An evaluation of GPS technology as a tool to aid pasture management

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Abstract

In countries with temperate climates such as New Zealand and Ireland, grazing pasture plays an essential role in dairy production and farm profitability. In these climates, pasture growth occurs year-round in a seasonal pattern, making pasture a low-cost, high-quality feed source if well managed. However, the overall success of this system depends on on-farm management decisions, including pasture management (i.e., quality versus quantity) and meeting cow requirements (i.e., feed demand).

Knowledge of individual paddock performance and grazing information can assist with farm management decisions that maximise pasture productivity and profitability and reduce the dependence on imported feeds. Some farmers record pasture covers and grazed paddocks as part of their regular farm walks to enable feeding and farm management decisions. However, this is not common on many farms. Furthermore, these records are not necessarily kept electronically or on paper after the immediate decisions have been made. Therefore, this research aimed to determine the accuracy and precision of Global Positioning System (GPS) enabled devices (i.e., solar-powered ear tags and cow collars) and establish if they could be used to automate the recording of on-farm grazing events and determine the area allocated.

Prior to field testing, static testing of three GPS device types (Agtech and mOOvement solar-powered ear tags and Oyster2 collars) suitable for use on cattle was conducted to determine their accuracy (location error) and precision (Circle Error Probable, CEP). The mean location error (MLE) was similar for the Agtech and Oyster2 devices at 5.4 m and 5.7 m, respectively, compared with 34.2 m MLE for the mOOvement devices. In addition, the mean 95% CEP was calculated for all device types, with the Oyster2 devices having the lowest at 11.9 m, followed by Agtech at 13.9 m and mOOvement at 77.6 m.

The ability to use GPS devices to record grazing events automatically was tested on a 400-cow dairy herd in Canterbury, New Zealand. A small proportion of the milking herd was fitted with GPS enabled devices (i.e., ~2.8% Agtech & mOOvement ear tags (11 animals) and 0.5% digitanimal collars (2 animals)). According to the device fix rate, these devices recorded an animal's location at hourly or two-hourly intervals. The data was analysed for four days, from the 5th to the 8th of April 2021, for the AM (6 am – 3 pm) and PM grazing periods (3 pm – 6 am the following day). The digitanimal collars recorded 62.3% (of total observations) in the correct paddock, as opposed to adjacent paddocks or races, for the four days analysed, compared with 52.5% for the Agtech devices and 45.2% for the mOOvement ear tags.

A computer simulation of GPS fixes during a 6-hour daybreak was conducted to estimate the required number of devices and device fix rate. Four variables were adjusted across different scenarios to calculate the number of devices and the fix rate needed to identify which paddock a herd of cows were grazing correctly. The variables were a) the location error of individual GPS devices, b) paddock shape, c) paddock size, and d) the number of GPS fixes (i.e., number tags/herd * device fix rate * hours in the paddock). The proportion of GPS position fixes correctly within the paddock boundary was then calculated. The simulation, combined with the on-farm study, suggested that to identify the grazed paddock using GPS devices approximately 1% of herd size should be fitted with devices with a one hour or more frequent fix rate. For herds of less than 300 cows, it is recommended to use a minimum of three devices per herd.

The ability of GPS devices to determine the grazing area allocated was tested using a further simulation exercise. This was done by dividing a simulated one-hectare square paddock into sixteen equal-sized squares. The method showed promise but was sensitive to the fix threshold selected (i.e., number of fixes per square). In general, a higher fix threshold is required to estimate the area allocated accurately with reduced area allocated. Therefore, if attempting to estimate the area allocated, a higher fix rate is needed than for paddock identification.

This preliminary investigation has shown that it is feasible to use GPS devices to determine the area allocated and record grazing events on-farm depending on the device type and settings. For example, to identify the grazed paddock, it is appropriate for ~1% of the herd size to be fitted with devices; however, to determine the area allocated, a higher number of devices is likely required ~3% of herd size. Nevertheless, before this technology could become standard on-farm practice, further work is required, including a comprehensive on-farm study. This is needed to provide better data to assess the accuracy and precision of the individual devices and other potential on-farm complications, including paddock shape, use of crops, and multiple herds during the winter and early spring periods (e.g., dry cows, springers, colostrums and milkers). Nonetheless, with a greater focus on maximising pasture utilisation on dairy farms today and the increasing range (e.g., direct to satellite options) and decreasing cost of GPS devices, there is likely to be greater interest in this technology in the future.

Acknowledgements

The work behind this thesis has been an enjoyable experience but a challenge, nonetheless, often leaving me wondering if we would ever get this far and have a finished product to present. Nevertheless, after many months of hard work, we have reached the end of the ride. I could not have completed it on my own. Therefore, I would like to express my gratitude to the following individuals and organisations, as this research would not have been possible without their support and guidance.

