harvest speed of 0.75 seconds per apple and an efficiency of 80%, the number of pickers is identical to the first scenario, but the number of robots is lower, and the NPV and IRR are higher.

Running the robot at one second per apple and 100% efficiency significantly changes the labour to capital ratio as it reduces pickers required by 47% (from 8.76 to 4.66 FTEs), however, it requires a higher capital investment as more robots are required even though a higher NPV and IRR are generated compared to 0.75 and 80% case. This demonstrates that depending on the labour to capital ratio and what is important to potential adopters, speed or efficiency could be the key parameter in the modelled orchard.

For growers who have trouble sourcing pickers due to the labour shortages, substituting as many pickers with the highest possible number of robots could be the option as is the case with the speed of one second per apple and efficiency of 100%. However, for those growers who may not be financially stable and do not have trouble sourcing pickers then saving up to buy more robots while hiring more pickers could be appealing as is the case in the combinations of 0.75 seconds per apple and 80% or 0.70 seconds per apple and 80%.

Table 6.10. Summary of sensitivity analysis for increasing robot's harvesting speed and efficiency (10 Envy orchard in full production, per 18 days harvesting window)

Harvesting		Pickers (FTE)	No. of robots	NPV ($)	IRR (%)
Speed (second/apple)	Efficiency (%)				
1.00	80	8.76	4	7,270,874	24.73
1.00	100	4.66	5	7,615,241	25.24
0.95	85	7.91	4	7,470,597	25.13
0.90	85	6.88	4	7,602,698	25.29
0.90	90	6.96	4	7,688,353	25.56
0.75	80	8.76	3	7,759,399	25.63
0.70	85	7.58	3	8,008,233	26.08

Robots should harvest faster but not necessarily as more efficient to achieve the best outcome in terms of the labour substitution with robots and the NPV. If robot was harvesting fastest (i.e. 0.70 seconds per apple) but not harvesting all fruit (i.e. 85%), growers can substitute more labour with a lower capital requirement using a lower number of robots, and generate $737,359 more returns compared to the base case, and $392,993 more returns compared to the case of one second per apple and 100% efficiency. This also allows robots to harvest the block faster in the limited harvesting window than if it was to harvest faster and more efficient.

Labour uncertainties

Harvesting the orchard with robots requires two types of labour: skilled labour to operate the robot and pickers to pick unharvested fruit due to the assumed harvesting speed and efficiency. Therefore, three sensitivity analyses were conducted to assess the impacts of changes in uncertainties associated with using labour including wages, availability, and efficiency on the NPV and IRR of the investment decision for 10 ha of Envy orchard.

6.7.5. Increase in labour wages

Increasing labour wages for robot operators, pickers, and post-harvest operators by 5% had a relatively small effect on the NPV with an IRR of 24.16%, warranting the profitability of the investment (Table 6.11). Increasing wages by 50% for robot operators and 5% for pickers and post-harvest operators decreased the NPV by 19% at which the investment still generated positive returns. Therefore, even at a higher wage rate the NPV is still positive and investment is feasible, but the key element is labour availability that can have a higher impact on the NPV, which will be analysed in the subsequent section.

Table 6.11. Summary of sensitivity analysis to increases in labour wages (10 ha of Envy orchard in full production)

Wages			NPV ($)	IRR (%)
Robot operator ($/hr)	Harvest ($/kg)	Post-harvest ($/kg)		
36.00	0.12	0.42	7,270,874	24.73
37.80	0.13	0.44	6,993,283	24.16
39.69	0.13	0.46	6,756,049	23.67
41.67	0.14	0.49	6,376,995	22.88
54.00	0.14	0.49	6,180,042	22.46

6.7.6. Reduction in labour availability

As long as growers can source their robot operators, labour shortages for harvest cannot interfere with the robot harvesting process given a robot does not rely on pickers during the harvesting process. However, the labour availability becomes important when growers intend to harvest fruit for the second pick given there are unharvested fruit from the unharvested area and harvesting efficiency and speed of the robots. Therefore, if labour availability for harvest is uncertain, growers will not be able to pick these fruit, which would result in a significant drop in the NPV, but the return prospective of the investment is still warranted. Reducing the availability of pickers for robot harvesting by 30 and 50% decreased the NPV by 35 and 57%, respectively (Table 6.12).

Table 6.12. Summary of sensitivity analysis to decreases in labour availability (10 ha Envy orchard in full production, 18 days harvesting window)

Pickers availability (%)	NPV ($)	IRR (%)
100	7,270,874	24.73
70	5,393,702	20.79
50	4,642,833	19.08

From the most optimistic (i.e. 50%) to the most pessimistic (i.e. 30%) scenario of available labour pool, growers will make $1.87 to $2.63 million less returns, respectively with the return probability of the investment varies between 19.08 to 20.79%. However, a high return probability may not be convincing in the case of labour shortages. This would be problematic for the orchard industry as fruit has to be harvested within the limited harvesting window. As a result, growers may consider leaving the industry or utilising other alternatives such as platform harvesting system to not only reduce their dependencies on pickers but also increase the efficiency of workers (Sinnett et al., 2016).

Labour availability can also be affected by the skill levels and skill types of workers. For example, different skillsets are required for pre-harvest labour operations and post-harvest labour operations given they are different operations. As a result, employers cannot easily substitute labour from one operation to another (Cassey et al., 2016). Any shocks to the labour market can create a sudden labour shortage in particular for skilled level operations (Cassey et al., 2016). For example, as in the context of the current research, in the case of widespread labour shortages in the horticulture industry, employers may increase demand for manual harvest or post-harvest labour, but they cannot fully substitute the labour for operators because of the skill level required to operate the robot due to its complex nature of operation. For employers it may be more costly and time consuming to train a robot operator with no prior experience than a manual labourer for the harvest and post-harvest operations. As a result, employers may increase the demand for operators by increasing the wages more compared to manual harvesting or manual post-harvesting roles.

Based on the results, it is expected that the availability of robot operators could have the highest impact on wages in future when robots are commercially available and its operations advances and becomes more complex thus requiring more skilled workers demanding higher wages, which could make it more difficult for employers to move labour from other operations or even sectors.

6.7.7. Reduction in labour availability and labour efficiency

Offering a higher wage would not affect the outcomes (Table 6.11), but if there is insufficient labour available to pick the fruit then it will affect the NPV and IRR of the investment (Table 6.12). This section discusses the results of the analysis for the impact of reducing both the labour availability and labour efficiency on the NPV (Table 6.13). Note that these changes do not represent the real case scenarios because it is unknown how the availability of labour affects the efficiency of harvesting labour and consequently the NPV of the orchard business.

As can be observed from the results, NPV is significantly reduced as labour availability and labour efficiency are reduced. Comparing the default case with the changes in the labour availability and efficiency, if growers have only 70% labour available, it is assumed they experience a total of 10% reduction in the efficiency of their pickers, but this results in generating $1.42 million less income. Reducing their available labour pool by half and labour efficiency by 20%, growers will lose almost $2.3 million in profit. As the availability of labour becomes more constraining and the efficiency of labour drops, not all unharvested fruit by robot can be picked or if picked they may not be suitable for export market due to lower graded quality, and this will reduce the total exportable harvested yield and consequently the profitability of orchard.

Notwithstanding, if picker efficiency decreases the profitability of other varieties (i.e. Jazz and Royal Gala) may also decline because it is more profitable to pick them manually and not by robot (Table 6.1 and Table 6.2). Thus, as labour efficiency drops harvesting these varieties becomes less profitable, while robot harvesting becomes more competitive.

Table 6.13. Summary of sensitivity analysis to decreases in labour availability and efficiency (10 ha of Envy orchard in full production)

Pickers availability (%)	Pickers' efficiency for		NPV ($)	IRR (%)
	Robots' unharvested area (%)	Robots' harvested area (%)		
100	90	85	7,270,874	24.73
70	85	80	5,846,127	21.77
50	80	75	4,980,197	19.86

It is important to note that the significant reductions observed in the NPV is more related to the availability of labour than the efficiency. This is self-explanatory when comparing the results in Table 6.12 and Table 6.13. There is not a big difference between the NPVs when only the labour availability is reduced compared to the case of reducing the availability and the efficiency of labour. Therefore, the profitability of robot harvesting in particular for a relatively high value and high yield variety (i.e. Envy) is directly related to the availability of labour in this case. Therefore, it is profitable for growers to utilise robot harvesting only when they have at least 50% of their required pickers available. Otherwise, the robot needs to operate faster and be efficient enough to substitute more labour (Table 6.10), or growers could purchase more robots, even though it has been assumed that growers do not purchase robots in excess capacity in the single-varietal orchard. This option could be more suitable for larger growers who are financially stable but have trouble supplying their required labour and do not mind if they cannot utilise their additional purchased robots in their full harvesting capacity.

Growers may have no control or choice over the availability of labour or even selecting the experienced pickers from the available labour pool, but they may have the option to manage pickers with no prior experience by providing them with minimal training to improve their picking performance and efficiency. However, in reality this may not always be feasible depending on the trainability and interest of pickers and more importantly given that fruit has to be picked within the limited picking window, thus not much time could be spent for training new pickers, while for smaller growers training costs could also be a hurdle.

In addition, growers may want pickers to work harder and faster given the limited picking window and pick as much fruit as possible with easier access meaning that for example, they may leave the top grown fruit unpicked as it is harder to reach and it can take longer to pick. As pickers speed up picking low hanging fruit, growers may end up with a higher percentage of lower quality graded fruit that may not suit the export market, resulting in lower packout rate and return as these lower graded fruit are priced lower and more suitable for local or processing market.

Even though operating the robot faster and more efficient may be an easier and more desirable option for growers that are coping with the labour shortages, but this may not be possible at the current development stage of the robot. However, growers may still not accept the lower harvest efficiency of labour because of the short harvesting window and limited labour pool (Zhang et al., 2017). As a result, they may consider utilising alternatives such as platform harvesting system in the interim to reduce the pressure on the business profit and better cope with the availability and quality of labour (Sinnett et al., 2018). However, it must be remembered that growers cannot completely replace labour with a platform as it does not significantly reduce the labour requirement as discussed in section 6.3 and 6.4, rather it may make labour more efficient (Sinnett et al., 2018). For example, utilising platforms to harvest a 10 ha of Envy orchard reduces the labour requirement by only 7% compared to 52% when utilising robot and pickers (Table 6.1, Table 6.2, and Table 6.3).

Previous research is not conclusive on the benefits of utilising platforms on increasing the efficiency of labour. Elkins et al. (2011) and van der Merwe (2015) found that the gained efficiency from utilising platforms for harvesting depends on the orchard design e.g. tree height and structure, while the prior experience and training of workers with using the machine and working as a team are also important (Wells et al., 2017).

However, other researchers have indicated that utilising platforms to harvest increases labour efficiency or the time taken to harvest apples (Sinnett et al., 2018) compared to using a ladder, and depending on the variety picked, by 10 to 49% (Schupp et al., 2011), 15 to 33% (Hornblower, 2016), 29% (Zhang and Heinemann, 2017), 20 to 65% (Baugher et al., 2009), and 43 to 63% (Zhang et al., 2017).

Utilising platforms as the only harvesting solution in the orchard may not be the ultimate answer for growers coping with the labour shortages but if platforms are utilised complementarily with robots to further substitute the labour requirements, it may be a better solution in this situation. However, this will greatly alter the labour to capital ratio as purchasing and operating platforms requires a greater capital investment in addition to purchasing and operating robots, which may only be feasible for bigger growers who are financially stable and supplying labour is their only problem.

6.8. Orchard system transition

As discussed in chapter 5, the orchard system transition provides growers with the opportunity to switch from manual to platform as the most viable option in coping with labour shortages given that robots are still in commercial trial stage. The model incorporates key decision factors including tree canopy structure and variety into one model to assess the investment decision. The model evaluates the profitability of 5 ha of replanted orchard under two scenarios: Replacing all Braeburn (3D) with Envy (2D) in the first year, i.e. 5 ha in one year or replacing Braeburn (3D) with Envy (2D) over the period of five years, i.e. 1 ha per year (Table 6.14).

Table 6.14. Summary of orchard system transition with scenario one: Replanting 5 ha in the first year and scenario two: Replanting 5 ha over five years (Based on full production level – year six).

Scenario	Total yield (kg)[1]	No. of platforms	Platforms FTE	Pickers (FTE)[2]	NPV ($)	IRR (%)
One	484,091	2	8	4.53	11,781,953	26.53
Two	484,091	2	8	4.53	10,862,345	22.66

[1]Total yield includes platform and manual harvested yield for the new orchard.
[2]Pickers FTE required to complement platform harvesting.

Replacing 5 ha of Braeburn with Envy in the first year (i.e. scenario one) generated an NPV of $11.78 million compared to $10.86 million for scenario two of replacing 1 ha of Braeburn with Envy over a period of five years over the 25 years, where the profitability outlook of the investment for both scenarios guarantee a positive returns. Considering the generated cash flow of both scenarios over ten years (Figure 6.1), growers can get a cash flow from 100% of replanted trees in year six by implementing scenario one given all replanted trees reach full production at the same time, whereas in scenario two due to the gradual tree replacement at an annual rate of 20% over five years, the full production level for all replanted trees are delayed until years ten, resulting in lower total income from the orchard system transition. As a side note, the resultant NPVs and total cash flow also include the cash flow from the current orchard (i.e. 15 ha baseline orchard model) planted with Jazz and Royal Gala.

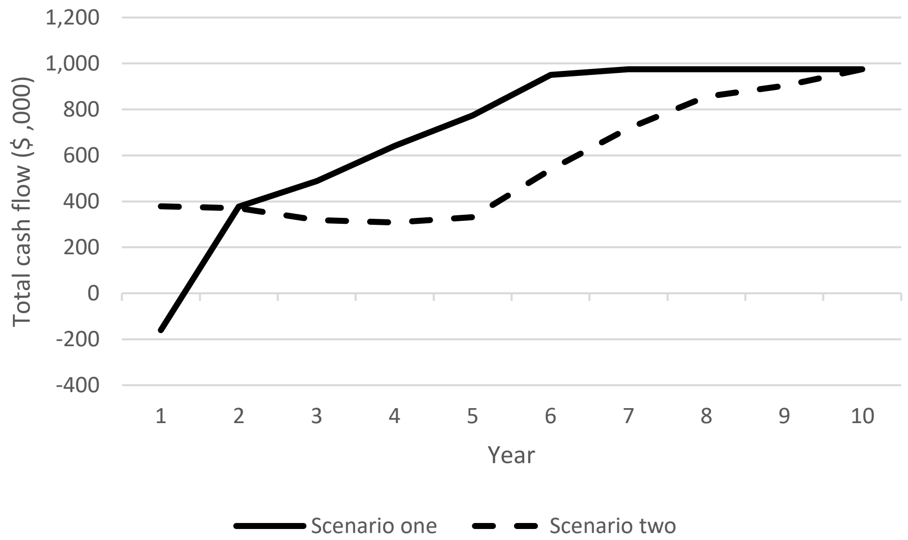

Figure 6.1. Total cash flow of orchard system transition year 1-10 with scenario one: Replanting 5 ha in the first year and scenario two: Replanting 5 ha over five years.

In scenario two, even though growers had four years of cash flow from Braeburn while replacing the trees, in the analysis these cash flows were insufficient to generate relatively more net returns for growers compared to when orchard was replaced all at once with Envy in the first year. In both scenarios, a positive NPV is a necessary but not a sufficient condition to trigger the investment in the orchard system transition when comparing the profitability between the two scenarios. This is because investment in orchard system transition and platform harvesting requires a substantial capital investment. For growers who have trouble acquiring labour and are keen to reduce their in-orchard labour requirement, then scenario one may be more appealing. On the other hand, if a grower is not financially stable, any additional expenditures may put the orchard business at risk, then scenario two may be more appealing despite making lower returns. For growers it might be important to have a cash flow for the first five years to financially support the business with the orchard system transition while gradually adapting to the new system and improving their tree management practices (e.g. pruning) suitable for platform, and ultimately robot harvesting.

Beyond the differences of net returns between the two scenarios, growers can use the replanted section as a trial orchard to assess the feasibility of replanting the entire orchard without being required to invest significantly in the entire orchard and have the option to use the cash flow from the established orchard to financially support establishing and maintaining the new orchard. In addition, the replanted orchard has the potential of generating higher profit by replanting Braeburn with Envy, thus producing higher value and yield fruit comparatively.

Both scenarios warrant the future possibility of utilising robot harvesting when robots will become commercially available, given the orchard is structured in a 2D tree canopy structure. In addition, it will allow an easier and smoother transition to robot harvesting when the technology becomes commercially available. In a similar vein, this has been shown with the adoption of AMS, even though the robot can potentially eliminate the labour need for milking cows, it can greatly alter the labour to capital ratio as it requires a great capital investment – which may make the investment decision more difficult for farmers who are already carrying a large financial debt yet have trouble acquiring milking labour (Dijkhuizen et al., 1997). In addition, research on adoption of AMS technology in New Zealand indicate that some farmers have recognised the importance of having multiple sources of incomes to reduce the risks associated with the early adoption of any new technology namely AMS (Woodford et al., 2015).

6.9. Twenty-four hours robot operation

Although, the potential benefit of robotic harvester can be improved if it is used to harvest an orchard planted with a relatively high value and high yield variety such as Envy, however, a significant change in production could be achieved with the possibility of robot harvests fruit 24 hours a day, which may increase the profitability of orchard and even generating more returns to harvest relatively lower values and yielding varieties.

As expected, it is more profitable to operate the robots twenty-four hours than merely daylight hours (Table 6.15). For example, the NPV per ha of single-varietal Envy orchard increased from $727,087 per ha with daylight hours operation to $829,966 per ha with 24 hours operation while robot harvested yield per ha increased from 69,413 t/ha to 74,480 t/ha using 60% less robots (from five to two robots) and 15% less pickers (from 8.76 to 7.41 FTEs), and providing a higher warrant on the profitability of the investment with an increase in IRR from 24.73 to 26.73%. A similar trend is also observed for each of Jazz and Royal Gala.