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List of abbreviations

API	Application Programming Interface
CEP	Circle Error Probable
c/kg DM	Cents per kilogram dry matter
GPS	Global Positioning System
IoT	Internet of Things
kgDM	Kilograms of drymatter
kgDM/ha	Kilograms of drymatter per hectare
kgMS	Kilograms of milksolids (fat + protein)
kgMS/ha	Kilograms of milksolids per hectare
LE	Location Error
LIC	Livestock Improvement Corporation
LoRa	Long Range, a type of wireless communication system
LoRaWAN	Long-range Wide-area Network
MJME	Megajoules of Metabolisable Energy
MJME/kgDM	Megajoules of Metabolisable Energy per kilogram of dry matter
MLE	Mean Location Error
MVMS	Milk Vat Monitoring System
NDVI	Normalised Difference Vegetation Index
NZD	New Zealand Dollar
PBI	Pasturebase Ireland
PGF	Pasture Growth Forecast
RPM	Rising Plate Meter

SD	Standard Deviation
SPACE	Satellite Pasture and Cover Evaluation
tDM	Tonnes dry matter
tDM/ha	Tonnes dry matter per hectare
USD	United States Dollar

Chapter 1

Introduction

1.1 Background

The primary industries, including the dairy, sheep and beef, and forestry sectors, currently occupy around half of New Zealand's total land area (Ministry for the Environment & Stats NZ, 2021). For the year ending June 2020, they earned $48 billion in export revenues. In particular, the dairy industry contributed $20.1 billion or approximately $0.25 of every export dollar (Figure 1.1) (Dorigo & Ballingall, 2020; Ministry for Primary Industries, 2020). This is almost double the following category of meat and wool, which contributed approximately $10.7 billion (Ministry for Primary Industries, 2020). Around 50,000 people are employed in the dairy industry directly on-farm or in dairy processing roles, representing $3.4 billion in annual wages to the New Zealand economy. In addition to direct employment, the dairy industry, which includes farmers and processors such as Fonterra (the largest dairy processor in New Zealand), Synlait, Tatua, and Open Country Dairy, also supports many other New Zealand businesses that provide inputs or services to the sector. In the year to June 2020, these services and inputs were worth $40.8 billion to the New Zealand economy (Dorigo & Ballingall, 2020). Dairying has a significant impact on the New Zealand economy annually, as shown above.

Compared to many other dairy-producing countries, the New Zealand industry is unique in that most New Zealand farmers operate grazing systems, with cows grazing outside 365 days of the year. New Zealand's temperate climate is critical to the success of this system, allowing year-round pasture growth, although in a seasonal pattern, and in-situ grazing (Holmes *et al.*, 2002; Verkerk, 2003; Holmes & Roche, 2007; Wilkinson *et al.*, 2020). This provides a cost advantage compared to many other milk-producing countries (Figure 1.2), where cows are primarily housed indoors and fed a mixed ration diet (Verkerk, 2003; Dillon *et al.*, 2005; Dillon *et al.*, 2008). New Zealand accounts for around 3% of world milk production and 25% of the world's total exported milk, making it one of the world's largest milk traders as less than 5% of local production is consumed domestically (Shadbolt *et al.*, 2017; FAO, 2021). Consequently, large scale exports of milk and milk products to overseas markets are required, which means domestic producers are prone to price volatility in an environment without subsidies or incentives common in other countries such as the European Union and the United States (Verkerk, 2003; Burke & Verkerk, 2010; Shadbolt & Apparao, 2016; Ballingall & Pambudi, 2017; Destremau & Siddharth, 2018; FAO, 2021). Therefore, by utilising a pastoral grazing production system, New Zealand milk producers can reduce costs helping to ensure profitable milk production is achieved (Holmes *et al.*, 2002; Verkerk, 2003; Dillon *et al.*, 2005; Holmes & Roche, 2007; Dillon *et al.*, 2008).

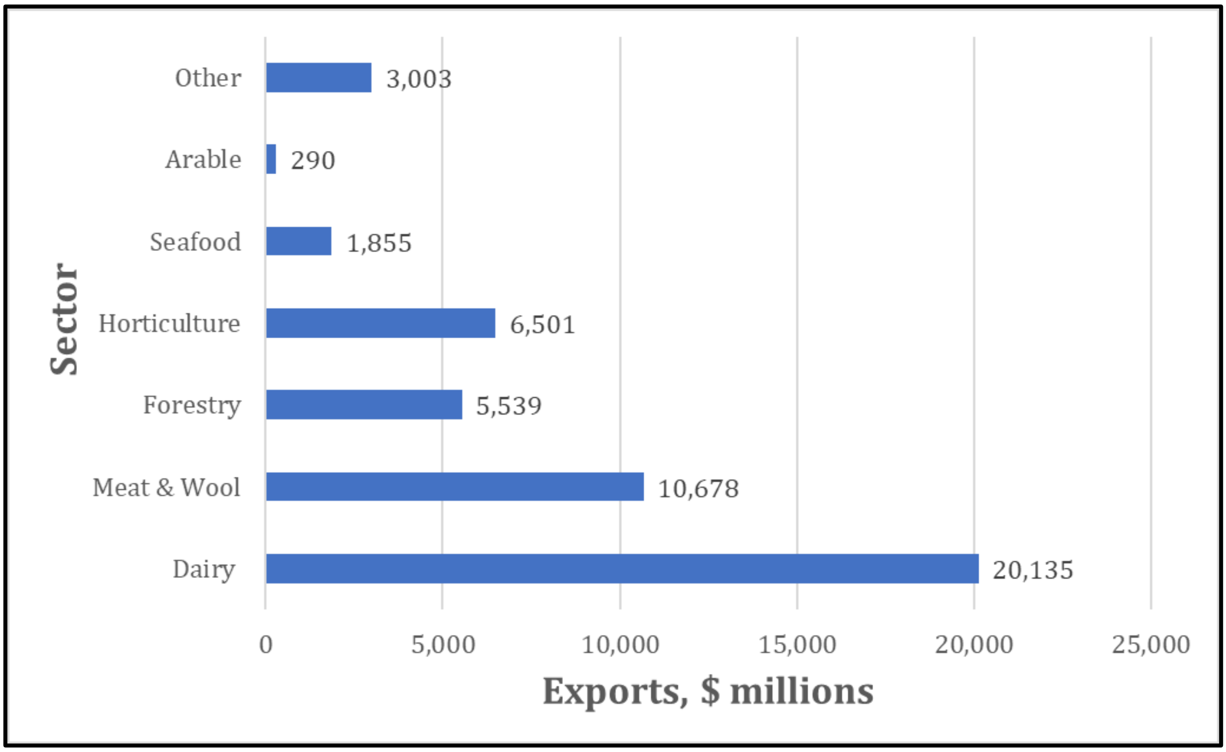

Figure 1.1: Contribution of individual sectors towards total primary industries export revenue for the year ending June 2020. Adapted from Ministry for Primary Industries (2020) data.

As farm productivity and profitability are positively correlated with pasture utilisation and pasture being the cheapest feed source on-farm, management aims to balance feed supply (i.e., pasture growth) with feed demand (i.e., herd feed requirements) (Holmes *et al.*, 2002; Holmes & Roche, 2007; Hanrahan *et al.*, 2018; Neal *et al.*, 2018; Murphy *et al.*, 2020; Murphy *et al.*, 2021a). However, this is not easy as the weather is unpredictable (i.e., floods or droughts) and outside the farmers' control. These events can significantly affect pasture growth, feed supply, pasture utilisation, and milk production (Verkerk, 2003). Therefore, various pasture assessment tools have been developed to help farmers balance the herd's seasonal feed demand with the annual pasture growth cycle over the past two or three decades. These include basic methods such as visual assessment, sward sticks, Rising Plate Meter (RPM), and capacitance probes or more technologically advanced methods, including the C-Dax tow behind pasture meter and satellite imagery. However, despite this, the proportion of farmers regularly measuring pasture mass is low, with previous estimates ranging from 10-50% in studies from New Zealand, Ireland, and the United Kingdom (Clark *et al.*, 2006; Creighton *et al.*, 2011; French *et al.*, 2015; McDonald *et al.*, 2016; McConnell, 2017; Eastwood *et al.*, 2020). Some of the reasons cited are that pasture measurement is boring, labour intensive and tedious (Clark *et al.*, 2006; Dalley *et al.*, 2009; Ali *et al.*, 2016).

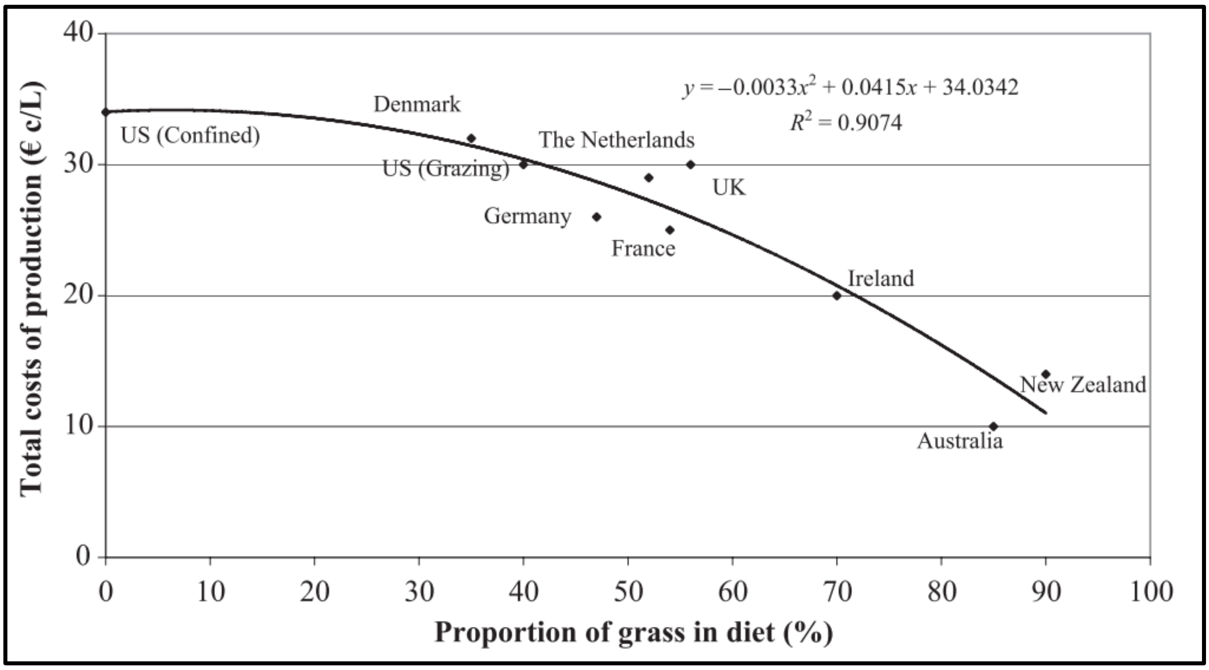

Figure 1.2: Relationship between the total cost of production (euro cents (€ c)/L) and the proportion of grass in the cow's diet. From Dillon *et al.* (2008, p. 24). Reprinted with permission.