Table 6.15. Robot harvesting 10 ha single-varietal orchard for three apple varieties (24 hours operation with excess capacity)

Variety	Harvested yield (kg)		No. of robots	Pickers (FTE)	NPV ($)	IRR (%)
	Robot	Manual				
Envy	746,803	226,863	2	7.41	8,299,667	26.73
Jazz	687,160	208,744	3	6.82	1,326,951	9.96
Royal Gala	695,174	221,748	3	7.25	1,390,128	9.99

Comparing the outcomes of the analysis with the single-varietal orchard's (Table 6.2), although higher net returns are generated across varieties comparatively, the relativity between the outcomes of the analysis have not changed – having a relatively high value and or yielding variety (i.e. Envy) can generate a higher net return and provide a better prospective on the profitability of the investment compared to a relatively low value or yielding variety (i.e. Jazz or Royal Gala). Note that the resultant changes are observed with the assumption that robots are allowed to operate in excess capacity when operated for 24 hour a day.

Beyond the numerical aspect of the model, the outcomes signify the application and adaptability of the model to changing dynamics by allowing to incorporate new parameters and assumptions based on changes and advancements of the robot technology (i.e. 24 hours a day operation), and examine how such changes could affect the performance and profitability of robot harvesting. This is a key aspect of the model considering that the robotic technology is a fast-moving area, where new changes and advancements happen every day, which require the adaptability of those who study and model the adoption feasibility and application of these robots.

6.10. Conclusion

The economic results presented here are predicated on conservative assumptions due to lack of information on capital investment and operating costs as well as the performance of the robotic harvest technology. In addition, the technology is not yet commercially available, thus no commercial information is available and no previous researches have studied the feasibility of the technology. This chapter aimed to analyse the economic feasibility of utilising a robotic harvest technology based on single-varietal and multi-varietal orchard models compared to platform and manual harvesting system – taking into account key factors such as orchard size, canopy structure, and apple variety.

The results of the analysis identified varietal value and yield as the key drivers of the orchard profitability across all orchard sizes. For relatively low value and or yielding varieties such as Jazz or Royal Gala, robots are less profitable in single-varietal orchard compared to bi-varietal orchard planted with relatively low value and yielding varieties. In a multi-varietal orchard, a relatively high value and high yield variety, such as Envy, is crucial to compensate for the costs incurred for robot harvesting other varieties. Findings of the present study revealed that the greatest potential benefit of utilising harvesting robots was reducing the number of pickers required by an average of 52%, and platform harvesting by an average of 7%.

The purchase cost of robot is considered as the most expensive element in the investment decision that could affect the profitability of robot harvesting in particular harvesting lower value or lower yield variety. Therefore, the break-even investment price for the robot was assessed across varieties and orchard sizes in the single-varietal orchard. The break-even purchase price averaged $2,924,421 for Envy, $674,895 for Jazz, and $689,608 for Royal Gala.

Sensitivity analyses showed that both speed and efficiency are key parameters in the modelled orchard and positively affected the net returns of the investment and must be considered by researchers and manufacturers. However, for developers and potential adopters of robots, it should be more important that robots operate faster, but not necessarily as more efficient in order to generate more profit while substituting the highest number of pickers and leaving less unharvested fruit on trees in the limited harvesting window. In addition, a reduction in robot price by 12% and 42% can generate an equivalent level of profit as that of manual or platform harvesting, respectively. NPV and IRR were more affected by decreases in labour efficiency and availability than wage increases.

The results of the orchard system transition scenario revealed that growers will be able to make more profit from their orchard by having the old trees all replanted in the first year and reaching full production for the entire orchard in year six compared to the second scenario with a gradual replantation over a period of five years, where full production is reached in year ten for the entire orchard. Growers who are not financially stable, scenario two may be a better option as it generated a cash flow from the older variety while replantation is completed. It also provides a more gradual transition from manual to platform harvesting and finally robot harvesting, allowing growers to better adapt with a new system by levelling up their tree management skills to maintain tress for platform harvesting.

The outcomes of the analysis of operating the robot for 24 hour a day revealed that growers will generate higher returns at the current harvesting speed and harvesting efficiency compared to operating the robot in daylight hours in the single-varietal orchard, while using less pickers and smaller number of robots with a higher robot harvested yield, NPV, and IRR.

Chapter 7. Conclusion

This chapter summarises and concludes the findings of the thesis. The first section of the chapter discusses the research question, aim, and objectives. Next, the chapter discusses the finding of the analysis and links the research objectives and the results. Furthermore, the chapter explains the implications of using robotic technology from different aspects. Finally, the limitations of the developed model are explained, which could be considered as opportunities for future research.

7.1. Research summary and conclusion

7.1.1. Introduction and research background

The New Zealand apple industry is the second-largest fresh fruit export industry in New Zealand after kiwifruit with an export value of nearly $900 million in 2020 (MPI, 2019 and 2020). The industry relies on manual labour throughout the year (Pollard, 2018; MPI 2019 and 2020). In recent years, labour shortages for harvesting have been jeopardising the competitiveness and profitability of the apple industry around the world and particularly in New Zealand. This has led industry participants to consider use of alternative technologies as a solution to deal with labour shortages, one of the alternative technologies is robotic harvesting of apples. However, robotic apple harvesters are still in the commercial trial stage, and therefore, there are no examples of the experience and performance of commercial orchards adopting the robotic harvester, as well as no evidence or commercial information about robotic harvester performance and operating that represents best practice.

In addition, no studies have assessed the economic feasibility of the technology. This study responds to the researchers who suggested use of the robotic harvest technology as another alternative to address labour shortages, but have not conducted a feasibility analysis for the technology (Calvin and Martin, 2010; Merwe, 2015; Sinnett et al., 2018; Zhang, 2018). As such, findings of this research are highly relevant and valuable to many researchers, apple growers, and industry participants around the world and particularly in New Zealand. The simulations of various scenarios and resultant outcomes of this thesis can provide a broad perspective and real insights for developers and potential adopters of the technology.

7.1.2. Research question and aim

The main question that this research has aimed to answer was:

Is robot harvesting Envy, Jazz, and Royal Gala varieties structured in two-dimensional (2D) tree canopy system economically feasible in New Zealand fresh apple industry?

In order to answer the research question, this study identified key factors involved in the investment decision process such as different apple varieties, orchard size and types with various characteristics, and developed a model representing a range of biophysical systems. Subsequently economic feasibility of these systems is analysed using NPV of the investment as the method of analysis. The developed model incorporates various aspects of apple production with respect to robot harvesting including physiological (e.g. tree canopy structure and variety-specific characteristics), technological (e.g. robot harvesting efficiency), and operation and economic trade-offs (e.g. purchase and operating costs of robot).

7.1.3. Research objective

This thesis specifically focused on the following specific objectives:

1. To identify the economic feasibility of utilising robot or platform (an available solution) on harvest operations of multiple varieties of apples with varying prices and yields across different orchard sizes.
2. To identify the threshold and scale at which investment in a robotic harvester becomes profitable for single-varietal, bi-varietal, and multi-varietal orchards using different scenarios.

To answer these research objectives, a multi-faceted model was developed to assess the returns from an investment in harvesting robot technology based on single-varietal, or bi- and multi-varietal orchard models compared to platform and manual harvesting systems, while taking into account key elements such as orchard size and variety-specific characteristics, e.g. weight and value. The model determined the investment returns for each orchard type across all varieties and orchard sizes utilising different harvesting methods.

Results suggest that fruit value and yield are the key drivers for the adoption of harvesting robots. Robots and platforms are economically less profitable for low value and low yielding varieties in single-varietal orchards. In a bi-varietal orchard planted with relatively low value and yielding varieties using robots and platforms generated higher income than single-varietal orchard with a relatively low value and yielding variety. In a multi-varietal orchard, a relatively high value and high yield variety is crucial to compensate for the costs incurred for robot harvesting other varieties. A harvesting platform is a more feasible option than robot presently given robot is not commercially available yet. Utilising harvesting robots reduced pickers required by an average of 48% to 54% across varieties and orchard sizes compared to manual harvesting, and platform harvesting by an average of 7% compared to manual harvesting. This study also identified the break-even price for a robotic harvester in a single-varietal orchard, and resultant break-even prices across three varieties exceeded the assumed price for the robot (i.e. $500,000), with the highest price averaged $2,924,421 for Envy as a higher value and yielding variety followed by $689,608 for Royal Gala and $674,895 for Jazz, as lower value and yielding varieties, comparatively.

Sensitivity analysis for a single-varietal orchard model revealed that the NPV was positively affected by an increases in harvesting speed as well as harvesting efficiency of the robot. Robots should operate faster but not necessarily as more efficient to achieve the best outcome in terms of the labour to capital ratio, substituting as many pickers possible and generating a high net returns, and leaving less unharvested fruit on trees within the limited harvesting window. Considering the impacts of the labour uncertainties on the net returns of the investment, decreases in labour availability and efficiency reduced the NPV of the investment more than the increases in labour wages. Note that the resultant NPVs from all the analyses warranted the return prospective of the investments given the resultants IRRs in all cases were significantly higher than the assumed discount rate of the model (i.e. 5%).

For potential adopters these results mean that the investment in robots could be the ultimate solution in coping with labour shortages, while for late adopters or those growers who may not financially afford to invest in the robots or may be uncertain about the performance of robots with respect to their prospective profitability and purchase price, they can be assured that by waiting to adopt the robots they can expect robots to improve more in terms of harvesting performance and become more affordable and accessible, as this has been the case with the adoption of AMS (Woodford et al., 2015).

7.2. Model limitations

7.2.1. Number of platforms

The information available on the number of platforms required with respect to the orchard size being covered are not conclusive. Orchardists and operators believe one platform could be used to harvest an orchard size ranging from 10, 12.5 to 24 hectares in a season (Hardie, 2020; Sinnett et al., 2018). However, such information is unavailable for a robotic harvester at its current stage of commercial trial. As such, it would not be easy to make a complementary argument and comparison between the outcomes of the analysis when making the investment decision on robotic or platform harvesting system.

The number of harvesting platforms and robots required were calculated based on the harvesting speed of each machine with respect to the harvested yield and area of the orchard (see section 4.5.4). This provided a common point of reference and comparison between the two systems with respect to the outcomes of the analysis given that the same set of parameters and elements yet with different values are used for each system.

When comparing the outcomes for the platform from the analysis to the available information, the number of platforms required for each orchard size may be higher than what it is required in reality. However, it is important to note that despite such a difference, the presented and discussed results fulfil the application of the developed models in the context they were defined for in the current research – utilising robotic or platform harvesting systems for relative profitability and performance while reducing the reliance on pickers. This is attained by substituting more pickers with harvesting platforms or robotic methods, thus resulting in a higher number of machines than what it is required in reality. Notwithstanding, as more information comes available about the performance of the robots in future, more realistic values for the parameters of the analysis could be used to provide outcomes closer to the real application of the technology in orchards.

7.2.2. Analytical method

The main focus of the current research is to evaluate the relative performance and profitability of utilising a robotic harvester. Given the complexity of apple production as well as the uncertainties involved in the investment and operation of the robotic harvester, NPV was selected as the appropriate analytical tool to present the outcomes of the analysis, which otherwise it would have not been possible if more sophisticated analytical methods such as real option analysis or other analytical approaches discussed in chapter 3 was used. Using such sophisticated approaches could be complicated by the context of the current research having variation of types across orchards such as varietal price and yield, and orchard sizes. In addition, when presenting outcomes, it would be difficult to disentangle the impacts of uncertainty and economics of investment. As a result, the key aspect of the model – analysing the relative profitability and performance of the technology, could have been lost by using a more complex analytical method.

Note that there are still elements of uncertainty related to the investment decision and performance of robots such as harvesting efficiency and speed, labour wages, availability, and efficiency, and purchase cost of robot that have been considered in the sensitivity analysis to account for the risk of the investment. In the context of the current research mainly being focused on the Hawke's Bay region, it was not possible to account for risks common across all regions given that the type of risks growers copes with producing apples vary across regions and orchards both in New Zealand and around the world. However, this research does acknowledge the weakness of NPV approach as not being able to capture the uncertainties and irreversibility in an investment decision (Dixit and Pindyck, 1994). Therefore, a more sophisticated approach for investment analysis such as real option analysis or stochastic modelling techniques may be an alternative for future research to account for other sources of uncertainties in the model (Østergaard, 1971; Wilkie, 1987).

7.2.3. Machine operation efficiency

For the simplicity of calculation, it is assumed that operation efficiency remains the same across orchard size and varieties for each harvesting system. In reality, operation efficiency may vary depending on orchard size, shape, and topography, which can affect the harvesting direction and distance. Harvesting direction and distance of the robot harvesting is determined by the length of orchard row and the number of orchard rows (i.e. orchard blocks). For example, Tozer and Isbister (2007) have reported that wheat harvesters run in 'up and back' or round and round harvesting directions, where 'up and back harvesting is more common than round and round harvesting in Western Australia with the use of Global Positioning System (GPS) and autosteer equipped harvesters. Further, the authors noted that harvesting distance for the harvesters were determined by the area of a harvesting zone and the related geometrical properties. Therefore, if the robots harvest in a round and round harvesting direction with short row distance, then it is expected that as orchard size increases operation efficiency may decrease accordingly, given that the robots need to make more turns (i.e. round and round harvesting) and go for re-fuelling more often in larger orchards. On the other hand, if the robots harvest in a 'up and back' harvesting direction with longer orchard row distance, then as the orchard size increases the harvesting robots need to make less turns per unit area, thus harvesting efficiency may increase. The average length of apple orchard rows in New Zealand and the US are about 150 metres (McKay. L., personal communication, 2019; Miller, n.d.). However, there is no information available about what is the ideal orchard row for the optimal operation of robot.

In addition, in the current research, constant harvesting and operation efficiencies are assumed over the time of the machine's useful life to simplify the calculations. However, over time efficiency may decrease as machines wear out or break down more. When newer machines are purchased efficiency improves, which will impact on the output of the model such as yield. For robot, such information is unavailable at this stage of commercial trial, however, it is assumed that efficiency increases over time as robot technology advances. To account for this, sensitivity analyses were conducted to simulate the harvesting efficiency improvement and its impact on the profitability of robot harvesting was analysed.

7.2.4. Labour allocation

In the current research, for the simplicity of calculations, it is assumed that 100% of manual labours are available and allocated to each block. In reality, labour allocation depends on how long it takes manual pickers to pick a block, which depends on how the fruit colour has developed and the volume of the crop in that block. Every block/variety is different and labour requirements should be adjusted accordingly (McKay. L., personal communication, 2019).

In addition, it is assumed that a robot is utilised to harvest the first pick and pickers will be used for the second pick to harvest unharvested fruit (Wiltshire, 2019a). However, yield may be different each year. Low yield for a particular year could mean that labour may not be very efficient, among other reasons. Second pick as the unharvested fruit by robot likely to take longer to be picked by manual labour given the assumption that robot harvests fruit based on colour (Tao and Zhou, 2017), which could mean fruit are harvested in an inconsistent pattern on trees. As a result, this may require pickers to search all over tree and climb and descend the ladders more often to pick more fruit, which can make the picking process longer and reducing picking efficiency. More importantly, the time spent to pick fruit in the second pick could outweigh the value of fruit. Therefore, the marginal cost of harvesting in the second pick could be higher than the marginal value of fruit. Growers need to take into account the marginal cost of harvesting a high value and high yield variety (e.g. Envy) relative to its marginal value when harvesting the orchard for several picks. If marginal value does not outweigh the marginal cost of harvesting, then growers may be better off not to harvest the orchard for several passes.

7.2.5. Number of robots and platforms calculation

In the present study, it is assumed that machines are purchased in integer numbers, i.e. number of machines are rounded because machines cannot be partially purchased. This has made the number of machines required more realistic as it has introduced use of pickers to compensate for the number of machines as well as harvesting the unharvested fruit due to the harvesting efficiency and speed of machines. However, growers may decide to buy more machines but utilise the additional purchased machines below their full operating capacity, thus the entire orchard area would be harvested by machines. However, there would still be left-over fruit due to the harvesting efficiency and speed of machines.

One may suggest that orchard sizes considered in the current research could be adjusted in a way to make the number of machines a whole number by default. However, it must be remembered that the harvesting speed of machines vary by variety and orchard size because of the parameters assumed for each variety such as fruit weight and number of fruit per tree. Changing orchard size changes harvesting speed meaning that everything has to be changed when the calculation is performed for a different variety. Therefore, it was simpler to take into consideration use of pickers to work around this problem. More importantly, this will make the mechanical harvesting model more realistic given that in reality harvesting machines are not going to replace manual labour completely due to the assumed harvesting efficiency and speed.

7.2.6. Orchard age

In the present model, it is assumed that newly established orchard run for 25 years based on the productive age of apple trees. Most growers may not make decision based on the productive age of apple trees, but profitability, meaning they would keep trees longer if they are profitable (Davis and Thiele, 1981). However, changes can occur earlier in the orchard as new varieties are developed over time, thus growers will take out older trees and replace them with newer cultivars.

7.2.7. Sensitivity analysis

A note regarding the sensitivity analysis is that the results that come out of the analyses are based on the mathematical construct. For example, considering the impacts of increasing harvesting efficiency and speed on the number of robots required, the number of robots could be different in reality because growers may decide to purchase another robot to fully harvest unharvested fruit and substitute more labour. However, it should be taken into consideration that purchasing an additional number of robots could mean that growers may have to deal with the extra robots not working to full capacity.

7.2.8. Robots and platforms salvage value

In contrast to the single-varietal orchard, for the bi- and multi-varietal orchards, it is assumed that machines (robots or platforms) can be purchased in excess capacity such that the maximum capacity of machines is met and all fruit are harvested within the harvesting window. In reality, operating machines up to their maximum capacity mean that they operate longer, meaning they may wear out more quickly, thus reducing their useful life and losing their value more quickly. However, given that bi- and multi-varietal orchards are predicated on the single-varietal orchard model, and for the simplicity of calculations, a constant salvage rate is assumed for operating machines across all orchards.

7.2.9. Varietal price, yield, and demand

In the present model, for the simplicity of the calculations it is assumed that varietal characteristics such as yield, price, and demand remain the same over the lifetime of the orchard. However, in reality such attributes are subject to change over time depending on market situations and customer preferences.

7.2.10. Harvesting window

For the simplicity of calculation, it is assumed that the harvesting window remains the same across varieties included in the model. This is important for bi- and multi-varietal orchards to avoid allocation of robot harvesting problem in overlapping harvesting window. In addition, location defines the overlapping harvesting window, which can be affected by climate change as will be discussed in section 7.3.2.

7.3. Implications

Widespread adoption of the robotic apple harvester in the agriculture industry can have profound impacts and implications, which are discussed in this section. Even though these implications may be more relevant in the context of the apple industry, it can also be relevant to other crop industries. The economic, technological, and horticultural components incorporated into the developed bio-economic model can provide a common ground for discussion and collaboration among participants of the industry including academics, government, agribusinesses, growers, engineers and manufacturers, and trade unions. There are implications that should be taken into consideration beyond the assumptions and discussion of the current research, which could help the participants of the industry to have a broader perspective in finding the most effective solution in coping with the risks and uncertainties in the industry, e.g. labour shortages.

Potential implications could be studied under various factors such as political, economic, environmental, cultural, and social (Sparrow and Howard, 2020). However, regardless based on what aspect the implications of using robots are analysed, how robots are utilised will determine the balance between risks and benefits of using the technology that could serve its defined objective and create a win-win scenario for all participants of the industry (De George, 2003; Johnson, 2015). Therefore, it is important to have a sound policy and framework in place to maximise the benefits and minimise the risks (Sparrow and Howard, 2020). Note that the points that are discussed in this section regarding the agricultural robotic industry also apply in the same manner to the robotic apple harvester, given the robotic harvester is indeed part of the larger agricultural robotic industry.

7.3.1. Policy and research

Even though introducing robotic harvesting has the potential to improve the sustainability of apple production, it also poses a risk of ownership centralisation in the industry as smaller or financially less wealthy growers could fail to adopt the technology and benefit from it (Key, 2019; Sheng and Chancellor, 2019), given that the purchase cost of the robot is considered as financially the most burdensome element of the investment decision.

Policy makers and researchers could provide more support to make the robot more affordable and accessible for utilisation by smaller growers and for wider ranges of agricultural produces (Sparrow and Howard, 2020). For example, smaller orchardists who grow both apples and pears could benefit from utilising the robotic harvester to harvest both crops to reduce the risks and impacts of labour shortages. Moreover, governments could fund the early adoption of the robots, which could ensure that smaller or growers with financial debts would also benefit from using the technology (Fleming et al., 2018; Lowenberg-DeBoer et al., 2019).

Another anticipated outcome of utilising the robotic harvester would be a reduction in labour employed in the apple industry and an increase in the use of capital. In the long-run, it is highly likely that robots will be a substitute for manual labour and may result in many people in rural areas losing their jobs especially people in fruit picking, food handling, and food packing (Werkheiser, 2018). Therefore, it will be essential for governments to develop policies to manage this labour outflow and minimise the social, economic, and political implications.

In a broader sense, the horticulture industry will become more capital intensive, which could make it more difficult for new orchardists to enter the industry or worse smaller or financially struggling growers leaving the industry. Therefore, it will be necessary for governments to collaborate with key industry participants including growers, agribusinesses, and researchers to identify multi-objective agricultural policies and initiatives with the specific purpose of facilitating the transition to a more automated agricultural industry (Sparrow and Howard, 2020).

In addition, linking academic research with highly applied commercial research beneficial for the industry and quantifying the possible impact of the use of robots in agriculture will be essential (Lowenberg-DeBoer et al., 2020). One of the examples of such collaborations is the recent initiative announced by the New Zealand government named Agri-tech Industry Transformation Plan (ITP) – “a joint Government and industry strategic approach” (HortNZ, 2020; RNZ, 2020). One of the initiatives is to establish “a horticultural robotics academy” and to collaborate with local Agri-tech companies to invest, develop, and commercialise robotics and automation systems in horticulture as potential solutions for coping with challenges in the industry such as labour shortages (Fyfe, 2020; HortNZ, 2020; RNZ, 2020).

As robotic technology becomes more sophisticated in terms of software and hardware components built into it, thus a new support industry will be required to service such technologies in agriculture. This is evident from the initiation of ITP by the New Zealand government to better support the industry in future. Otherwise, without sufficient support, the robotic harvesting system can be more a liability than an asset for potential adopters (Dijkhuizen et al., 1997).

It should be noted that such collaborations require a legal contract agreement in place to clarify the extent and nature of the collaboration and do not be subject to modification by regulation (Shah, 2018). This may put the legislators and policy makers under pressure about the impacts and implications of regulation on the interests of all participants of the industry in particular manufacturers who develop robots (Carbonell, 2016; Fleming et al., 2018; Wolfert et al., 2017). As a result, this could make it more difficult for governments to mediate any potential conflicts between farmers and manufacturers of robots about the control over the produced data from using robots on farms given that robots have proprietary software installed on them and are more integrated into the corporate IT systems than the machines they replaced (Carbonell, 2016; Fleming et al., 2018; Wolfert et al., 2017). It is anticipated that the future of robotic agriculture may happen within two types of extreme ecosystems: closed or proprietary ecosystems with farmers being part of a highly integrated food supply chain; or open or collaborative ecosystems with farmers and other industry participants in the agri-food network being flexible in selecting their business partners and food production technology (Wolfert et al., 2017).

It is now the case that new robotic technologies, e.g. apple robotic harvester, use Artificial Intelligence (AI) technology as the core of their development to automate farm tasks, which requires the engagement and attention of farmers to start designing their farms that can accommodate the quick and smooth transition and adoption of new robotic technologies (Legun and Burch, 2021). It is assumed that as AI technology advances, it will also improve the performance of robotic technologies in near future, and it seems highly likely that robots will ultimately outperform manual workers in accomplishing their designated tasks, e.g. harvesting. Therefore, it is essential for legislators and policy makers to take legal uncertainties associated with utilising robots in agriculture into account before robots have completely replaced manual workers in farms (Sparrow and Howard, 2020).

7.3.2. Environmental aspects

There could be many environmental implications relevant to utilising the robotic harvester, but two of the most important ones include soil compaction and climate change.

Soil compaction

Soil compaction is one of the environmental problems caused by operating large and heavy agricultural machinery in the field (Grimstad et al., 2015; Shockley et al., 2019). Soil compaction can limit root penetration, water, and air infiltration in the soil. It can damage the soil structure and lower yield (Grimstad et al., 2015; Shockley et al., 2019). For example, it has been reported that soil compaction can reduce corn and soybean yield by 7% (Murdock and James, 2008). Therefore, replacing heavy agricultural machinery with lighter models or alternatives not only could minimise the problems associated with soil compaction but also may guarantee a long operation time for the robot, and has to be considered by the developers of the robotic apple harvester (Clarke, 2017; Grimstad et al., 2015; King, 2017; Shockley et al., 2019). This is critical to avoid damage to the soil structure in particular during wet periods to ensure the machine can operate without getting stuck in the soil. It may also make the robot more fuel efficient thus guaranteeing longer operation time in orchard (Grimstad et al., 2015; Shockley et al., 2019). However, there are critics believing that avoiding soil compaction should not impose a constraint when designing robotic machines. They believe that instead of having one large autonomous machine in field it is better to have three or four lighter medium-sized machines (Lyon, 2019). Note that information about the weight of a robotic apple harvester is unavailable at its current stage of commercial trial.

There may be different ways to resolve the soil compaction when using robots, which could include re-designing the mechanical aspects of the robot. It has been reported that the tyre with the largest tyre-soil contact area (i.e. the widest tyres) and most even contact pressure distribution (i.e. the pressure that is exerted by a track or tyre on the soil surface) in combination with a reduction in the tyre inflation pressure can decrease soil compaction (Salokhe and Ninh, 1993; Ten Damme et al., 2019). Another strategy could be to swap tyre wheels with tracks for the robots, which can reduce the soil pressure by around 65%, and improve the stability and traction (McConnell, 2016).

Climate change

It has been reported that even though robots can operate more productively than manual workers, however, production methods predicated on the robotic technology may not easily and quickly be adaptable to the new environmental changes due to climate changes, which can make the agricultural systems more vulnerable and might lead robots to operate less effectively (Sparrow and Howard, 2020). This is an important matter, because if potential adopters of the robot will invest a high capital in robots, they want to know the implications of climate change on their investment decision. For example, hotter summers can ripen fruit quicker and affect the harvesting window and robot operation – requiring a greater number of harvesting units to harvest fruit quickly within the limited harvesting window.

Climate changes can affect different aspects of apple production such as fruit size, yield, quality, and harvesting window (Boudichevskaia et al., 2020; Daly, 2019; Kenny, 2001). Climate changes can affect how fruit are grown with its diverse impacts on winter chilling, flowering and bud burst, harvest date and yield, fruit quality, extreme high temperatures, and frost and hail, but the impacts will vary by crop type (Daly, 2019; Clothier et al., 2012). Apples require temperate climate with minimum number of cold nights or chilling hours to break dormancy (Clothier et al., 2012; Clothier, 2018). Otherwise, dormancy period will prolong, resulting in not allowing all buds to flower at the same time. This means apples will not ripen simultaneously on trees, resulting in different harvesting period (Boudichevskaia et al., 2020; Kumar et al., 2016; Vedwan and Rhoades, 2001; Clothier, 2018; Fang et al., 2016; Sharma et al., 2014; Sugiura et al., 2005; Rai et al., 2015). Climate affected apples can develop poor colour and soft texture, and getting sunburnt as well as not storing well, which will affect its exportability (Clothier, 2018; Else and Atkinson, 2010; Tobin, 2021).

Although rising temperatures in apples increase fruit growth, it will also adversely affect fruit quality such as through more sunburn on apples (Luedeling, 2012; Clothier et al., 2012). For example, severely hot and dry condition in summer and higher temperature in winter in New Zealand largest growing regions such as Hawke's Bay or Nelson region can lead growers to think about a new location to grow their apples (Fedaeff, 2017; MFE, 2020; Kenny, 2001) to initiate fruit ripening or flowering that require winter or cool autumn temperatures. This could result in relocating orchards further south that could consequently shift the apple production from Hawke's Bay and Nelson to a southward consolidation (Heyes, 2019; Kenny, 2001). Although from a climate viewpoint, it may be a logical strategy, but other factors such as growing environment, soil characteristics, cultivar, post-harvest operations, transportation, and orchard facilities constructions can hinder orchard relocation (Barden and Neilsen, 2003).

It may be the case that the desire to utilise robot harvesting in the presence of climate changes depend upon more standardisation of agricultural production outputs including developing new crops or varieties that will be better suited to the robotic harvesting in future in the presence of climate changes, especially if it is not feasible for growers to relocate their orchards to new locations with climates more suitable for apple production (Heyes, 2019; Sparrow and Howard, 2020). As a result, scientists have developed new varieties of apples that are better adapted to the changing climatic conditions by requiring less/no winter chilling to break up dormancy, less water, and are more resistant to pests and diseases (Boudichevskaia et al., 2020; Arya et al., 2014; ASA, 2020; Clothier, 2018). Therefore, the adoptability of the robot in the presence of climate changes may not only be about the robot management, and re-structuring its operating environment, i.e. tree structure, but also related to the input and fruit management.

7.3.3. Social aspects

The impacts of robotic apple harvesting on the labour market especially on the social demographic of rural communities must be considered in two phases: the short to medium and long terms. In the short to medium terms, robotic harvesters will likely operate semi-autonomous or require humans to supervise or complement them while operating in orchards (Bechar and Vigneault, 2016). Therefore, it is unlikely that the robot could replace the current workforce including RSE workers and they will still be needed in the industry (Wiltshire, 2019a). This is because robots cannot harvest 100% of fruit due to harvesting performance. Therefore, growers can use different harvesting technologies in combination, e.g. utilising robot for the first pick and manual pickers for the second pick (Wiltshire, 2019a) or a combination of these along with platform. This can reduce the current dependencies associated with manual labour and make it easier for growers to get manual labour in particular during peak harvesting period. As a result, the horticulture industry can be more sustainable and socially more acceptable in the short to medium term.

In the long term, the situation may be different when the robotic technology has advanced to the level that it will outperform and replace significant amounts of manual labour. As a result, fewer economic opportunity may be available for those living in rural areas, which may worsen inequalities of wealth distribution and quality of life in rural areas and offset the positive lifestyle implications of adoption of the robotic system including reduced labour intensity, increased family time, and flexibility of work (Sparrow and Howard, 2020).

On the other hand, similar to using other agricultural technologies (e.g. AMS), it is expected that robotic harvesting could make a shift in the way manual labour is used in apple production as the robot will potentially replace most of the apple pickers in orchards. This could possibly direct the pool of available labour to undertake more skilled tasks in orchard or post-harvest operations or even other sectors, because the skill levels required to operate and maintain robots will likely be very different to those previously existed in rural areas (Rotz et al., 2019). This has been evident with AMS, which the robot replaced milking labour with labour to manage equipment and complex IT systems (Engel and Hyde, 2003; Rotz et al., 2003; Tse et al., 2018; Jacobs and Siegford, 2012).

7.3.4. Economic aspects

Adoption of the robotic harvester may not be easily justified on an economic basis especially for smaller growers or those who are financially struggling. For example, with efficient utilisation of platform harvesting, fruit may be harvested at a lower cost and better net returns. However, this also depends on the availability of labour. Utilising the robotic harvester can potentially increase the productivity by efficient uses of inputs and reduce the labour costs by significantly using a less pickers to produce fruit (Sparrow and Howard, 2020). However, such benefits could be countered by higher capital costs required to purchase and operate robots, which could make it difficult or impossible for smaller or not financially stable growers to benefit from it.

In a broader perspective, growers who successfully adopt the robotic harvesters in wealthier countries could out-compete growers in global South in competing markets (Fleming et al., 2018). Thus, any decisions made on the basis of economic consensus implicate ethics and social justice as it is closely related to the market, regulation, and contract enforcements (Satz, 2012). Therefore, on the ethical basis, it is important that widespread use of the robotic technology can promote social justice and equal wealth distribution among potential adopters of the technology, while the relevant economic and social implications with regard to the labour employment in rural areas should be countered by the obligations of members of society, in particular primary sector and agribusinesses to offer meaningful jobs to workers who are displaced as a consequence of widespread adoption of robotic technology (Byard, 2017).

There are critics who doubt that the robotic technology will have any economic benefits for the foreseeable future, because at the current development stage the perceived economic benefits do not outweigh the associated costs (Chapman, 2020). In order to take the full advantage of the robotic systems in field works, the technology requires more development in the years to come, while how crops are planted should support this trend to make automation and robot operation feasible and as efficient as possible in fields (Chapman, 2020).

7.3.5. Robot ownership structure

Given the high costs involved in purchasing and operating the robots, larger growers who usually supply most of the production in the industry, are the most likely to invest in a robotic harvest technology, since a large, fixed investment can be spread over more area (Calvin and Martin, 2010). In addition, when robotic harvester becomes commercially available, it is likely that costs for early adoption may be higher than other available alternatives namely platform harvesting system, until the infrastructure is in place to support the sale and maintenance of the equipment. As a result, smaller growers or those that are not financially stable may fail to benefit from using the robots in their orchards. These growers may face high risks of losing the market and profitability of their orchards due to lacking the technologies, skills, and financial stability to meet the market demands (Reardon et al., 2009).

Contract-farming (i.e. contract-harvesting) and/or co-operative ownership business model/s can be considered as potential solution/s to mitigate prevalent market failures such as the ownership centralisation of the robots in the industry and the risks facing smaller or financially struggling growers by allowing them to benefit from utilising the robotic harvester (Bellemare and Bloem, 2018; Bellemare and Lim, 2018; Grosh, 1994). Contract-farming or contract-harvesting in the context of the current research, is an alternative to purchasing a robotic harvester, when a third party purchases the robots and rents them out based on an agreement to harvest fruit for multiple growers for a fee. This can enable smaller growers or those that are not financially stable to use robots in their orchards at a fraction of the purchase price of the robots.

The contract-farming business model is not a new concept (Grosh, 1994; Key and Runsten, 1999; Meemken and Bellemare, 2019). It has been practiced in dairy industry for decades known as share-milking or contract-milking that robotic milkers, owned and operated by third parties are rented out to local dairy farmers at a shared cost (DairyNZ, 2020). As in the case of the robotic harvesters, the ownership and operating costs of the robots are only incurred for the main owner/s of the robots, who could generate more income by charging up a percentage from growers for each rent out.

Another relevant business model is co-operative ownership, which includes organisations/equities/equipment that are owned and controlled by the members of the cooperatives (Gold and Staples, 2012; Reynolds, 2013). It is established based on the idea of creating wealth, providing services, and benefiting members of the co-operatives (Gold and Staples, 2012; Reynolds, 2013). The ownership is based on holding an ownership share, where it is financed using member equity, investment shares, grants, fund raising, or loans, or a combination of all these, and profit is distributed between members based on the patronage/use of the co-operatives (Gold and Staples, 2012; Reynolds, 2013).

The robotic harvesters could be owned by the apple growers' co-operatives, even though such co-operatives do not exist in New Zealand apple industry, but NZAPI as the main representative organisation for the New Zealand apple and pear industry (NZAPI, 2019) could be considered as the potential representative for such co-operative. However, it is likely that by the time the robots become commercially available such co-operative initiatives come into existence by apple growers especially those who may have a lower chance of adopting and using the robots, i.e. smaller or financially struggling growers.

Contract-harvesting and co-operative ownership are considered win-win business models for both owner or manufacture of the robots and apple growers. The owner/s or operator/s of the robots can take advantage of scalability power of such business models, i.e. contract-harvesting and the co-operative ownership, to spread the ownership and operating costs of the robots over a larger area (i.e. more growers) by renting out the robots in New Zealand and even in Australia in the Southern hemisphere and the US in the Northern hemisphere's apple production season.

In addition, introducing such business models to utilise the robotic harvesters can give the industry more resilience in the presence of climate change where harvesting windows and apple production locations may change, as it was briefly discussed in the case of New Zealand in section 7.3.2. Given New Zealand is not a big country, varying harvesting windows enable the mobile deployment and rotations of the robots around the country for the operator/s or owner/s of the technology. This could make it easier for the horticulture industry to cope with the labour shortages across the country as the robots could potentially substitute most of the harvesting labour in the apple industry that could be allocated to other sectors in the industry.