Several studies have examined the feasibility of using Global Positioning System (GPS) technology to record paddock grazing events and estimate pasture mass (Haultain, 2014; Woodward *et al.*, 2019). However, although these studies demonstrated that it was possible to record paddock grazing events and estimate pasture mass, it has not become commonplace on-farm, possibly due to the cost of the GPS devices and lack of integration with computer software. Nevertheless, several companies such as mOOvement (Brisbane, Queensland, Australia) and Agtech (Brisbane, Queensland, Australia) have recently released solar-powered GPS ear tags to the market with much-improved computer integration and at a lower price point than earlier devices. This opportunity provides the context and motivation for the current study, which aims to determine the accuracy and precision of GPS-enabled devices (i.e., ear tags and cow collars) and identify if they can be used to determine the area allocated and record paddock grazing events automatically. Other objectives include calculating the number of devices required per herd to identify the grazed paddock and establish if they can aid on-farm decision-making and increase farm productivity on New Zealand dairy farms, particularly around pasture management. The objectives of this study are outlined in Section 1.2, while Section 1.3 outlines the structure of this research report.

This research was conducted as part of the NIWA-led Justified Irrigation MBIE [1] Endeavour Programme (C01X1617LIC) in conjunction with LIC and DairyNZ and approved by the Ruakura Animal Ethics committee.

1.2 Research objectives

This study had three main objectives:

1. Establish the accuracy and precision of GPS identification devices under New Zealand conditions, particularly cow collars (Oyster2) and GPS solar-powered ear tags (Agtech and mOOvement).
2. Determine if the current generation of GPS devices can be used to determine the area allocated and record paddock grazing events automatically.
3. Identify the number of GPS devices required per herd and the fix rate needed to provide accurate and timely information on the paddock being grazed and the grazing area allocated.

1.3 Thesis structure

Chapter 2 of this thesis examines the literature on the importance of pasture measurement on dairy farms. It reviews pasture assessment methods, discusses how to calculate pasture harvested on-farm, and examines current technology, such as automation and milk monitoring systems. Finally, GPS technologies and their implications for the livestock sector, particularly the dairy sector, are explored.

[1] Ministry of Business, Innovation and Employment (MBIE)

The accuracy and precision of the test GPS devices are discussed in Chapter 3, including both the location error and the Circular Error Probable (CEP). Next, the methodology and statistical analysis used to calculate them are explained, followed by a presentation of the findings and a discussion of the practical implications of these results for agricultural use.

Chapter 4 presents the results of an on-farm experiment in the Canterbury region of New Zealand to determine if the current GPS devices available can be used to identify paddocks grazed and the area allocated on a commercial dairy farm. The methodology, including the fieldwork and the statistical analysis undertaken, is described, followed by a discussion of the results.

Chapter 5 of this thesis uses a simulation exercise to calculate the number of GPS devices required per herd and the fix rate needed to identify the grazed paddock. Furthermore, the issue of calculating the area allocated using GPS observations is explored. This chapter explains the methodology used, followed by a presentation of the results and a discussion of the implications for on-farm use. Since Chapters 3-5 are written in the form of mini papers suitable for submission to a scientific journal, there is some repetition of earlier chapters, particularly the methodology sections.

Chapter 6 summarises the main findings of this study, the potential implications for dairy farmers and the research limitations of the current study. Following this, areas for future research are identified before the final remarks are made. Figure 1.3 provides a diagrammatic representation of the thesis structure.