7.3.6. In-orchard sorting

This research assumes that adoption of harvesting robots will have implications on a number of harvest and post-harvest (sorting and grading) components. This may include an increase in the harvest yield of apples, an imbalance in harvest and post-harvest operations of apples with different characteristics (varietal size, firmness, colour, and shelf-life), and finally, an imbalance in the supply and demand levels of labour in harvest and post-harvest operations, given that more labour will be freed up from harvest operation to be allocated to perform other tasks in the orchard or post-harvest operation (Lehnert, 2013; Zhang, 2018; Zhang et al., 2019; Zhang and Heiman, 2017).

Integrating harvesting and post-harvesting operations such as through using an in-orchard sorting function in a robotic harvesting technology, e.g. grading fruits during harvesting, could help growers to reduce cost and time by not sending lower-quality fruit to the packing house and lowering the incidence of post-harvest problems from contaminated fruit (Lehnert, 2013; Zhang, 2018; Zhang et al., 2019; Zhang and Heiman, 2017). In-orchard sorting functionality that has been commercially trialled in the US by equipping an on-board sorting module on fruit harvesting platforms. Results of the initial trials revealed that it increased the overall benefit of utilising platforms by over 40% and generated a positive net returns despite increases in machine prices and annual costs (Lehnert, 2013; Zhang, 2018; Zhang et al., 2019; Zhang and Heiman, 2017). However, there is no information whether robotic harvesters will have such functionality. This is not the focus of the current research as it is assumed that robotic harvest technology will mainly be utilised for harvesting apples.

7.3.7. Food safety and market disruptions

It has been reported that food safety is an important consideration for consumers that can define their purchase decisions (Askew, 2020). Food safety has become more important following the Covid-19 pandemic, as it has significantly disrupted the consumer food markets and created new challenges in fresh food safety (Askew, 2020). The Covid-19 pandemic has negatively affected sales by changes in logistics and customer purchasing patterns (O’Callaghan, 2020) as consumers have become more cautious about their food safety, quality, and transparency (Askew, 2020). It has been reported that 40% of consumers are more cautious about washing unpackaged vegetables and fruit than before the pandemic (Saha, 2020). For example, before the start of the pandemic, consumers did not care whether apples were picked by robot, platform, or manually. However, now they care because of Covid and want their fresh fruit to be human touchless from farm to plate. For packhouses this may not be an issue because they are mostly automated but for harvesting operations it may be a consumer issue, because they have to pick apples by hand (O'Callaghan, 2020).

Robots were introduced as a solution to the labour shortage issue, and now it can even be considered as a solution for the food safety problem (Mandow, 2020). In addition to food safety issue, following the social distancing, and health and safety measures between the workers working in the orchard could also be an issue (Mandow, 2020). For example, when fruit are harvested by platform, there may only be two workers allowed to work on each machine. As a result, lower volumes of apples may be picked, which might be an issue in the limited harvesting window. It may also negatively affect the picking efficiency given that pickers have to work with consideration of certain hygiene measures such as being regularly tested for Covid-19 or using masks or gloves while picking. Therefore, if growers want to have the same volume of apples harvested, they need to have more platforms in the orchard. However, this could mean that growers may have to deal with the additional cost as well as the redundant harvesting capacity of operating multiple platforms in the orchard.

Robot harvesting may be considered to be the most ideal option in the current situation, however, at its current level of harvesting efficiency and speed as well as not being commercially available, robots cannot be the only option for growers to rely on for the foreseeable future. To cope with the food safety issue, apple packhouses in New Zealand have started marketing one of the attributes of apples exported from New Zealand being the fact that they are "washed, packed, and almost sealed here in New Zealand before getting exported" (Mandow, 2020). This is important because export markets such as Asia considers New Zealand as a country that has successfully controlled and tackled Covid-19, which could help as a marketing slogan for the country's fresh apple export at this stage (Mandow, 2020).

7.3.8. Future research

Given the limitations defined above, future research could be conducted by incorporating these limiting factors. Although the model here is constructed based on one country, New Zealand, it would be possible to adapt this model for other countries where robot harvesting is trialed, e.g. the US and Australia, using other varieties with different parameters such as size, weight, yield, and value compared to the varieties considered in the current research. This could provide a more comprehensive analysis about the potential of the robotic harvester, which could be useful for manufacturer of the robot to consider when developing new models.

In the current research, it is assumed that growers purchase platforms starting from year one and robots starting from year three of orchard establishment. However, in reality this may not be the case for all growers, which can be taken into account in future research to analyse how delaying purchasing platforms until year two or three and robots until year four, five, or six could affect the labour to capital ratio and profitability of the orchard.

This study was conducted based on conservative assumptions due to lack of information on capital investment and operating costs as well as farm trial data for the robotic harvester that could be used to better support the analysis and make it more applicable to New Zealand apple industry. Therefore, future research could follow the assumptions and findings of this research to further investigate the feasibility of the robotic harvester not only in the apple industry, but also other fresh market fruit industry intended for robot harvesting. It is expected that the robotic apple harvester considered in this analysis would improve and more trials be conducted in the future that more information about the performance and price of the robot may become available that could be used to refine the current model.

7.4. Conclusion

Adoption of the robotic apple harvester may be difficult to justify for the orchardists who grow relatively low value and yield varieties based on an economic basis. Given robotic apple harvesters are still in the commercial trial stage, potential adopters can opt for platform harvesting system given it fits within the same orchard architecture as robot and can reduce the current reliance on manual labour not only for harvest but also pre-harvest tasks, thus it can create a different demographic of labour as less fit or new workers to harvest more apples, while it may improve the efficiency of workers and make it physically less demanding, taking into account health and safety measures, and still generate a net return comparable to the case of using a manual harvesting system. It should be noted that platform can either be a final or interim step depending on various factors such as the final cost, labour availability and grower's decision. The grower may decide not to fully utilise robots but they may want to use it in combination with other alternatives such as ladder or/and platform.

Robot adoption depends on various interconnected factors including varietal, robot, and labour. From a varietal perspective, the potential benefit of robotic apple harvester can be improved if it is used to harvest an orchard planted with a relatively high yield and value variety such as Envy, as growers could better balance out the relative cost of robot harvesting and return on their capital investment. However, it should be noted that many premium or popular apple varieties exist because of consumer demands. Therefore, it is uncertain whether in long term Envy will remain a higher price variety to Jazz or Roya Gala, because consumer preferences change all the time as it has been a similar case with Braeburn given it is increasingly being replaced with newer and more demanding cultivars like Envy (PipfruitNZ, 2017; NZAPI, 2019).

From a labour perspective, labour availability and efficiency can play a more significant role than wages in making the adoption decision more appealing for growers. If labours are not readily available and it is uncertain whether growers can still source unskilled labour to be trained and how efficiently they can pick apples, then growers may be more willing to adopt robots.

From the robot perspective, an increase in production and net returns can be achieved as was shown in section 6.9, with the possibility of robot harvest fruit 24 hours a day that increase the profitability of orchard and making lower values and yielding varieties with robot more profitable compared to daylight operation. In addition, it is important that the robot can operate faster but not necessarily as more efficient to alter the labour to capital strategically while picking as much fruit as possible within the limited harvesting window and generate the highest possible net returns. Moreover, it is also important how affordable robot is in terms of ownership and operation cost for potential adopters. However, at the current development stage and costs associated with purchasing and operating the robot, it is expected that the robots will likely be adopted by larger growers, while smaller or those growers not financially stable likely will fail to benefit from using the robots. Therefore, making the robots available to growers as a co-operative or contract-harvesting business model will likely be the best solution for growers in the industry to benefit from.

Besides the economic factors, robotic harvesters have the potential to be considered as a solution for non-economic factors such as food safety issues. This is more apparent in the post-Covid-19 pandemic era, which has not only made it more difficult for growers to source their required workers due to border closures, but also has led consumers to be more cautious about food safety when they make purchase decisions and prefer to have their fresh fruit touchless from farm to plate. This may not be a problem for packhouses as most are automated, but it may be an issue for harvesting operations because pickers have to pick apples by hand. Even though robots cannot be the only option for growers to rely on for the foreseeable future as they are not commercially available, in the current situation robot harvesting may be the most ideal solution.

References

Aitken, A. G., and Hewett, E. W. (2017). New Zealand Horticulture Freshfact. *The New Zealand Institute for Plant and Food Research Ltd.*

Aitken, A. G., Kerr, J. P., Hewett, E. W., and Hale, C. N. (2004). Growingfuture: Advanced orchard systems lead to top yields for New Zealand apples. *Martech Consulting Group*, 1–7.

Aizstrauta, D., Ginters, E., and Eroles, M. A. P. (2015). Applying theory of diffusion of innovations to evaluate technology acceptance and sustainability. *Procedia Computer Science*, 43(C), 69–77. https://doi.org/10.1016/j.procs.2014.12.010

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2), 179–211. https://doi.org/https://doi.org/10.1016/0749-5978(91)90020-T

Alder, G. (2019). Fruit tree for a year-round harvest in southern California. Retrieved on 4 Nov, 2020, from https://gregalder.com/yardposts/fruit-trees-for-a-year-round-harvest-in-southern-california/

Allen, S. (2017). Four modern milking Parlor designs. Retrieved on 7 Feb, 2020, from https://www.dairydiscoveryzone.com/blog/4-modern-milking-parlor-designs

Anderson, R. C., and Weersink, A. (2014). A Real Options Approach for the Investment Decisions of a Farm-Based Anaerobic Digester. *Canadian Journal of Agricultural Economics*, 62(1), 69–87. https://doi.org/10.1111/cjag.12019

APAL (Apples and Pears Australia Ltd.). (2012). Training systems. Apple and Pears Australia Ltd. Retrieved on 26 Aug, 2018, from http://apal.org.au/industry-info/intensive-pear-production/training-systems/

Arad, B., Balendonck, J., Barth, R., Ben-Shahar, O., Edan, Yael., Hellström, T., Hemming, J., Kurster, P., Ringdahl, O., Tielen, T., and van Tuijl, B (2020). Development of a sweet pepper harvesting robot. *Journal of Field Robotics*. 1– 13. https://doi.org/10.1002/rob.21937

Arts, J., Frambach, R. T. and Bijmolt, T. (2011). Generalizations on consumer innovation adoption: A meta-analysis on drivers of intention and behavior. *International Journal of Research in Marketing*, 28(2), 134–144.

Arya, P., Kumar, G., Acharya, V., and Singh, A. K. (2014). Genome wide identification and expression analysis of NBS-encoding genes in Malus x domestica and expansion of NBS gene family in Rosaceae. *Public Library of Science*, 9:e107987

ASA (Aotearoa Science Agency). (2019). New Zealand apple industry under threat from climate change. Retrieved on 8 Oct, 2020, from https://www.stuff.co.nz/business/farming/110420710/new-zealand-apple-industry-under-threat-from-climate-change.

Ashton, A. (2018). Fruit-picking labour shortage declared in Hawke's Bay. Retrieved on Feb 7, 2020, from http://www2.nzherald.co.nz/thecountry/horticulture/news/article.cfm?c_id=227andobjectid=12011672

Askew, K. (2020). We are in the middle of a food safety technological revolution': Tetra Pak talks the future of food safety. Retrieved on 10 Dec, 2020, from https://www.foodnavigator.com/Article/2020/08/19/We-are-in-the-middle-of-a-food-safety-technological-revolution-Tetra-Pak-talks-the-future-of-food-safety

Askin. D and Askin. V. (2018). *Financial Budget Manual*. V40. Faculty of Agribusiness and Commerce, Lincoln University, New Zealand.

Baerenklau, K. A., and Knapp, K. C. (2007). Dynamics of Agricultural Technology Adoption: Age Structure, Reversibility, and Uncertainty. *American Journal of Agricultural Economics*, 89 (1), 190–201. Retrieved from http://www.jstor.org/stable/4123572

Baeten, J., Donné, K., Boedrij, S., Beckers, W., and Claesen, E. (2007). Autonomous Fruit Picking Machine: A Robotic Apple Harvester. *Field and Service Robotics*. Results of the 6th International Conference, 531–539. https://doi.org/10.1007/978-3-540-75404-6_51

Barden J. A., and Neilsen G.H. (2003). Selecting the orchard site, site preparation and orchard planning and establishment. Chapter 11. *In Apples: Botany Production and Uses*. Ferree D.C. & Warrington I.J. (eds), CAB International.

Barker, M. (2020). UK to host 'world first' robotic fruit farm. Retrieved on 09, Sept, 2020, from http://www.fruitnet.com/fpj/article/182698/uk-to-host-world-first-robotic-fruit-farm

Barden, J. A., and Neilsen, G. H. (2003). Selecting the orhcard site, site preparation and orchard planning and establishment. In F. D. Curtis and I. J. Warrington (Eds.), *Apples, botany, production and uses* (pp. 237-265). Wallingford, UK: CAB International.

Barritt, B. H., and Van Dalfsen, K. B. (1992). *Intensive Orchard Management: A Practical Guide to the Planning, Establishment, and Management of High Density Apple Orchards*. 1st Edition. Good Fruit Growers. Iowa City, IA, U.S.A.

Bartlett, H. (2018). Nelson growers in a pickle due to shortage of fruit pickers. Retrieved on 7 Feb, 2020, from www.stuff.co.nz/business/102476589/nelson-growers-in-a-pickle-due-to-shortage-of-fruit-pickers

Baugher T, Schupp J, Lesser K. Harsh R M, Lewis K, Seavert C, Auvil, T. (2009). Mobile platforms increase orchard management efficiency and profitability. *Acta Horticulturae*, 824: 361–364.

Baumes, H. S., and Conway, R. K. (1985). An Econometric Model of the U.S. Apple Market. Washington D.C. United States Department of Agriculture, *Economic Research Service*.

Bechar, A., and Vigneault, C. (2016). Agricultural robots for field operations: Concepts and components. *Biosystems Engineering*,149, 94–111.

Bedford, C. (2020). New Zealand's seasonal labour shortage, and how to solve it. Retrieved on 8 Oct, 2020, from https://devpolicy.org/new-zealands-seasonal-labour-shortage-and-how-to-solve-it-20201002.

Bellemare, M. F., and Bloem, J. R. (2018). Does contract farming improve welfare? A review. *World Development*. 112, 259–271.

Bellemare, M. F., and Lim, S. (2018). In all shapes and colours: Varieties of contract farming. *Applied Economics Perspective Policy*. 40, 379–401.

Berry, R. (1972). Break-Even Analysis: A Practical Tool in Farm Management. *American Journal of Agricultural Economics*, 54(1), 121-125. doi:10.2307/1237743

Black, F., and Scholes, M. (1973). The Pricing of Options and Corporate Liabilities. *Journal of Political Economy*, 81(3), 637–654. https://doi.org/10.1086/260062

Black. E, and Kolodny, L. (2019). This robot can pick tomatoes without bruising them and detect ripeness better than humans. Cnbc. Retrieved on 11 May, 2019, from https://www.cnbc.com/2019/05/11/root-ai-unveils-its-tomato-picking-robot-virgo.html.

Blanpied, G.D., and Silsby, K. (1992). Predicting Harvest Date Windows for Apples. Information bulletin 221. *A Cornell Cooperative Extension Publication*.

Block. S. (2007). Are "Real Options" Actually Used in the Real World? *The Engineering Economist*, 52:3, 255-267, DOI: 10.1080/00137910701503910

Bogue, R. (2020). Fruit picking robots: has their time come?. *The International Journal of Robotics Research and Application*. 141–145, DOI 10.1108/IR-11-2019-0243. 47/2 (2020) 141–145

Bonnet, G. (2020). Covid 19 coronavirus - New Zealand's historic border closure six months on. Retrieved on 29 Dec, 2020, from https://www.nzherald.co.nz/nz/covid-19-coronavirus-new-zealands-historic-border-closure-six-months-on/NBQZVTXVR5TXWSBXF5CEQPKDL4/

Boudichevskaia, A., Kumar, G., Sharma, Y., Kapoor, R., Singh, A. K. (2020). Challenges and strategies for developing climate-smart apple varieties through genomic approaches. *Genomic Designing of Climate-Smart Fruit Crops*, pp 23-71, https://doi-org.ezproxy.massey.ac.nz/10.1007/978-3-319-97946-5_2

Brakenrig, M. (1994). Adoption of Automatic Milking Technologies. Retrieved on 7 Feb, 2020, from http://dspace.lincoln.ac.nz/handle/10182/6421

Briscoe, T. (2019). Robotic apple picker under close scrutiny as world-first commercial harvest underway in New Zealand. Retrieved on 1 Nov, 2020, from https://www.abc.net.au/news/rural/2019-04-02/eyes-fixed-firmly-on-first-commercial-robotic-apple-harvest/10962880

Brower, M., and Scofield, S. (2008). Preventing Harvest Injuries. *The New York Centre for Agricultural Medicine and Health (NYCAMH).*

Brown, S.K.; Maloney, K.E. (2009). Making Sense of New Apple Varieties, Trademarks, and Clubs. New York Fruit Quarterly. 17 (3): 9–12.

Burks, T., Bulanon, D., and Metha, S. (2018). Opportunity of Robotics in Precision Horticulture. In *Agricultural Automation: Fundamentals and Practices*, (Editors: Qin Zhang, Francis J. Pierce). CRC Press.

Bulanon D. M., and T. Kataoka. Fruit detection system and an end effector for robotic harvesting of Fuji apples. *Agricultural Engineering International*: CIGR Journal, 2010, 12(1): 203-210.

Burks, T., Bulanon, D., Suk You, K., Ni, Z., and Sundararajan, A. (2013). Orchard and Vineyard Production Automation. In *Agricultural Automation: Fundamentals and Practices*, (Editors: Qin Zhang, Francis J. Pierce). CRC Press.

Burry, M. (2020). Coronavirus: Further strain on fruit picking labour shortages. Retrieved on 4 Sept, 2020, from https://www.rnz.co.nz/news/country/411844/coronavirus-further-strain-on-fruit-picking-labour-shortages.

Bursac, P. (2013). How to Improve Apple Colour? Retrieved on 20 Nov, 2020, from https://www.fgv.com.au/grower-services/latest-updates/technical-articles/403-how-to-improve-fruit-color

Busdieker-Jesse, N. L., Nogueira, L., Onal, H., and Bullock, D. S. (2016). The economic impact of new technology adoption on the U.S. apple industry. *Journal of Agricultural and Resource Economics*, 41(3):549–569

Byard, R. W. (2017). Farming deaths – An ongoing problem. *Forensic Science, Medicine, and Pathology*, 13(1), 1–3. https://doi.org/10.1007/s12024-017-9839-8

Cahn, M.B., Stevens, R.B., and van de Klundert, A. C. A. (1997). Economic outcomes of early cropping and tree decisions in Braeburn apples on Malling 9 rootstock. *Acta Horticulturae*, 551–558.

Calvin, L., and Martin, P. (2010). The U.S. Produce Industry and Labour Facing the Future in a Global Economy. Economic Research Report Number 106. *Economic Research Service. United States Department of Agriculture*.

Carbonell, I. (2016). The ethics of big data in big agriculture. *Internet Policy Review*, 5(1), 1–13. https://doi-org.ezproxy.massey.ac.nz/10.14763/2016.1.405

Carey, J. M., and Zilberman, D. (2002). A Model of Investment under Uncertainty: Modern Irrigation Technology and Emerging Markets in Water. *American Journal of Agricultural Economics*, 84(1), 171–183.

Cargill, B. F. (1983). Harvesting high density red tart cherries. In Proceedings of the International Symposium on Fruit, Nut and Vegetable Harvesting Mechanisation (pp. 195–200). *American Society of Agricultural Engineers*, St Joseph, Michigan.

Carrabba, J. (2005). Pruning Safety Tips. *The New York Centre for Agricultural Medicine and Health (NYCAMH).*

Carrabba, J. (2008). Reducing Repetitive Stress Injuries Related to Orchard Pruning. *The New York Centre for Agricultural Medicine and Health (NYCAMH).*

Carrabba, J. (n.d.). Make Safety a Priority This Harvest Season. *The New York Centre for Agricultural Medicine and Health (NYCAMH).*

Cassey, A. J., Lee, K., Sage, J., and Tozer, P. (2018). Assessing the Impact of a Labor Shortage on Post-Harvest Activities and Markets. *Agricultural and Food Economics*. 6. 10.1186/s40100-018-0112-6.

Catalá, L. P., Durand, G. A., Blanco, A. M., and Bandoni, J. A. (2013). Mathematical model for strategic planning optimisation in the pome fruit industry. *Agricultural Systems,* 115, 63–71. https://doi.org/10.1016/j.agsy.2012.09.010

Catalá, L. P., Moreno, M. S., Blanco, A. M., and Bandoni, J. A. (2016). A bi-objective optimisation model for tactical planning in the pome fruit industry supply chain. *Computers and Electronics in Agriculture*, 130, 128–141. https://doi.org/10.1016/j.compag.2016.10.008

Chapman, M. (2020). Automation will not save New Zealand. Retrieved on 5 Dec, 2020, from https://www.hortnz.co.nz/news-events-and-media/mikes-blog/automation-will-not-save-new-zealand.

Charles, Dan (2014). Want to Grow These Apples? You'll Have to Join the Club. The Salt. Retrieved on 15 May, 2021, from https://www.npr.org/sections/thesalt/2014/11/10/358530280/want-to-grow-these-apples-youll-have-to-join-the-club

Childs, R A., Milligan, R. A., White, G. B., and Stiles, W. C. (1983). *A Dynamic Programming Approach to Apple Orchard Replacement* (Res. 83–11.). Cornell University.

Chumko, A. (2019). World-first robotic apple picker could curb seasonal labour shortage. Retrieved on 9 Feb, 2020, from https://www.stuff.co.nz/business/farming/agribusiness/111545853/worldfirst-robotic-apple-picker-could-curb-seasonal-labour-shortage

Cittadini, E. D., Lubbers, M. T. M. H., de Ridder, N., van Keulen, H., and Claassen, G. D. H. (2008). Exploring options for farm-level strategic and tactical decision-making in fruit production systems of South Patagonia, Argentina. *Agricultural Systems*, 98(3), 189–198. https://doi.org/10.1016/j.agsy.2008.07.001

Clarke, A. (2017). Robotics set to increase farm productivity. *Farmers Weekly,* 1160, 72–73

Close, D. C., and Bound, S. A. (2017). Advances in understanding apple tree growth: The manipulation of tre growth and development. In K. Evans (Ed.), *Achieving sustainble cultivation of apples*: Burleigh Dodds Source Publishing Limited.

Clothier, B. (2018). Many ways for our crop growers to adapt to climate change. Retrieved on 8 Oct, 2020, from https://www.stuff.co.nz/the-press/opinion/107731637/many-ways-for-our-crop-growers-to-adapt-to-climate-change?rm=a.

Clothier, B., Hall, A., and Green, S. (July 2012). Adapting the horticultural and vegetable industries to climate change. In: Impacts of climate change on land-based sectors and adaptation options. *Ministry for Primary Industries*, New Zealand.

Coriolis. (2006). Overview of the New Zealand Apple Industry in a Global Context. Pipfruit New Zealand. 1–31. Coriolis Research Ltd. Retrieved from https://coriolisresearch.com/pdfs/coriolis_nz_pipfruit_overview.pdf

D'Esnon, A. G., Rabatel, G., Pellenc, R., Journeau, A., and Aldon, M. J. (1987). Magali: a self-propelled robot to pick apples. *American Society of Agricultural Engineers* (USA).

DairyNZ (Dairy New Zealand). (2020). Following a thorough due-diligence process (doing your homework) is key to establishing a successful sharemilking or contract milking relationship. Retrieved on 1 Nov, 2020, from https://www.dairynz.co.nz/business/setting-up-for-success/do-your-homework/sharemilking-and-contract-milking-arrangements

Daly, M. (2019). 2018 warmest year on record for New Zealand, says climate scientist. Retrieved on 8 Oct, 2020, from https://www.stuff.co.nz/national/109707579/2018-warmest-year-on-record-for-new-zealand-says-climate-scientist?rm=a.

Damos P, Colomar L. A, and Ioriatti C. (2015). Integrated Fruit Production and Pest Management in Europe: The Apple Case Study and How Far We Are From the Original Concept? *Insects*. 6(3): 626-57. https://doi.org/10.3390/insects6030626

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *Management Information Systems Quarterly*, 13(3), 319–3440.

Davis, F. D., Bagozzi, R. P., and Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, 35, 982–1002.

Davis, J., and Thiele, G. F. (1981). Simulation modelling for orchard management. *Agricultural Systems*, 7(1), 21–36. https://doi.org/10.1016/0308-521X(81)90026-3

De George, R. T. (2003). *The Ethics of Information Technology and Business*. Blackwell Publishing. The UK.

de Koning, K., and Rodenburg, J. (2004). *Automatic milking: State of the art in Europe and North America. In a Better Understanding of Automatic Milking*. Ed. A. Meijerling, H. Hogeveen, and C.J.A.M. De Koning, 27–37. Wageningen: Wageningen Academic Publishers.

Dekoning, K., Vandervorst, Y., and Meijering, A. (2002). Automatic Milking Experience and Development in Europe. *North American Conference on Robotic Milking*. Toronto, Canada.

DeLaval. (n.d.). Automatic milking platforms. Retrieved on Feb 07, 2019, from https://www.delaval.com/en-au/our-solutions/milking/parlours.

Devadoss, S., and Luckstead, J. (2010). An analysis of apple supply response. *International Journal of Production Economics*, 124(1), 265–271. https://doi.org/10.1016/j.ijpe.2009.11.024

Dickens, W., Lorenz, G., Groshen, E. L., Holden, S., Messina, J., Schweitzer, M. E., Turunen, J., and Ward, M. E. (2007). How Wages Change: Micro Evidence from the International Wage Flexibility Project. *Journal of Economic Perspectives*, 21 (2): 195-214.

Dijkhuizen, A. A., Huirne, R. B. M., Harsh, S. B., and Gardner. R.W. (1997). Economics of robot application, *Computers and Electronics in Agriculture*, 17 (1), 111-121. https://doi.org/10.1016/S0168-1699(96)01228-8.

Dininny, S., and Mullinax, TJ. (2016). Creators of vacuum harvester aim to have machines ready in 2018. Retrieved 9 February 2020, from https://www.goodfruit.com/creators-of-vacuum-harvester-aim-to-have-machines-ready-in-2018/

Dixit, A. K., and Pindyck, R. S. (1994). *Investment under Uncertainty*. Princeton University Press. Princeton, New Jersey.

DOL (Department of Labour). (2010). Final Evaluation report of the Recognised Seasnal Employer policy (2007-2009). Department of Labour. Wellington.

Earle-Richardson, G. B., Jenkins, D.S., Strogzta, E.M. Bell, May, J.J. (2006). Development and intial assessment of objective fatigue measures for apple harvest work. *Applied Ergonomics, 37(6):719-27*.

Eddy, D. (2018). Change is Coming to the Fruit Industry: Mechanisation is Taking Shape. *Growingproduce*. Retrieved on 10 Aug, 2020, from www.growingproduce.com/fruits/change-coming-mechanisation-taking-shape.

Edwards. W. (2015). Estimating Farm Machinery Costs, *Ag Decision Maker*. Iowa State University Extension and Outreach, file A3-29, 1-11.

Elkins, R.B., J.M. Meyers, V. Duraj, J.A. Miles, D.J. Tejeda, E.J. Mitcham, W.V. Biasi, L., and Asín, J. A. (2011). Comparison of platform versus ladders for harvest in northern california Pear Orchard. *Acta Horticulturae,* 241–249. https://doi.org/10.17660/ActaHortic.2011.909.26

Else, M., and Atkinson, C. (2010) Climate change impacts on UK top and soft fruit production. *Outlook Agri*. 39:257–262

Engel, P. D., and Hyde, J. (2003). A Real Options Analysis of Automatic Milking Systems. *Agricultural and Resource Economics Review*, *32*(2), 282–294.

Fang, S., Qi, Y., Han, G., Li, QX., and Zhou, GS. (2016). Changing trends and abrupt features of extreme temperature in mainland China from 1960 to 2010. *Earth Syst Dynam Diss*. 6:979–1000

Farzin, Y. H., Huisman, K. J. M., and Kort, P. M. (1998). Optimal timing of technology adoption. *Journal of Economic Dynamics and Control*, 22(5), 779–799. https://doi.org/10.1016/S0165-1889(97)00097-3

Fedaeff, N. (2017). Hawke's Bay climate change projections. Landcare Research New Zealand Limited.

Fern Ridge Fresh. (2016). Packing Specifications. Hawkes Bay, New Zealand.

Feuz, R., and Larsen, R. (2020). Even Robots Need a House: The Robotic Milking System Facility Investment Decision Case Study. Applied Economic Teaching Resources. 2. 32-40. Agricultural and Applied Economics Association (AAEA).

Finger, N. (2017). What will the 'future orchard' look like? Retrieved Aug 26, 2018, from http://apal.org.au/will-future-orchard-look-like/

Fiske, T. (2010). Worker Input Results in New Improved Apple Belt. *The New York Centre for Agricultural Medicine and Health (NYCAMH).*

Flaws, B. (2020). Is pay the problem? How much in-demand orchard workers really earn. Retrieved on 20 May, 2021 from https://www.stuff.co.nz/business/farming/122835805/is-pay-the-problem-how-much-indemand-orchard-workers-really-earn

Fleming, A., Jakku, E., Lim-Camacho, L., Taylor, B., and Thorburn, P. (2018). Is big data for big farming or for everyone? Perceptions in the Australian grains industry. *Agronomy for Sustainable Development*, 38(24), 1–10

Flett, R., Alpass, F., Humphries, S., Massey, C., Morriss, S., and Long, N. (2004). The technology acceptance model and use of technology in New Zealand dairy farming. *Agricultural Systems*, 80(2), 199–211. https://doi.org/https://doi.org/10.1016/j.agsy.2003.08.002

Fragar, L., and Franklin, R. (2000). The health and safety of Australia's farming community. Retrieved 9 Aug, 2018, from https://sydney.edu.au/medicine/aghealth/uploaded/Research%20Reports/health_safety_aus_farming_community_2000.pdf.

French, B. C., and Bressler, R. G. (1962). The Lemon Cycle. *Journal of Farm Economics*, 44(4), 1021. https://doi.org/10.2307/1235524

French, B. C., and Matthews, J. L. (1971). A Supply Response Model for Perennial Crops. *American Journal of Agricultural Economics*, 53(3), 478–490. https://doi.org/10.2307/1238225

French, B. C., King, A. G., and Minami, D. D. (1985). Planting and removal relationships for perennial crops: an application to cling peaches. *American Journal of Agricultural Economics*, 67(2), 215–223. https://doi.org/10.2307/1240672

Freshfacts. (2018). Fresh Facts Data Tool. Retrieved 10 Feb, 2018, from www.freshfacts.co.nz/#data-tool

Friesen, W. (2018). Beyond the RSE: Systems of pacific labour migration to New Zealand. *New Zealand Population Review*, 44, 111–129.

Frykberg, E. (2020). Horticultural labour shortage could mean food shortage, industry warns. Retrieved on 4 Sept, 2020, from https://www.rnz.co.nz/news/country/415782/horticultural-labour-shortage-could-mean-food-shortage-industry-warns.

Fyfe, J. (2020). New plan aims to help agritech sector grow. Retrieved on 1 Nov, 2020, from https://www.newshub.co.nz/home/rural/2020/07/new-plan-aims-to-help-agritech-sector-grow.html

GA (Government of Australia). (n.d.). Fair Work OMBUDSMAN, Horticulture Showcase: Hours of work and overtime. Retrieved July 23, 2020, from www.fairwork.gov.au/horticulture-showcase/hours-of-work-overtime

Gallardo, R. K., and Brady, M. P. (2015). Adoption of labor-enhancing technologies by specialty crop producers: The case of the Washington apple industry. *Agricultural Finance Review*, 75(4), 514–532. https://doi.org/10.1108/AFR-05-2015-0022

Gallardo, R. K., and Zilberman, D. (2016). The economic feasibility of adopting mechanical harvesters by the highbush blueberry industry. *HortTechnology,* 26. 299-308. https://doi.org/10.21273/HORTTECH.26.3.299

Gallardo, R. K., and Zilberman, D. (2017). The Economics of Perennial Crops' Production Automation. In *Automation in Tree Fruit Production: Principles and Practice* (ed. Q. Zhang). CAB International. Boston.

Gao, H., and Cai, J., and Liu, X. (2009). Automatic Grading of the Post-Harvest Fruit: A Review. *International Federation for Information Processing*. 317. 141-146. 10.1007/978-3-642-12220-0_22.

Gautam, HR., Bhardwaj, ML., and Kumar, R. (2013). Climate change and its impact on plant diseases. *Current* Science. 105:1685–1691.

German, H. (2015). *Agricultural Finance: From Crops to Land, Water and Infrastructure*. 1st Edition. The Wiley. United Kingdom.

Giles, F. (2018). Get in Gear Now for Agriculture's Robotic Revolution. Growingproduce. Retrieved on 11 Apr, 2018, from https://www.growingproduce.com/fruit/get-in-gear-now-for-agricultures-robotic-revolution.

Girona, J., Mata, M., del Campo, J., Arbonés, A., Barta, E., Marsal, J. (2006). The use of midday leaf water potential for scheduling deficit irrigation in vineyards. *Irrigation Science*. 24: 115–127.

Globalpetrolprice. (2020). New Zealand Diesel prices. Retrieved March 16, 2020, from Globalpetrolprice: https://www.globalpetrolprices.com/New-Zealand/diesel_prices/

Gold, A., and Staples, M. (2012). Mckinsey on cooperatives. Mckinsey & Company.

Grant, A. (2020). Tips For Harvesting Apples And Post Harvest Apple Storing. McKinsey & Company. New York. Retrieved on 2 Nov, 2020, from https://www.gardeningknowhow.com/edible/fruits/apples/harvesting-and-storing-apples.htm

Grant, A. (2012). Five trends and their implications for agricultural coops. Mckinsey & Company. New York.

Grant, K., Gallardo, R. K., Brown, D., McFerson, J., Lewis, K., Einhorn, T., and Sazo, M. M. (2018). Report on the 2017 Apple Precision Agriculture Survey. *IMPACT Centre*, Washington State University.

Grimstad, L., Pham, C., Phan, T., and From, P. (2015). On the design of a low-cost, light-weight, and highly versatile agricultural robot. *IEEE International Workshop on Advanced Robotics and its Social Impacts*. 10.1109/ARSO.2015.7428210.

Groot, M. J. (1999). A decision support system for fruit crops for economic and ecological calculations. *Acta Horticulturae*, 171–174. https://doi.org/10.17660/ActaHortic.1999.499.19

Grosh, B. (1994). Contract farming in Africa: An application of the new institutional economics. *Journal of African Economics*. 3, 231–261.

Gray, J. (2016). Golden apple industry on its way to $1 billion target. Retrieved on 16 May, 2021, from https://www.nzherald.co.nz/business/golden-apple-industry-on-its-way-to-1-billion-target/VWUL5VF25UWYRSAD3UV2AEJESQ/

Gupta, B. (2012). Training Systems in Intensive Apple Cultivation: Slender Spindle. Retrieved on 26 Aug, 2018, from http://www.farmerclub.org/2012/08/training-systems-in-intensive-apple.html.

Gutierrez, P. H., and Dalsted, N. L. (2012). Break-Even method of investment analysis. *Colorado State University Extension*. Farm and Ranch Series, No. 3.759.

Haley, S., Currans, K. G., and Croft, B. A. (1990). A computer aid for decision making in apple pest management. *Acta Horticulturae*, (276), 27–34. https://doi.org/10.17660/ActaHortic.1990.276.3

Hansen, M. (2011). Fruiting walls suit machinery. Retrieved on 10 Dec, 2020, form https://www.goodfruit.com/fruiting-walls-suit-machinery/

Hardie, A., (2020). New platforms for apples. *The Orchardist*. March 2020. New Zealand.

Harding, R. (2018): Moteo apple orchards show the way of the future. Retrieved July 17, 2020, from https://www.nzherald.co.nz/thecountry/news/article.cfm?c_id=16&objectid=12057889.