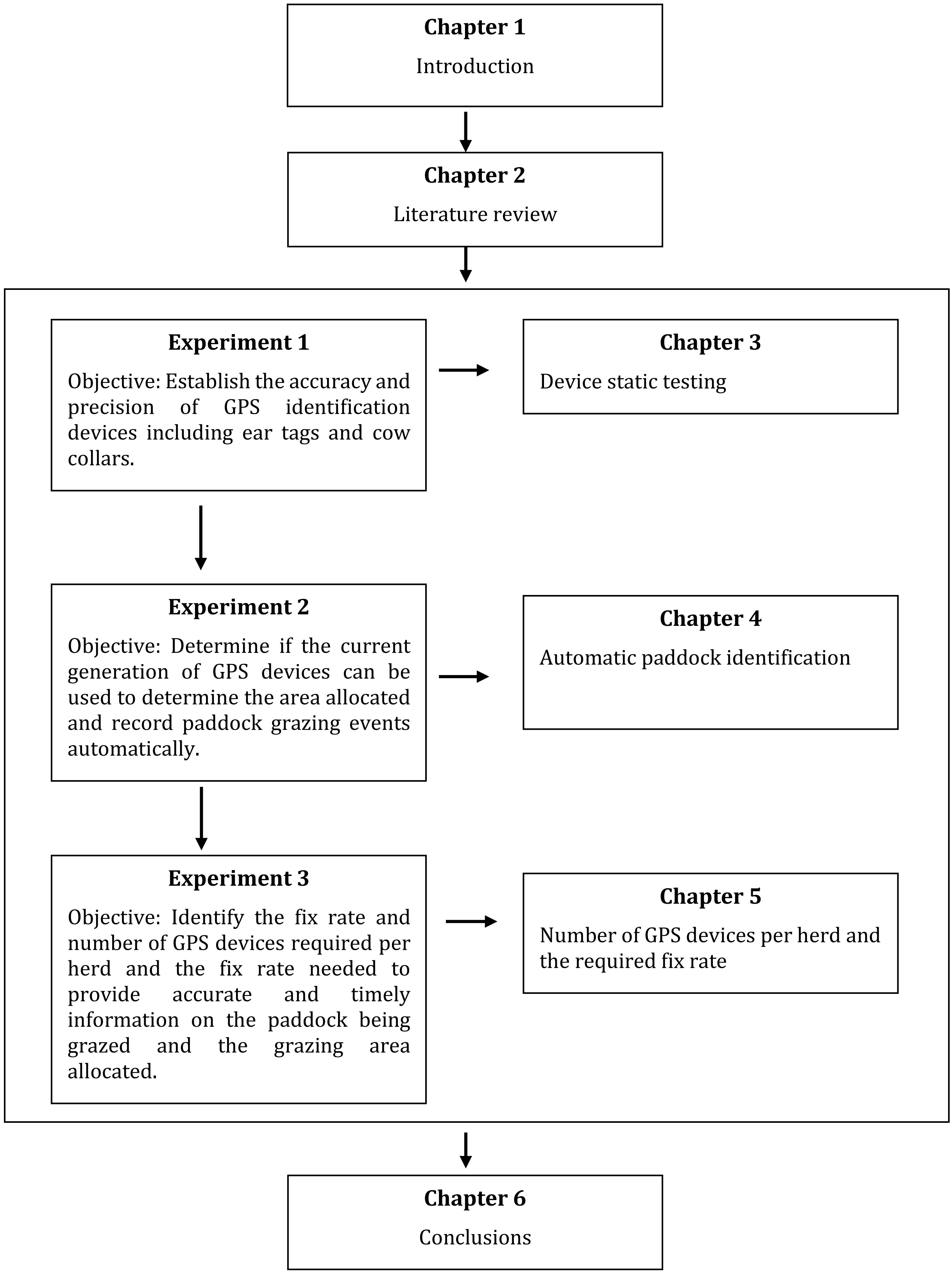

Figure 1.3: Diagrammatic representation of thesis structure.

Chapter 2

Literature review

2.1 Introduction

In pasture-based dairy systems where imported supplements are a minority of the diet, management must balance the herd's seasonal feed demand (Figure 2.1) with the annual pasture production cycle (Figure 2.2) (Holmes *et al.*, 2002; Holmes & Roche, 2007; Chapman *et al.*, 2013). Consequently, most New Zealand dairy farms are spring calving to better align with the seasonal growth pattern of perennial ryegrass (*Lolium perenne*) and white clover (*Trifolium repens)*. These are the main pasture species found on New Zealand dairy farms (Holmes *et al.*, 2002; Verkerk, 2003; Holmes & Roche, 2007; Valentine & Kemp, 2007). Grazed pasture and crops are the primary feed source on New Zealand dairy farms, making up on average 80% of the cow's annual diet. The balance consists of imported supplements (14%) and grazing off (6%) (Holmes *et al.*, 2002; Holmes & Roche, 2007; DairyNZ Limited, 2020).

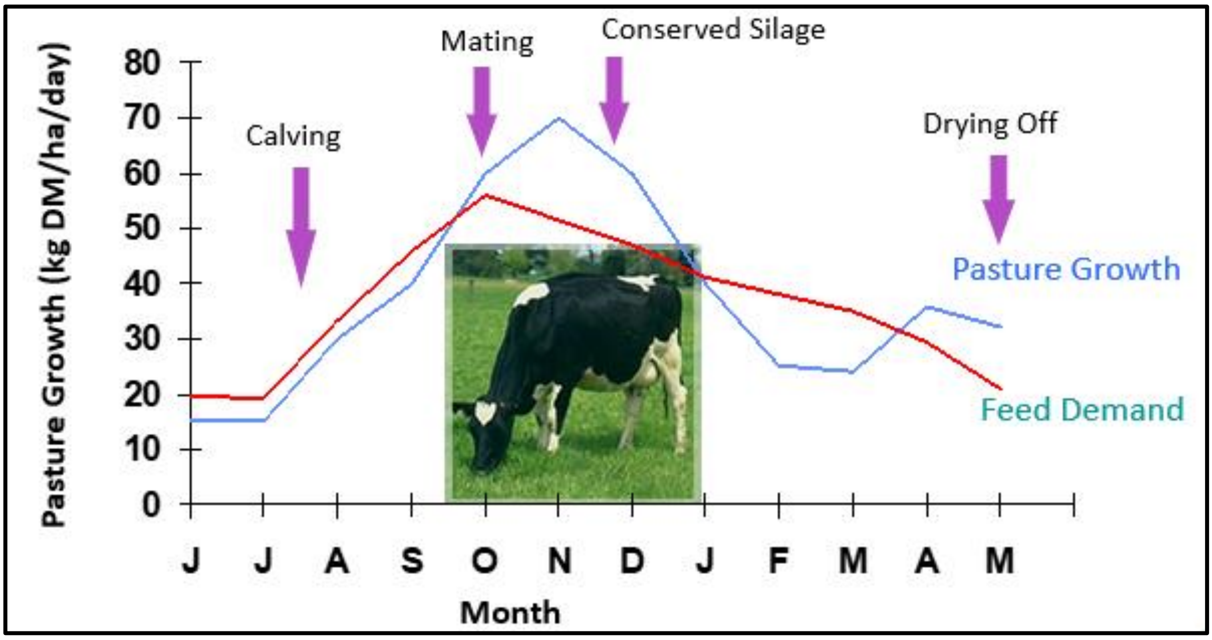

Figure 2.1: A typical pasture growth and animal requirement curve for a Waikato dairy farm calving from July 10. From C. Glassey, personal communication, August 11, 2021.