Hemmes, M. (2020). Cecilia Flores Paez on the success of Envy: We are very fortunate to have such a great apple variety. Retrieved on 10 Dec, 2020, from https://www.freshplaza.com/article/9260254/we-are-very-fortunate-to-have-such-a-great-apple-variety/

Hester, S. M., and Cacho, O. (2003). Modelling apple orchard systems. *Agricultural Systems*, 77(2), 137–154. https://doi.org/10.1016/S0308-521X(02)00106-3

Heyes, J. (2019). Climate Explained: How climate change will affect food production and security. Retrieved on 10 Dec, 2020, from https://www.stuff.co.nz/environment/climate-news/117899905/climate-explained-how-climate-change-will-affect-food-production-and-security

Hill, R. (2020). Coronavirus: Horticulture looks to forestry to solve labour shortage. Retrieved on 4 Sept, 2020, from https://www.nzherald.co.nz/business/news/article.cfm?c_id=3andobjectid=12317092

Hillier, F. S., and Lieberman, G. J. (2005). *Introduction to Operations Research* (8th edition). McGraw-Hill.

Hoang, M. (2018). Red Delicious No Longer King As Yakima Valley Embraces Apple Diversity. Retrieved Sep 11, 2018, from www.yakimaherald.com/news/business/regional/red-delicious-no-longer-king-as-yakima-valley-embraces-apple/article_9642bed6-b3ee-11e8-bb6f-fb0cb2757052.html

Hogeveen, H., Ouweltjes, W., de Koning, C. J. A. ., and Stelwagen, K. (2001). Milking interval, milk production and milk flow-rate in an automatic milking system. *Livestock Production Science*, 72, 157–167.

Hooker, L. (2018). The strawberry-picking robots doing a job human won't. Retrieved on 26 Aug, 2018, from https://www.bbc.com/news/business-43816207.

Horrigan, L., Lawrence, R. S., and Walker, P. (2002). How sustainable agriculture can address the environmental and human health harms of industrial agriculture. *Environmental Health Perspectives*, 110 (5), 445–456.

Hornblower, C. (2016). Improving harvest efficiencies with picking platforms. *Future Hort Technology*, 27(2), 240-247.

HortNZ (Horticulture New Zealand). (2020). Horticulture post-Covid recovery strategy: An industry led Government enabled partnership for the future. New Zealand.

HortNZ (Horticulture NZ). (2019). Seasonal employment agreement for horticulture worker. Retrieved July 23, 2020, from www.hortnz.co.nz/assets/Uploads/Employment-Agreement-Fillable-Form-Notes-Inc-Jul-19.pdf

Huffman, W.E. (2012). "The Status of Labor-saving Mechanisation in U.S. Fruit and Vegetable Harvesting". *Choices*. Q2. http://choicesmagazine.org/choices-magazine/theme-articles/immigration-and-agriculture/the-status-of-labor-saving-mechanisation-in-us-fruit-and-vegetable-harvesting

Hughes, J. (2018a). Apple growing systems are evolving. *The Orchardist*, 5.

Hughes, J. (2018b). Considering Future Orchard Production Systems. *Fruition Horticulture*. Retrieved from www.fruition.net.nz/2016/05/resource-title-2/

Hughes, J. (2020). Apple growing systems – running hot. *The Orchardist*. Retrieved on 16 Oct 2020, from https://www.pressreader.com/new-zealand/the-orchardist/20200301/281599537536616.

Hyde, J., and Engel, P. (2002). Investing in a Robotic Milking System: A Monte Carlo Simulation Analysis. *Journal of Dairy Science*, 85(9), 2207–2214.

Hyde, J., Dunn, J. W., Steward, A., and Hollabaugh, E. R. (2007). Robots don't get sick or get paid overtime, but are they a profitable option for milking cows? *Review of Agricultural Economics*, 29(2), 366–380. https://doi.org/10.1111/j.1467-9353.2007.00348.x

Hyde, J., Stokes, J. and D. Engel, P. (2003). Optimal Investment in an Automatic Milking System: An Application of Real Options. *Agricultural Finance Review*. 63. 75-92. 10.1108/00215010380001142.

Hydralada. (n.d.). The Nblosi Quad Lift platform. Retrieved on 26 Aug, 2018, from https://www.hydralada.com/nz/products/horticulture/nblosi.

Hydralada. (2018). Hydralada offer a complete harvesting system. Retrieved on 16 May, 2021, from https://blog.hydralada.com/quadlift-orchard-platform

Isaacs, L. K., Bean, T. L. (1995). An overview of the Ohio migrant farmworker safety needs assessment. *Journal of Agricultural Safety and Health* 1(4): 261-272. doi: 10.13031/2013.19468.

Isik, M. (2006). Implications of alternative stochastic processes for investment in agricultural technologies. *Applied Economics Letters*, 13(1), 21–27. https://doi.org/10.1080/13504850500378205

Isik, M., Coble, K. H., Hudson, D., and House, L. O. (2003). A model of entry-exit decisions and capacity choice under demand uncertainty. *Agricultural Economics*, 28(3), 215–224. https://doi.org/10.1016/S0169-5150(03)00016-1

Jacobs, J. A., and Siegford, J. M. (2012). Invited review: The impact of automatic milking systems on dairy cow management, behavior, health, and welfare. *Journal of Dairy Science,* 95(5), 2227–2247.

Jangra, M. S., and Sharma, J. P. (2013). Climate resilient apple production in Kullu valley of Himachal Pradesh. *International Journal of Farm Sciences*. 3:91–98.

Jazzapple (2018). Jazz starts season with 'UK's tastiest apple' Triumph. Retrieved on 10 Dec, 2018, from https://jazzapple.com/uk/news/jazz-starts-season-with-uks-tastiest-apple- triumph.

Jiang, H., Wang, Wei., and Li, C. (2017). Innovation, practical benefits and prospects for the future development of automatic milking systems. *Frontiers of Agricultural Science and Engineering*. 4. 37-47. 10.15302/J-FASE-2016117.

Johnson, D. G. (2015). Technology with no human responsibility? *Journal of Business Ethics*, 127(4), 707–715

Jones, M. (2016). Installation for Washington Fruit Company. Retrieved on 3 Dec, 2020, from http://www.fruitnet.com/asiafruit/article/161379/installation-for-washington-fruit-company

Jones, M. (2020). Record campaign for New Zealand apples and pears. Retrieved on 13 Oct, 2020, from http://www.fruitnet.com/asiafruit/article/182567/record-campaign-for-nz-apples-and-pears.

Jones, M. (2014). Apple Futures II programme launched in New Zealand. Retreived on 16 May, 2021, from http://www.fruitnet.com/asiafruit/article/163443/apple-futures-ii-programme-launched-in-nz

Jones, J.W., M, J., B. A.B., Boote, K.J., Conant, R.T., Foster, I., Godfray, H.C., Herrero, M., Howitt, R.E., Janssen, S., Keating, B. A., Munoz-Carpena, R., Porter, C. H., Rosenzweig, C., and Wheeler, T.R. (2017). Toward a new generation of agricultural system data, models, and knowledge products: State of agricultural systems science, *Agricultural Systems*, Vol. 155, Pages 269-288, ISSN 0308-521X, https://doi.org/10.1016/j.agsy.2016.09.021.

Karkee, M., Silwal, A., and Davidson, J. R. (2018). Mechanical harvest and in-field handling of tree fruit crops. In *Automation in Tree Fruit Production: Principles and Practice* (ed. Q. Zhang). CAB International. Boston.

Kay, R. D., Edwards, W. M. M., and Duffy, P.A. (2016). *Farm Mangement*. 8th Edition. The McGraw-Hill Companies.

Kenny, G. (2001). Climate Change: Likely Impacts on New Zealand Agriculture. A report prepared for the Ministry for the Environment as part of the New Zealand Climate Change Programme. Earthwise Consulting Ltd. Hastings.

Key, N., and Runsten, D. (1999). Contract farming, smallholders, and rural development in Latin America: The organization of agroprocessing firms and the scale of out grower production. *World Development*. 27, 381–401.

Key, N. (2019). Farm size and productivity growth in the United States Corn Belt. *Food Policy*, 84, 186–195.

King, A. (2017). Technology: The future of agriculture. *Nature*, 544, S21–S23.

Kilgour, M., Saunders, C., Scrimgeour, F., and Zellman, E. (2007). New Zealand Agribusiness: Structure, Conduct and Performance: Kiwifruit: The key elements of success and failure in the New Zealand kiwifruit industry. Agribusiness Research and Education Network, New Zealand.

Kondo, N., and K., Kawamura. (2013). Postharvest Automation, *Agricultural Automation: Fundamentals and Practices,* CRC Press, edited by Qin Zhang and Francis J. Pierce: 367-383(2013).

Koning, K. De. (2011). Automatic milking: Common practice on over 10,000 dairy farms worldwide. In *Dairy Research Foundation Symposium* (pp. 14–31).

Kotagama, H. B., Al-alawi, A. J. T., Boughanmi, H., Zekri, S., Jayasuriya, H., and Mbaga, M. (2013). Economic Analysis Determining the Optimal Replanting Age of Date Palm, *Journal of Agricultural and Marine Sciences*. Volume 1. 10.24200/jams.vol19iss0pp, 51-61.

Kumar, G., Arya, P., Gupta, K., Randhava, V., and Acharya, V., and Kumar Singh, A. (2016). Comparative phylogenetic analysis and transcriptional profiling of MADS-box gene family identified DAM and FLC-like genes in apple (Malus x domestica). *Scientific Reports*, 6:20695

Kupferman, E. (2006). Minimizing bruising in apples. Washington State University. Retrieved on 10 Dec, 2020, from https://www.goodfruit.com/minimizing-bruising-in-apples/

Lee-Jones, D. (May 2019). Fresh Deciduous Fruit Annual: New Zealand. Report No. NZ1907. *United States Department of Agriculture (USDA).*

Lee-Jones, D. (November 2019). Fresh Deciduous Fruit Annual: New Zealand. *United States Department of Agriculture (USDA).*

Legun, K. and Burch, K. (2021). Robot-ready: How apple producers are assembling in anticipation of new AI robotics. *Journal of Rural Studies*, 82, 380-390.

Lehnert, R. (2010). High density apple systems cost more. Retrieved on 26 Aug, 2018, from https://www.goodfruit.com/high-density-apple-systems-cost-more/

Lehnert, R. (2013). In-orchard sorting, a prototype machine divides apples into fresh, processing, and juice grades. *Good Fruit Grower* (November), 20–21. Retrieved on 10 Oct, 2020, from https://www.goodfruit.com/in-orchard-sorting/

Lehnert. L. (2012). Growers try the DBR vacuum apple harvester. Retrieved on 26 Aug, 2018, from https://www.goodfruit.com/growers-try-the-dbr-vacuum-apple-harvester.

Lely. (n.d.). Lely astronaut-a4 milking system. Retrieved from https://www.lely.com/solutions/milking/astronaut-a4/

Lewis, K. M. (2015). Labour management in modern orchards and opportunities for mechanisation. *Washington State University Extension*. Retreived from https://apal.org.au/wp-content/uploads/2019/09/Karen-Lewis-Future-Orchards-Mar-2015.pdf

Ley, Colin. (2019). Berry picking robot Hank could be perfectly timed for Brexit Britain. Retrieved on 11 June, 2019, from https://agfundernews.com/berry-picking-robot-hank-could-be-perfectly-timed-for-brexit-britain.html

Llewellyn, R. S. (2007). Information quality and effectiveness for more rapid adoption decisions by farmers. *Field Crops Research*, 104 (1–3), 148–156.

Lowenberg-DeBoer, J., Behrendt, K., Godwin, R., and Franklin, K. (2019). The impact of swarm robotics on arable farm size and structure in the UK. Paper presented to the 93rd Agricultural Economics Society Annual Conference. Coventry, UK.

Lowenberg-DeBoer, J., Huang, I. Y., Grigoriadis, V., and Blackmore, S. (2020). Economics of robots and automation in field crop production. *Precision Agriculture*, 21, 278–299

Luedeling, E. (2012). Climate change impacts on winter chill for temperate fruit and nut production: A review. *Scientia Horticulturae*, Volume 144, 218-229. https://doi.org/10.1016/j.scienta.2012.07.011

Lusk, J. (2016). *Unnaturally Delicious : How Science and Technology Are Serving up Super Foods to Save the World.* New York: St. Martin's Press.

Lyon, N. (2019). Lightweight robotic machines no magic cure for soil compaction. Retireved on 26 Oct, 2020, from www.graincentral.com/cropping/lightweight-robotic-machines-no-magic-cure-for-soil-compaction.

Mandel, R., Lawes, R., and Robertson, M. (2010). Farmer perspectives of precision agriculture in Western Australia: Issues and the way forward. Paper Presented at the *Australian Agronomy Conference*, Lincoln, New Zealand.

Mandow, N. (2020). An apple harvest no one will ever forget. Retrieved on 26 Oct, 2020, from https://www.newsroom.co.nz/2020/05/01/1150030/an-apple-harvest-no-one-will-ever-forget.

Mannering, R. (2015). Pipfruit productivity increase 50%. *The Orchardist*.

Mathijs, E. (2004). Socio-economic aspects of automatic milking. EU-program Quality of Life and Management of Living resources. European Commission.

McConnell, A. (2016). Swaping out tires for Camso tracks. Retieved on 7 December, 2020, from https://www.agriculture.com/machinery/tractors/swapping-out-tires-for-camso-tracks

McFerson, J. R. 2011. Tree fruit: Seeking a labor solution. Retrivecved on 03 Feb 2020, from http://www.growingproduce.com/uncategorized/tree-fruit-seeking-a-labor-solution.

McKay, L., and Rogers, M. (2018). T&G Trial Block in Hastings. Hastings. New Zealand.

Meemken, E., and Bellemare, M. (2019). Smallholder farmers and contract farming in developing countries. *Proceedings of the National Academy of Sciences of the United States of America*. 117. 10.1073/pnas.1909501116.

Meijering, A., and Hogeveen, H. (2004). *Automatic Milking: A Better Understanding.* Wageningen: Wageningen Academic Publication.

Melke, A. (2015). The physiology of chilling temperature requirements for dormancy release and bu-break in temperate fruit trees grown at mild winter tropical climate. *Journal of Pant Studies*, 4. doi:10.5539/jps.v4n2p110

Meskens, L., Vandermersch, M., and Mathijs, E. (2001). Implications of the introduction of automatic milking on dairy farms: Literature review on the determinants and implications of technology adoption. Department of Agricultural and Environmental Economics, Katholieke Universiteit Leuven, 43.

Meyerhoff, A. (2009). Work safely with orchard ladders. *The New York Centre for Agricultural Medicine and Health (NYCAMH).*

Meyerhoff, A. (2010). Reducing Repetitive Motion Injuries. *The New York Centre for Agricultural Medicine and Health (NYCAMH).*

Meyerhoff, A. (n.d.). Basic First Aid Tips for Orchard Worker Falls. *The New York Centre for Agricultural Medicine and Health (NYCAMH).*

MFE (Ministry for the Environment). (2020). Climate change projections for the Gisborne and Hawke's Bay region. Retrieved on 21 May, 2021, from https://environment.govt.nz/facts-and-science/climate-change/impacts-of-climate-change-per-region/projections-gisborne-hawkes-bay-region/#:~:text=Compared%20to%201995%2C%20temperatures%20are,temperatures%20exceed%2025%CB%9AC.

Miller., Z. (n.d.). Orchard design, *Western Ag Research Centre*. Montana State University. Retrieved 28 Sept, 2020, from https://agresearch.montana.edu/warc/guides/Orchard_Design.html#:~:text=The%20length%20of%20rows%20should,tree%20density%20and%20management%20system.

Milkovich, M. (2020). Harvester makes sort work in the orchard: Experimental machine capable of separating fresh, cull apples could reduce postharvest handling costs. Retrieved on 2, Dec, 2020, from https://www.goodfruit.com/harvester-makes-sort-work-in-the-orchard

Miller, S. A., Smith, G. S., Boldingh, H. L., Johansson, A. (1998). Effects of Water Stress on Fruit Quality Attributes of Kiwifruit. *Annals of Botany*. 81: 73–81.MIT (Massachusetts Institute of Technology Review). (2019). A robot apple-picker is now harvesting fruit in New Zealand orchards. Accessed on 122 May 2021.

Mizushima, A., and Lu, R. (2011). Cost benefits analysis of in-field presorting for the apple industry. *Applied Engineering in Agriculture*, 27(1): 33–40.

Moore, G., and Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research*, 2(3), 192–222.

Morgan, J. (2010). Deregulation would be bad for kiwifruit growers. Retrieved on 16 May, 2021, from https://www.stuff.co.nz/business/industries/3265212/Deregulation-would-be-bad-for-kiwifruit-growers

Moss, C. B. (2013). *Agricultural Finance*. 1st Edition. Routledge International. London

Mpelasoka, B.S., Behboudian, M. H., Mills, T. M. (2001). Effects of deficit irrigation on fruit maturity and quality of 'Braeburn' apple. *Scientia Horticulturae*. 90: 279–290.

MPI (Ministry for the Primary Industries). (2012). Orchard Monitoring Report: Pipfruit Orchard Models for Hawke's Bay and Nelson Regions. *Ministry for Primary Industries. Wellington.*

MPI (Ministry for Primary Industries). (December 2017). Situation and Outlook for Primary Industries. *Ministry for Primary Industries. Wellington.*

MPI (Ministry for the Primary Industries). (2018). Orchard Monitoring Report: Pipfruit Orchard Models for Hawke's Bay and Nelson Regions. *Ministry for Primary Industries. Wellington.*

MPI (Ministry for Primary Industries). (June 2018). Situation and Outlook for Primary Industries. *Ministry for Primary Industries. Wellington.*

MPI (Ministry for Primary Industries) (December 2019). Situation and Outlook for Primary Industries. *Ministry for Primary Industries. Wellington.*

MPI (Ministry for Primary Industries) (March 2020). *Situation and Outlook for Primary Industries*. *New Zealand Ministry for Primary Industries.* Wellington.

MSD (The Ministry of Social Development). (2019). Seasonal Labour Shortages in Hawke's Bay and Bay of Plenty. *The Ministry of Social Development. Wellington.* Retrieved from https://www.msd.govt.nz/about-msd-and-our-work/newsroom/2019/seasonal-labour-shortages-in-hawkes-bay-and-bay-of-plenty.html

Murdock, L. W., and James, J. (2008). Compaction, tillage method, and subsoiling effects on crop production. University of Kentucky, *Cooperative Extension Service Bulletin*: AGR-197.

Murison, M. (2017). Panasonic unveils autonomous tomato picker in Tokyo. Retrieved on 2 Jan, 2018, from https://internetofbusiness.com/panasonic-robot-tomato-picker.

Musacchi, S., and Serra, S. (2018). Apple fruit quality: Overview on pre-harvest factors. *Scientia Horticulturae*. 10.1016/j.scienta.2017.12.057.

Myers, C. S. (1977). Determinants of corporate borrowing. *Journal of Financial Economics*, 5(2), 147–175. https://doi.org/10.1016/0304-405X(77)90015-0

New Zealand Apples. (2018). Fresh Facts Data Tool. Retrieved on 26 Aug, 2018, from www.freshfacts.co.nz/#data-tool

Noguchi, N., Ishii, K., and Terao, H. (1997). Development of an Agricultural Mobile Robot using a Geomagnetic Direction Sensor and Image Sensors. *Journal of Agricultural Engineering Research*, 67, 1–15.

NZAPI (New Zealand Apples & Pears Incorporated). (2018). New Zealand Apples and Pears Statistical Annual Report. Hastings.

NZAPI (New Zealand Apples & Pears Incorproated). (2019). Workforce development strategy. Hastings.

NZ Wine (New Zealand Wine) and MPI (Ministry for Primary Industries). (2020). Vineyard Benchmarking Report. New Zealand Wine Growers and the Ministry for Primary Industries.

NZHerald (New Zealand Herald). (2016). NZ's Compac bought for $70m. Retrieved on 3 Dec, 2020, from https://www.nzherald.co.nz/business/nzs-compac-bought-for-70m/R2VC722P464JQYHPRCQD3I6KQQ/

NZHerald. (2019). Apple-picking robot could be a game changer for the industry. Retrieved on 26 Aug, 2020, from https://www.nzherald.co.nz/business/news/article.cfm?c_id=3andobjectid=12216291

NZHerald. (2020a). Worker shortage 'a dire situation' for horticulture sector. Retrieved on 24 Nov, 2020, from https://www.nzherald.co.nz/the-country/news/worker-shortage-a-dire-situation-for-horticulture-sector/SMOX6KANYNWA2K67NTA3DFDPS4/

NZHerald. (2020b). New 'climate-change resistant' apple to be trialled in Hawke's Bay. retreived on 10 Oct, 2020, from https://www.nzherald.co.nz/hawkes-bay-today/news/article.cfm?c_id=1503462&objectid=12347120.

NZPocketGuide. (n.d.). Working a Fruit Picking Job in New Zealand. Retrieved June 20, 2020, from https://nzpocketguide.com/working-fruit-picking-job-new-zealand.

O'Callaghan, L. (2020). Scales steady through Covid-19. Retrieved on 13 Oct, 2020, from http://www.fruitnet.com/asiafruit/article/182780/scales-steady-through-covid-19.

Olson, K.D. (2011). *Economics of Farm Management in a Global Setting*. John Willey and Sons, Inc.

Østergaard, S. (1971). Stochastic Investment Models and Decision Criteria. *The Swedish Journal of Economics*, 73(2), 157-183. doi:10.2307/3439055

Österberg, P, and Nilsson, J. (2009). Members' Perception of Their Participation in the Governance of Cooperatives: The Key to Trust and Commitment in Agricultural Cooperatives. *Agribusiness*. 25. 181 - 197. 10.1002/agr.20200.

O'Sullivan, P. (2020). Local Focus: Orchard wages rising thanks to worker shortage and new RSE rules may lift it further. Retrieved on 20 May, 2021, from https://www.nzherald.co.nz/hawkes-bay-today/news/local-focus-orchard-wages-rising-thanks-to-worker-shortage-and-new-rse-rules-may-lift-it-further/A6OBI6GIK57BZUHG4UT4I2FJMI/

Otero, G., and Preibisch, K. (2010). Farmworker Health and Safety: Challenges for British Columbia. Retrieved on 26 Aug, 2018, from http://www.sfu.ca/~otero/docs/Otero-and-Preibisch-Final-Nov-2010.pdf.

Palmer, J. (2008). Apples and pears - Harvesting, transport and storage, Te Ara - the Encyclopaedia of New Zealand, Retrieved May 11, 2020, from http://www.TeAra.govt.nz/en/apples-and-pears/page-6.

Pathak, T., Maskey, M., Dahlberg, J., Kearns, F., Bali, K., and Zaccaria, D. (2018). Climate Change Trends and Impacts on California Agriculture: A Detailed Review. *Agronomy*. 8. 25. 10.3390/agronomy8030025.

Paulin, A. (2012). Finding the bad apples easier with latest technology. Retrieved on 3 Dec, 2020, from http://www.stuff.co.nz/nelson-mail/lifestyle-entertainment/6836787/Finding-the-bad-apples-easier-with-latest-technology

Patterson, D. T, Westbrook, J. K., Joyce, R. J. V., Lingren, P. D., and Rogasik, J. (1999). Weeds, insects and disease. climate change: impact on agriculture. *Climatic Change*, 43:711–727.

PayScale. (2020). Hourly Rate for Industry in New Zealand: Agriculture, Tractor Operator. Retrieved on 25 August, 2020, from https://www.payscale.com/research/NZ/Industry=Agriculture/Hourly_Rate

Pedersen, S. M., and Lind, K. M. (2017). Precision Agriculture – From mapping to site-specific application. In M. A. Oliver (Ed.), *Precision Agriculture: Technology and Economic Perspectives* (ed. S.M. Pedersen and K.M Lind). Springer International Publishing.

Peterson, D. L. (2005). Harvest mechanisation progress and prospects for fresh market quality deciduous tree fruit. *HortTechnology*, 15(1), 72–75.

Petrova, M. (2018). This robot picks a pepper in 24 seconds using a tiny saw and could help combat a shortage of farm labor. Retrieved on 20 Dec, 2018, from https://www.cnbc.com/2018/12/20/watch-this-robot-pick-a-peck-of-peppers-with-a-tiny-saw.html

Pipfruit NZ (Pipfruit New Zealand Incorporated). (2017). Pipfruit New Zealand Statistical Annual Report. Hastings.

Plant and food. (2012). Low residue apples for export. Plantandfood New Zealand. Retrieved 10 Feb, 2018, from www.plantandfood.co.nz/growingfutures/case-studies/low-residue-apples-for-export

Plant and food. (n.d.). About-us: History. Retrieved 10 Feb, 2018, from https://www.plantandfood.co.nz/page/about-us/history/

Pollard, A. (2018). New Zealand pipfruit - a primary sector success story. *The Journal, The New Zealand Intitute of Primary Management Incorporated*, 30–33.

Premkumar, G. and Roberts, M. (1999). Adoption of new information technologies in rural small businesses. *The International Journal of Management Science*, 27(1), 467–484.

ProPicker. (2015). Apple picking in New Zealand. Retrieved July 10, 2020, from https://www.picktheworld.org/apple-picking-new-zealand.

Puklavec, B., Oliveira, T. and Popovič, A. (2014). Unpacking business intelligence systems adoption determinants: An exploratory study of small and medium enterprises. *Economic and Business Review*, 16(2), 185–23.

Purvis, A., Boggess, W. G., Moss, C. B., and Holt, J. (1995). Technology Adoption Decisions under Irreversibility and Uncertainty: An Ex Ante Appproach. *American Journal of Agricultural Economics*, 77(3), 541–551. https://doi.org/10.2307/1243223

Rae, A. N., and Carman, H. F. (1975). A Model of New Zealand Apple Supply Response to Technological Change. *Australian Journal of Agricultural Economics*, 19(1), 39–51. https://doi.org/10.1111/j.1467-8489.1975.tb00144.x

Rai, R., Joshi, S., Roy, S., Singh, O., Samir, M., and Chandra, A. (2015) Implications of changing climate on productivity of temperate fruit crops with special reference to apple. *Journal of Horticulture*, 2:2

Ramasamy, S., Krishnan, V., Bedford, R., and Bedford, C. (2008). The Recognised Seasonal Employer policy: Seeking the elusive triple wins for development through international migration. *Pacific Economic Bulletin*, 23(3), 171-186.

Rasmussen, W. D. (1968). Advances in American Agriculture: The Mechanical Tomato Harvester as a Case Study. *Technology and Culture*. V9, p531. https://doi.org/10.2307/3101894

RBNZ (Reserved Bank of New Zealand). (2019). The price indexes, Statistics New Zealand and Reserve Bank of New Zealand. Retrieved Feb 10, 2019, from https://www.rbnz.govt.nz/statistics/m9.

RBNZ (Reserved Bank of New Zealand). (2020). Labour market, Statistics New Zealand and Reserve Bank of New Zealand. Retrieved on Sept 09, 2020, from https://www.rbnz.govt.nz/statistics/m1.

Redhead, F., Snow, S., Vyas, D., Bawden, O., Russell, R., Perez, T., and Brereton, M. (2015). Bringing the Farmer Perspective to Agricultural Robots. *Paper presented at 33rd Annual ACM Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/2702613.2732894

Reardon, T., Barrett, C.B., Berdegué, J. A., and Swinnen, J. F. (2009). Agri-food industry transformation and small farmers in developing countries. *World Development*. 37, 1717–1727.

Reynolds, A. (2013). Defining the Value of the Co-operative Business Model: An Introduction. *CHS Centre for Cooperative Growth*, Madison, Wisconsin. Retrieved from https://community-wealth.org/sites/clone.community-wealth.org/files/downloads/paper-reynolds13%5B1%5D.pdf

RNZ (Radio New Zealand). (2020). Agritech support plan to establish horticultural robotics academy. Retireved on 1 Nov, 2020, from https://www.rnz.co.nz/news/country/421698/agritech-support-plan-to-establish-horticultural-robotics-academy

Robinson, T., Hoying, S., Sazo, M. M., DeMarree, A., and Dominguez, L. (2013). A vision for apple orchard systems of the future. *New York Fruit Quarterly*, 21(3), 11–16.

RoboticsPlus. (n.d.). The apple packer. Retrieved on 3 Dec, 2020, from https://www.roboticsplus.co.nz/robotic-apple-packing

Robotic picking machine’s first apple harvest underway. Retrieved May 12, 2020, from https://www.goodfruit.com/robotic-picking-machines-first-apple-harvest-underway.

Rogers, E. (1983). *Diffusion of Innovations* (3rd Edition). Macmillian Publishing Co. https://doi.org/citeulike-article-id:126680

Roosen, J. (1999). A Regional Econometric Model of U.S. Apple Production. *American Journal of Agricultural Economics*. 81 (21663). Iowa.

Rotz, C.A., Coiner, C.U., and Soder, K.J. (2004). Automatic Milking Systems, Farm Size, and Milk Production. *Journal of Dairy Science*. 86. 4167-77. 10.3168/jds.S0022-0302(03)74032-6.

Rotz, S., Gravely, E., Mosby, I., Duncan, E., Finnis, E., Horgan, M., LeBlanc, J., Martin, R., Tait Neufeld, H., Nixon, A., Pant, L., Shallab, V., and Fraserb, E. (2019). Automated pastures and the digital divide: How agricultural technologies are shaping labour and rural communities. *Journal of Rural Studies*, 68, 112–122.

Saha, S. (2020). Five Trends Defining the Food Industry Post-Covid. Retrieved on 11 Dec, 2020, from https://foodsafetytech.com/column/five-trends-defining-the-food-industry-post-covid/

Salokhe, V., and Ninh, N (1993). Modelling soil compaction under pneumatic tyres in clay soil. *Journal of Terramechanics*. 30. 63-75. 10.1016/0022-4898(93)90020-X.

Sarig, Y. (2005). Mechanised fruit harvesting - site specific solutions. *Information and Technology for Sustainble Fruit and Vegetable Production Symposium*. 7:237-247.

Satherley., D. (2020). Coronavirus: Interest rates could drop to negative after new COVID-19 outbreak - economist. Retrieved on 18 Oct, 2020, from www.newshub.co.nz/home/money/2020/08/coronavirus-interest-rates-could-drop-to-negative-after-new-covid-19-outbreak-economist.html.

Satz, D. (2012). Why Some Things Should Not Be for Sale: The Moral Limits of Markets. Oxford: Oxford University Press.

Sauer, J., and Zilberman, D. (2009). Innovation behaviour at farm level – Selection and identification. In the 83rd annual conference. *The Agricultural Economics Society* (p. 31).

Sazo, M.M., A. De Marree, and T. Robinson. (2010). The platform factor – labor positioning machines producing good results for N.Y. apple industry. *New York Fruit Quarterly*. 18(2):5-10.

Scales (2014). An Investment in New Zealand's Primary Industry: Investment Statement, *Scales Corporation Limited*. New Zealand.

Scheuller, J. K. (2013). Agricultural Automation: An Intorduction. In *Automation in Tree Fruit Production: Principles and Practice* (Ed. Q. Zhang and F.J. Pierce). CAB International. Boston.

Schewe, R. L., and Stuart, D. (2015). Diversity in agricultural technology adoption: How are automatic milking systems used and to what end? *Agriculture and Human Values*, *32*(2), 199–213. https://doi.org/10.1007/s10460-014-9542-2

Schimmelpfennig, D. (2016). Farm Profits and Adoption of Precision Agriculture. U.S. Department of Agriculture, *Economic Research Report*. ERR-217. 46 pp.

Schmitz, A., and Moss, C. B. (2015). Mechanised agriculture: Machine adoption, farm size, and labor displacement. *AgBioForum*, 18(3), 278–296.

Schupp, J., and Baugher, T. (2017). Orchard Automation - Havest Assist Technologies. Retrieved on 26 Aug, 2018, from https://extension.psu.edu/harvest-assist-technologies

Schupp, J., T. Baugher, E. Winzeler, M. Schupp, and W. Messner. (2011). Preliminary results with a vacuum assisted harvest system for apples. *Fruit Notes*. 91:1-5.

Scoop News. (2020). Robotics Plus A THRIVE Top 50 AgTech Company. Retrieved on 3 Dec, 2020, from https://www.scoop.co.nz/stories/BU2002/S00398/robotics-plus-a-thrive-top-50-agtech-company.htm

Scott J. R., and Rasmussen, J. M. (1990). Peach Thinning Optimisation Model. *Acta Horticulturae*, 276.27. https://doi.org/10.17660/ActaHortic.

Scott, E. (n.d.). Farm Fatalities a Reminder to Work Safely. *The New York Centre for Agricultural Medicine and Health (NYCAMH).*

Sevier, J., and Lee, S. (2005). Precision farming adoption by Florida citrus producers: probit model analysis. *ASAE Annual International Meeting*. Retrieved on 26 Aug, 2018, from http://edis.ifas.ufl.edu/

Shah, A. (2018). Can you repair what you own? *Mechanical Engineering*, 140(9), 37–41.

Sharma, N. C., Sharma, S. D., Verma, S., and Sharma, C. L. (2014). Impact of changing climate on apple production in Kotkhai area of Shimla district. *International Journal of Farm Sciences*, 3:81–90

Sharpe, M. (2021). 'Pacific bubble' being considered, but won't bring seasonal worker numbers back to pre-Covid-19 level — Faafoi. Retrieved on 16 May, 2021, from https://www.stuff.co.nz/business/124775786/pacific-bubble-being-considered-but-wont-bring-seasonal-worker-numbers-back-to-precovid19-level--faafoi

Sheng, Y., and Chancellor, W. (2019). Exploring the relationship between farm size and productivity: Evidence from the Australian grains industry. *Food Policy*, 84, 196–204.

Shepardson, E., E. Markwardt, W. Millier, and G. Rehkugler. (1970). Mechanical harvesting of fruit and vegetables. New York State Agricultural Experiment Station. *New York's Food and Life Sciences Bulletin.* No. 5.

Shockley, J., Dillon, C., and Shearer, S. (2019). An economic feasibility assessment of autonomous field machinery in grain crop production. *Precision Agriculture*. 10.1007/s11119-019-09638-w.

Shortall, J., Shalloo, L., Foley, C., Sleator, R.D., and O'Brien, B. (2016). Investment appraisal of automatic milking and conventional milking technologies in a pasture-based dairy system. *Journal of Dairy Science*. 99. 10.3168/jds.2016-11256.

Siegner, C. Could robotics help to relieve the farm labour shortage? Retrieved on 12 Mar, 2018, from https://www.fooddive.com/news/could-robotics-help-to-relieve-the-farm-labor-shortage/518763.

Siemens, J. C., and Bowers, W. (1999). *Machinery Management: How to Select Machinery to Fit the Real Needs of Farm Managers*. East Moline, Il: Deere & Co., John Deere Pub.

Silwal, A., Davidson, J., Karkee, M., Mo, C., Zhang, Q., and Lewis, K. (2016a). Effort Towards robotic apple harvesting in Washington State. *American Society of Agricultural and Biological Engineers*, St Joseph, Michigan.

Silwal, A., Davidson, J.R., Karkee, M., Mo, C., Zhang, Q., and Lewis, K. (2017). Design, integration, and field evaluation of a robotic apple harvester. *Journal of Field Robotics*, 1–20.

Silwal, A., Karkee, M., and Zhang, Q. (2015). A hierarchical approach of apple identification for robotic harvesting. Annual International Meeting. *The American Society of Agricultural and Biological Engineers*. St. Joseph. https://doi.org/https://doi.org/10.13031/aim.20152167504

Sinnett, A., Farquharson, R., Ramilan, T., Goodwin, L., and O'Connell, M. (2018). Labour and mechanisation: Cost effectiveness and management considerations for pome fruit growers in Victoria. *Innovation Seed Funding for Horticulture Development*.

Skerrett, A. and McRae, T. (2019). Watch: World's first commercial robotic apple harvest underway. Retrieved on 2 Nov, 2020, from https://www.newshub.co.nz/home/rural/2019/03/watch-world-s-first-commercial-robotic-apple-harvest-underway.html
sorting technology. (2017). Trans. *American Society of Agricultural and Biological Engineers*, 60(5): 1537–1550

Sparrow, R., and Howard, M. (2017). When human beings are like drunk robots: Driverless vehicles, ethics, and the future of transport. *Transportation Research*, Part C, 80, 206–215.