DairyNZ classifies farms as a System 1-5 based on the quantity of imported feed. For a System 1 farm, grazed pasture and crop is the only feed source with no supplement being fed other than that conserved on-farm. In contrast, a System 5 farm imports approximately 25-40% of total annual feed requirements (Holmes & Roche, 2007; DairyNZ, 2021).

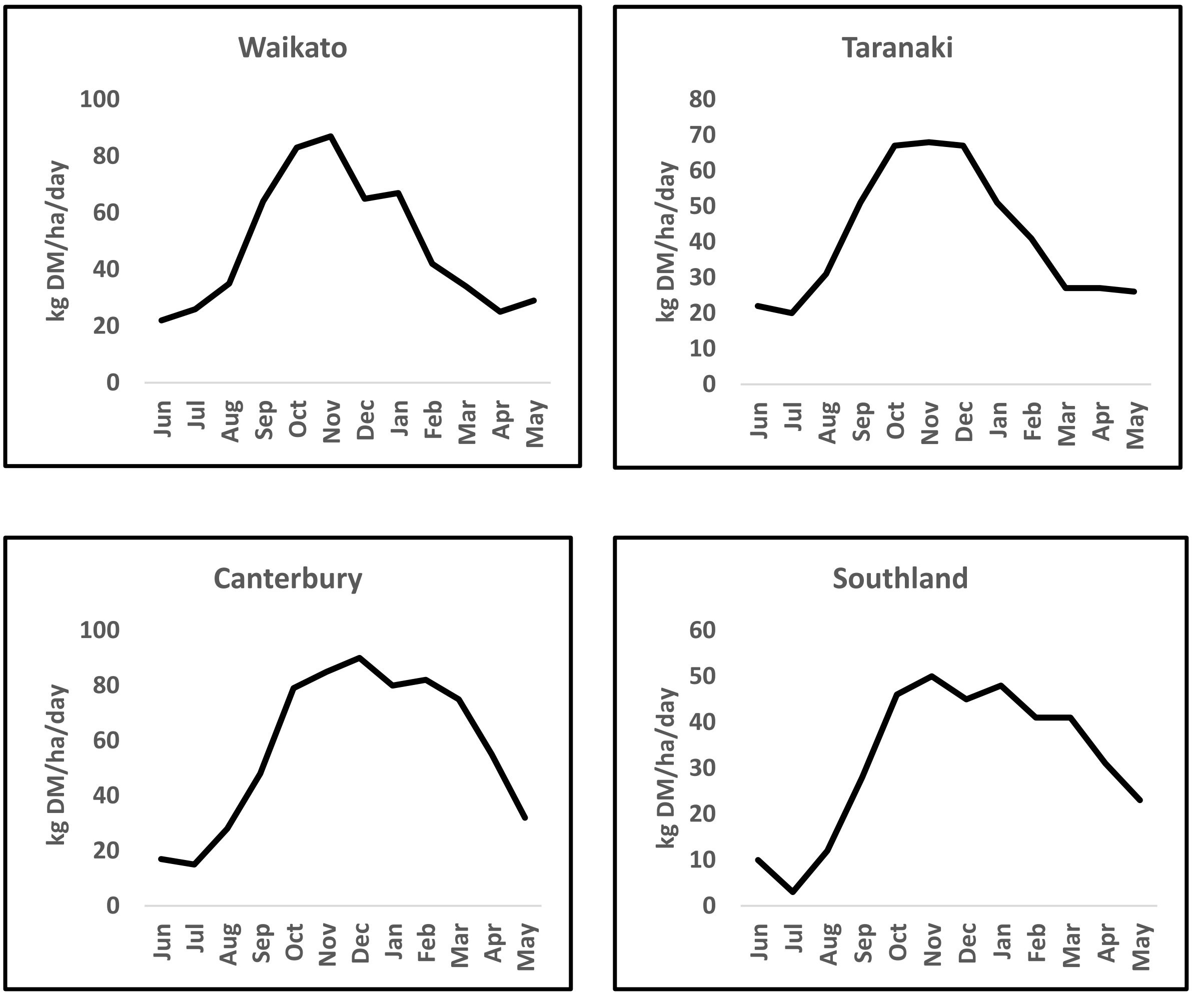

Figure 2.2: Seasonal profile of pasture production across four New Zealand sites: Waikato, Taranaki, Canterbury, and Southland. Adapted from DairyNZ (2017) data.

New Zealand's temperate climate allows for pasture growth and in situ grazing year-round. Therefore, making pasture a cheap feed source (Table 2.1) when it is well managed compared to alternative feeds like maize or meal concentrates such as palm kernel (Verkerk, 2003; Holmes & Roche, 2007; Valentine & Kemp, 2007; Ali *et al.*, 2016; Roche *et al.*, 2017; Wilkinson *et al.*, 2020).

Table 2.1: Direct cost (NZD cents/kg dry matter (c/kgDM)) of palm kernel expeller, maize silage and pasture silage compared with pasture. From Jarman (2020, p. 11).

Feedstuff	Direct cost (c/kg DM)
Pasture	15[1]
Palm kernel expeller	29
Maize silage	32
Pasture silage	35

[1] Includes capital cost of land

However, because pasture is a living organism, it presents unique management challenges. These include balancing pasture availability with cow demand and year-to-year variability in pasture growth and quality due to changing climatic conditions (Holmes *et al.*, 2002; Holmes & Roche, 2007; Chapman *et al.*, 2013). For example, grazing too soon reduces the potential for later regrowth, while delaying grazing beyond the emergence of the third leaf for ryegrass-based pastures will reduce pasture quality and subsequent animal performance (Holmes *et al.*, 2002; Verkerk, 2003; Holmes & Roche, 2007; Chapman *et al.*, 2014; Donaghy & Clarke, 2016; Roche *et al.*, 2017). Therefore, in pasture-based dairy systems, farm management decisions usually result in a compromise between pasture management (i.e., quality versus quantity) and cow requirements (i.e., feed demand) (Holmes *et al.*, 2002; Verkerk, 2003; Holmes & Roche, 2007).

Regular pasture measurement can help balance the needs of the pasture and cow demand. Firstly, it ensures that pastures are grazed at the optimal stage (~2,500-2,800 kgDM/ha) and to the correct residuals (~1,500-1,700 kgDM/ha), helping maintain pasture in an actively growing state and preserving pasture quality (Dalley *et al.*, 2009; Chapman *et al.*, 2014; Kerr & Montgomery, 2017). Secondly, pasture measurement and management can help facilitate the correct allocation of pasture to the dairy herd, helping to maintain optimal production and prevent pasture wastage (Fulkerson *et al.*, 2005; Holmes & Roche, 2007; Murphy *et al.*, 2020; Murphy *et al.*, 2021a). Thirdly, regular pasture measurement can help farmers identify pasture surpluses or deficits early and allow them to respond accordingly, which may mean conserving surplus pasture as hay or silage or feeding supplements, respectively (Dalley *et al.*, 2009; Kerr & Montgomery, 2017).

Good farmers can quickly identify a feed surplus or deficit and react accordingly through regular monitoring of pastures (Van Bysterveldt & Christie, 2007; Dalley *et al.*, 2009).

Holmes and Roche (2007, p. 228) summed it up well with the statement that "the difference between a good farmer and an average farmer is ten days". This chapter reviews the importance of pasture measurement on dairy farms, explains the current techniques available for pasture assessment, and discusses the practices for recording paddock grazing events. It also examines the methods for calculating pasture harvested on-farm and technology used on dairy farms, such as GPS, farm automation, and monitoring systems around the cowshed.

2.2 Importance of pasture measurement on dairy farms

In countries with temperate climates, such as New Zealand, Australia, and Ireland, grazing pasture plays an essential role in milk production, farm profitability, and global competitiveness (Easton *et al.*, 2002; Holmes *et al.*, 2002; Holmes & Roche, 2007; Eastwood *et al.*, 2020; Horan & Roche, 2020; Wilkinson *et al.*, 2020; Murphy *et al.*, 2021a). In these climates, pasture growth occurs in a seasonal pattern for most of the year, making pasture a low-cost feed source (Verkerk, 2003; Valentine & Kemp, 2007; Chapman *et al.*, 2013; Horan & Roche, 2020; Murphy *et al.*, 2021a). New Zealand dairy farmers rely primarily on grazing systems to manage pastures to maximise growth and utilisation (Holmes *et al.*, 2002; Verkerk, 2003; Holmes & Roche, 2007). Pasture utilisation is one of the main factors influencing the efficiency and profitability of pasture-based dairy systems (Holmes & Roche, 2007; Hanrahan *et al.*, 2018; Murphy *et al.*, 2020; Neal & Roche, 2020; Murphy *et al.*, 2021a). Utilisation can either be increased by growing more grass (e.g., changing soil fertility or sward composition) or improving the utilisation rate, which is affected by grazing management decisions, including pasture measurement and feed allocation (Teagasc, 2017).

Analysing Irish National Farm Survey data over eight years (2008-2015), Hanrahan *et al.* (2018) reported that for each additional tonne of dry matter utilised on dairy farms, gross profit increased by €273 (466 NZD)[2] and net profit by €173 (295 NZD). For Irish drystock farmers, each additional tonne of drymatter utilised is worth an additional €105 (180 NZD) (Maher *et al.*, 2021a; Maher *et al.*, 2021b). Likewise, utilising 12 years of DairyBase data based on New Zealand dairy farmers from 2005/06 to 2016/17, Neal *et al.* (2018) came to a similar conclusion. In this study, those farmers achieving the highest return on

[2] As at 1/02/2022 €1 = $1.71 NZD

assets harvested the most pasture and crop, which was associated with a higher operating profit of $300 /tDM on average. For the average New Zealand dairy farm milking 440 cows on 155 hectares, this is potentially an increase in operating profit by $46,500 if they can increase pasture growth and utilisation by one tonne of dry matter per hectare (LIC & DairyNZ, 2020).