Sparrow, R., and Howard, M. (2020). Robots in agriculture: prospects, impacts, ethics, and policy. *Precision Agriculture*. https://doi.org/10.1007/s11119-020-09757-9

Sporleder, T. L. and Bailey, M. D. (2001). Using real options to evaluate producer investment in new generation cooperatives. *American Agricultural Economics Association Annual Meeting.* Chicago, IL.

SPW (Southeast Produce Weekly). (2019). Robotic strawberry harvester one step closer to reality in Florida fields. Retrieved on 19 Apr, 2019, from https://southeastproduceweekly.com/2019/04/16/robotic-strawberry-harvester-one-step-closer-to-reality-in-florida-fields.
35-38.

Stokes, J. R., Rajagopalan, R. M., and Stefanou, S. E. (2008). Investment in a methane digester: An application of capital budgeting and real options. *Review of Agricultural Economics*, 30(4), 664–676. https://doi.org/10.1111/j.1467-9353.2008.00439.x

Stræte, E. P., Vik, J., and Hansen, B. G. (2017). The Social Robot: A Study of the Social and Political Aspects of Automatic Milking Systems. *International Jounral on Food Dynamics*, 220, DOI: http://dx.doi.org/10.18461/pfsd.2017.1722

Straub, E. T. (2009). Understanding Technology Adoption: Theory and Future Directions for Informal Learning. *Review of Educational Research*, 79(2), 625–649. https://doi.org/10.3102/0034654308325896

Stuart, D., Schewe, R., and Gunderson, R. (2013). Extending Social Theory to Farm Animals: Addressing Alienation in the Dairy Sector. *Sociologia Ruralis*, 53.

Sugiura, T., Kuroda, H., Sugiura, H., and Honjo, H. (2005). Prediction of effects of global warming on apple production regions in Japan. *Phyton-International Journal of Experimental Botany*, 45:419–422.

Sui, R., and Thomasson, J. (2013). Mechanisation, Sensing and Control in Cotton Production. In *Agricultural Automation: Fundamentals and Practices*, (Ed. Zhang, Q., and Pierce, F. J). CRC Press.

Sunding, D., and Zilberman, D. (2000). The Agricultural Innovation Process : Research and Technology Adoption in a Changing Agricultural Sector. *Handbook of Agricultural Economics,* 1–105. https://doi.org/10.1016/S1574-0072(01)10007-1

Swinton, S., and Lowenberg-Deboer, J. (2001). Global adoption of precision agriculture technologies: Who, when and why? *Paper Presented at the 3rd European Conference on Precision Agriculture*, 557–562. Retrieved on 7 Feb, 2019, from https://www.msu.edu/user/swintons/D7_8_SwintonECPA01.pdf

Taunton, E. (2021). Growers 'devastated' as apples rot in Hawke's Bay orchards. Retrieved on 20 May, 2021 from https://www.stuff.co.nz/business/farming/124768684/growers-devastated-as-apples-rot-in-hawkes-bay-orchards

Taherdoost, H. (2018). A review of technology acceptance and adoption models and theories. *Procedia Manufacturing*, 22, 960–967. https://doi.org/https://doi.org/10.1016/j.promfg.2018.03.137

T&G (Turners and Growers Global Ltd.). (2019). World's first commercial robotic apple harvest at T&G's Hawkes Bay orchards. Retrieved on 4 Sept, 2020, from https://tandg.global/worlds-first-commercial-robotic-apple-harvest-at-tgs-hawkes-bay-orchards-with-abundant-robotics.

T&G (Turners and Growers Global Ltd.). (2020). Sell-out season puts Envy apples on track to be billion-dollar brand. Retrieved on 12 May, 2021, from https://tandg.global/sell-out-season-puts-envy-apples-on-track-to-be-billion-dollar-brand/#:~:text=With%20this%20strong%20momentum%2C%20by,to%20meet%20global%20consumer%20demand.

T&G (Turners and Growers Global Ltd.). (2021). Picking platforms prove their worth in the race to get fruit off trees. Retrieved on 12 May, 2021, from https://tandg.global/picking-platforms-prove-their-worth-in-the-race-to-get-fruit-off-trees/

Tao, Y., and Zhou, J. (2017). Automatic apple recognition based on the fusion of color and 3D feature for robotic fruit picking. *Computers and Electronics in Agriculture*. 142. 388-396. 10.1016/j.compag.2017.09.019.

Taunton, E. (2018). Yamaha sinks $12m into Kiwi ag-tech company Robotics Plus. Retrieved on 3 Dec, 2020, from https://www.stuff.co.nz/business/farming/108782227/yamaha-sinks-12m-into-kiwi-agtech-company-robotics-plus

Ten Damme, L., Stettler, M., Pinet, F., Vervaet, P., Keller, T., Munkholm, L., and Lamandé, M. (2019). The contribution of tyre evolution to the reduction of soil compaction risks. *Soil and Tillage Research*. 194. 10.1016/j.still.2019.05.029.

Thiele, G. F., and Zhang, J. (1992). The Dynamic Apple Tree System Relationships to Aid Management Strategies. *Acta Horticulturae*, (313), 249–256. https://doi.org/10.17660/ActaHortic.1992.313.31

Thompson, J. F., and Blank, S. C. (2008). Harvest mechanisation helps agriculture remain competitive. *California Agriculture*, 54(3), 51–56. https://doi.org/10.3733/ca.v054n03p51

Time and Date. (2019). Daylight duration in Napier, New Zealand. Retrieved Ap 15, 2019, from https://www.timeanddate.com/sun/new-zealand/napier.

Tobin, C. (2021). South Canterbury orchardist thankful for RSE workers. Retrieved on 21 May, 2021, from https://www.stuff.co.nz/timaru-herald/news/124486178/south-canterbury-orchardist-thankful-for-rse-workers

Tornatzky, L. G., and Klein, K. (1982). Innovation characteristics and innovation adoption implication: A mete-analysis of findings. *IEEE Transactions on Engineering Management*, 29(1), 28–45.

Tozer, P., and Isbister, B. (2007). Is it economically feasible to harvest by management zone?. *Precision Agriculture*. 8. 151-159. 10.1007/s11119-007-9035-z.

Tozer, P. R. (2009). Uncertainty and investment in precision agriculture - Is it worth the money? *Agricultural Systems*, 100 (1–3), 80–87. https://doi.org/10.1016/j.agsy.2009.02.001

Tozer, P. R., and Stokes, J. R. (2009). Investing in perennial pasture improvement: A real options analysis. *Agricultural Economics*, 31(1), 88–102. https://doi.org/10.1111/j.1467-9353.2008.01427.x

Tozer, P. R., and Marsh, T. L. (2018). Dynamic regional model of the US apple industry: Consequences of supply or demand shocks due to pest or disease outbreaks and control. *Agricultural Systems*, 164, 252–263. https://doi.org/10.1016/j.agsy.2018.05.003

Treasury NZ (The Treasury New Zealand). (2020). Discount Rates. Retrieved on 10 Sept, 2020, from https://www.treasury.govt.nz/information-and-services/state-sector-leadership/guidance/financial-reporting-policies-and-guidance/discount-rates

Tse, C., Barkema, H. W., DeVries, T. J., Rushen, J., and Pajor, E. A. (2018). Impact of automatic milking systems on dairy cattle producers' reports of milking labour management, milk production and milk quality. *Animal*, 12 (12), 2649–2656.

Tustin, S. (1998). Matching pip fruit rootstock to orchard production requirements. *Proceedings of HortResearch Seminar*, Hastings, May 1998, 24-28

usapple. (2018). Envy apple wins US apple's 2018 Munch Madness tournament. Retrieved 4 Apr, 2018, from http://usapple.org/category/seasonal-inspiration.

USDA (United States Department of Agriculture). (2018). Fresh Apples, Grapes, and Pears : World Markets and Trade. *World Agricultural Outlook Board. Foreign Agricultural Service United States Department of Agriculture.*

USDA (United States Department of Agriculture). (December 2019). Fresh Apples, Grapes, and Pears: *World Agricultural Outlook Board. Foreign Agricultural Service United States Department of Agriculture.*

USDA (United States Department of Agriculture). (June 2020). Fresh Apples, Grapes, and Pears: World Agricultural Outlook Board. *Foreign Agricultural Service United States Department of Agriculture*.

Valle, H., Millist, N., and Galeano, D. (2017). Labour force survey. *Australian Bureau of Agricultural and Resource Economics and Sciences*. Canberra. Retrieved from http://data.daff.gov.au/data/warehouse/9aaam/2017/ABARESLabourForceSurvey/LabourForceSurvey_%2020170518_v1.0.0.pdf van der Merwe, G. J. (2015). The use of Harvesting Systems and Labourer Platforms in the South African Deciduous Fruit Industry. Master of Science Thesis. Stellenbosch University. South Africa.

van Henten, E. J., Hemming, J., van Tuijl, B. A. J., Kornet, J. G., Meuleman, J., Bontsema, J., and van Os, E. A. (2002). An Autonomous Robot for Harvesting Cucumbers in Greenhouses. *Autonomous Robots*, 13(3), 241–258. https://doi.org/10.1023/A:1020568125418

van Hooijdonk, B. M. (2009). The physiological basis of vigour control by apple rootstocks - an unresolved paradigm. A thesis written to fullfill a Doctor of Philosophy in Plant Physiology. Massey University. Palmerston North. New Zealand.

van Hooijdonk, B., and Tustin, S. (2015). Future orchard plantings systems - Propogation of designer apple trees. *The Orchardist*.

van Rijswick, C. (2018). World Fruit Map 2018: Global Trade Still Fruitful. *Rabobank Rabor Research Food and Agribusiness*.

Vedwan, N., and Rhoades, R. E. (2001). Climate change in the Western Himalayas of India: a study of local perception and response. *Climate Research*, 19:109–117

Volz, R.K., White, A.G., Brookfield, P.L., Weskett, R., Legg, S., Koorey, R., Tustin, D.S., Hughes, J. and White, M. (2004). Breeding and development of the new apple cultivar 'JAZZ TM'. *Acta Hortic*. 663, 891-894 https://doi.org/10.17660/ActaHortic.2004.663.162

Wagner, A. (2017). What this apple-picking robot means for the future of farm workers. Retrieved on 7 Feb, 2019, from https://www.pbs.org/newshour/science/apple-picking-robot-means-future-farm-workers.

Walker, J. (September 2014). Apple Futures second generation announced. *The Orchardist*.

Warner, G. (2008). Mechanisation meets with skepticism. *Good Fruit Grower* 59 (2):18-19. Retrieved on 10 Aug, 2020, from https://www.goodfruit.com/mechanization-meets-with-skepticism/

Warner. G. (2012). Harvester ready to go. Retrieved on 26 Aug, 2017, from https://www.goodfruit.com/harvester-is-ready-to-go.

Webster A.D. and Wertheim, S.J. (2003). Apple rootstocks. Chapter 5. *In Apples: Botany Production and Uses*. Ferree D.C. & Warrington I.J. (eds), CAB International

Well, M., Ifft, J., and Freedland, J.M. (2017b). Apple harvest platforms: Quantifying efficiency and determining economic benefits. *New York State Horticultural Society*.

Wells, M. (2017a). Economics of Orchard Mechanisation. *Lake Ontario Fruit Team*. Cornell Cooperative Extension. Eastern Horticulture Fruit Schools, Cornell University.

Werkheiser, I. (2018). Precision livestock farming and farmers' duties to livestock. *Journal of Agricultural and Environmental Ethics*, 31(2), 181–195.

West, T., R. Sullivan, C. Seavert, and S. Castagnoli. (2012). Enterprise budget. Oregon State.

Whitaker, K., and Middleton, S. (1999). The profitability of hail netting in apple orchards. Paper presented to the 43rd Australian Agricultural Economics Society. (p. 15). Christchurch.

Whitfield, D, O'Connell, M., and Goodwin, I. (2016). Effects of fruit number on yield, fruit weight and soluble solids of peach. *Acta Horticulturae*. 1130. 323-328. 10.17660/ActaHortic.2016.1130.48.

Whiting, M. (2018). Precision Orchard Systems. In *Automation in Tree Fruit Production: Principles and Practice* (ed. Q. Zhang). CAB International. Boston.

Wilkie, A.D. (1987). Stochastic investment models – theory and applications. *Insurance: Mathematics and Economics*. 6, Issue 1, P. 65-83, ISSN 0167-6687, https://doi.org/10.1016/0167-6687(87)90009-6.

Willett, L. S. (1993). The U.S. apple industry: Econometric model and projection. *Agricultural and Resource Economics Review*, 22(2), 138–149.

Willis, C., and Hanlon, W. (1976). Temporal model for long-run orchard decisions. *Canadian Journal of Agricultural Economics*, 24(3), 17–28. https://doi.org/10.1111/j.1744-7976.1976.tb02818.x

Wilton, J. (2018). Orchard management. *The Orchardist*, 3.

Wiltshire, L. (2019a). Apple-picking robot could be a game changer for the industry. Retrieved on 26 Oct, 2020, from https://www.nzherald.co.nz/hawkes-bay-today/news/apple-picking-robot-could-be-a-game-changer-for-the-industry/GVWTBAKPU5WZPIZVHT46P5S5DM/

Wiltshire, L. (2019b). Average picking pay of $23 an hour is not 'exploitation', Hawke's Bay growers say. Retrieved on May 14, 2020, from https://www.nzherald.co.nz/business/news/article.cfm?c_id=3&objectid=12192334

Winter, F. (1976). A simulation model for studying the efficiency of apple and pear orchards. *Gartenbauwissenschaft*, 41(1), 26–34.

Winter, F. (1986). A bio-economic simulation model for apple. *Garenbauwissenchaft*. with a Vacuum Assisted Harvest System for Apples. *Fruit Notes*, 76, 1-5.

Wolfert, S. L. G., Verdouw, C., and Bogaardt, M.-J. (2017). Big data in smart farming – A review. *Agricultural Systems*,153, 69–80.

Wood, R. (2003). The big apple of sorters. Retrieved on 3 Dec, 2020, from https://www.nzherald.co.nz/technology/the-big-apple-of-sorters/XAMZHSFOKSIIKQ3GCHXQB7JXCY/

Woodford KB, Brakenrig MH, Pangborn MC. (2015). New Zealand case studies of automatic-milking-systems adoption. *Proceedings of the New Zealand Society of Animal Production*, Volume 75: 127-131.

WorkSafe NZ (n.d.). A guide to developing safety management systems. Retrieved on 10, Apr, 2020, from https://worksafe.govt.nz/topic-and-industry/agriculture/a-guide-to-developing-safety-management-systems/

Yang, C., and Lee, W. S. (2013). Precision Agricultural Systems. In *Agricultural Automation: Foundamentals and Practices* (Ed. Q.Zhang and Pierce .F.J) (p. 34).

Youngman, A. (2016). Robot harvesting and weeding well on the way into mainstream. Retrieved from https://www.producebusinessuk.com/services/stories/2016/08/23/robot-harvesting-and-weeding-well-on-the-way-into-mainstream.

Zhang, Q. (Ed.). (2018). *Automation in Tree Fruit Production : Principles and Practices.* (ed. Q. Zhang). CAB International. Boston.

Zhang, Q., and Pierce, F. J. (Ed.). (2013). *Agricultural Automation Fundamentals*. Florida: CAB International.

Zhang, W., and Wilhelm, W. E. (2011). OR/MS decision support models for the specialty crops industry: *Annals of Operations Research*, 190(1), 131–148. https://doi.org/10.1007/s10479-009-0626-0

Zhang, Z., and Heinemann, P. H. (2017). Economic Analysis of a Low-cost Apple Harvest-assist Unit, *HortTechnology*, 27(2), 240-247.

Zhang, Z., Pothula, A, and Lu, R. (2017). Economic Evaluation of Apple Harvest and In-Field Sorting Technology. *American Society of Agricultural and Biological Engineers*. 60. 1537-1550. 10.13031/trans.12226.

Zhang, Z., Wang, X., Liu., H, Wang, Y., and Wang, W. (2019). Multi-purpose apple harvest platform economic evaluation modelling and software development. *International Journal of Agricultural and Biological Engineering*. 12. 74-83. 10.25165/j.ijabe.20191201.4360.

Zhang. C., and Chen, D. (2018). Precise Crop Load Management. In *Automation in Tree Fruit Production: Principles and Practice* (ed. Q. Zhang). CAB International. Boston.

Zhao, Z., Wahl, T., and Marsh, T. (2007). Economic effects of mitigating apple maggot spread. *Canadian Journal of Agricultural Economics*, 55(4), 499–514. https://doi.org/10.1111/j.1744-7976.2007.00105.x

Zilberman, D. (2008). *Diffusion of Agricultural Technology*. In the New Palgrave Dictionary of Economics, Edited by Steven N. Durlauf and Lawrence E. Blume (2nd ed., p. 3). Palgrave Macmillan UK.

Zilberman, D., Feder, G., and Just, R. E. (1985). Adoption of agricultural innovations in developing countries: A Survey. *Economic Development and Cultural Change*, 33(2), 255. https://doi.org/10.1086/451461

Zocca, A. (1983). Shaking harvesting trials with market apples. In proceedings of the *International Symposium on Fruit*, Nut and Vegetable Harvesting Mechanisation (pp. 65–72).

Appendices

Appendix 1. Manual harvesting three apple varieties across seven orchard sizes in full production

Size (ha)	Manual yield (kg)	No. of FTE pickers	NPV ($)	IRR (%)
		Envy		
20	2,015,520	53.04	16,065,847	26.44
30	3,023,280	79.56	24,098,771	26.44
40	4,031,040	106.08	32,131,694	26.44
50	5,038,800	132.60	40,164,618	26.44
100	10,077,600	265.20	80,329,236	26.44
200	20,155,200	530.40	160,658,472	26.44
		Jazz		
20	1,854,552	48.80	3,146,169	10.82
30	2,781,828	73.21	4,719,253	10.82
40	3,709,104	97.61	6,292,337	10.82
50	4,636,380	122.01	7,865,421	10.82
100	9,272,760	244.02	15,730,843	10.82
200	18,545,520	488.04	31,461,685	10.82
		Royal Gala		
20	1,970,376	50.06	3,968,788	11.40
30	2,955,564	75.10	5,953,182	11.40
40	3,940,752	100.13	7,937,576	11.40
50	4,925,940	125.16	9,921,969	11.40
100	9,851,880	250.32	19,843,939	11.40
200	19,703,760	500.64	39,687,878	11.40