Although pasture is the cheapest feed source on-farm, only around half of New Zealand dairy farmers use formal measurement tools for pasture assessment. For example, in a 2018 survey of five hundred New Zealand dairy farmers, 52% used visual assessment, 45% used measurement aids such as a platemeter and 3% used no assessment method. Of the technologies used by farmers, the RPM was the most common (32% of surveyed farmers), followed by the C-Dax pasture meter (11%) and satellite (1%)(Eastwood *et al.*, 2020). A similar survey of one hundred Irish dairy farmers who started milk production between January 2009 and August 2011 found that 51.2% had adopted grassland measurement (McDonald *et al.*, 2016).

While studies by Eastwood *et al.* (2020) and McDonald *et al.* (2016) suggest that around half of dairy farmers in New Zealand and Ireland conduct regular farm walks, the actual number may be lower based on earlier research (Clark *et al.*, 2006; Creighton *et al.*, 2011; French *et al.*, 2015). For example, these studies indicated that less than 20% of New Zealand farmers and 10-18% of Irish dairy farmers measured herbage mass or used feed budgeting techniques. Similarly, McConnell (2017) reported that it is estimated that less than 10% of United Kingdom dairy farmers conduct regular farm walks. Reasons for the lack of formal farm walks may be due to farm size, the skill level of employees, and the time required (Clark *et al.*, 2006; Dalley *et al.*, 2009). The lack of time is particularly evident in the spring when calving, cropping, and surplus pasture conservation occurs on the farm. However, this is a critical period when farm walks are beneficial since poor pasture management during this period can have long-lasting consequences for the remainder of the season (Dalley *et al.*, 2009).

Due to the absence of formal farm walks, many farmers take an educated guess regarding the management and allocation of their cheapest feed source. McDonnell (2021) expressed it very well when he said, “you can’t manage what you don’t measure”. Others share this view, including Anderson and McNaughton (2018, p. 191). They stated that “for a farmer to manage their pasture optimally, they must measure and record it regularly, and the majority of farmers do not". Since regular farm walks provide timely information on the current state of play and allow better decisions to be made, it is beneficial to conduct them regularly, ideally every 7-10 days (Yule & Atmore, 2006; Van Bysterveldt & Christie, 2007; Dalley *et al.*, 2009).

In a survey of five hundred New Zealand dairy farmers in 2018, only 41% conducted weekly farm walks in spring. A further 25% assessed pasture covers every 10 to 14 days (B. Dela Rue, personal communication, January 24, 2022). The remainder of surveyed farmers measured at less frequent intervals, as shown in Figure 2.3. Similarly, a LIC survey of 460 dairy farmers indicated that two-thirds of farmers conduct some form of pasture measurement. However, while two-thirds undertook some form of pasture measurement, only half did so regularly, with 36% recording the information electronically (Anderson & McNaughton, 2018).

Management decisions that regular farm walks can help with include deciding what rotation length to use, how much supplement to feed, whether to apply nitrogen or gibberellic acid and identifying pasture surpluses and deficits (Dalley *et al.*, 2009). Without timely information from pasture walks, these decisions are more challenging to make, which can mean unnecessary costs are incurred, or pasture allocation is inaccurate. Consequently, pasture is likely to be wasted, leading to a deterioration in pasture quality or a decline in animal performance if the daily allocation is insufficient (Fulkerson *et al.*, 2005; Yule & Atmore, 2006; Murphy *et al.*, 2021a).

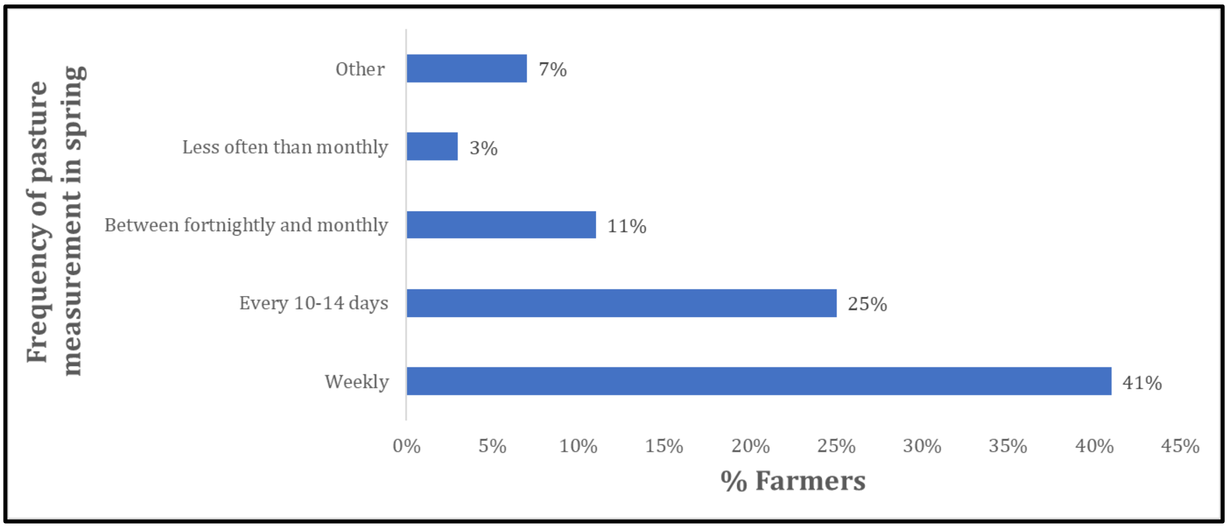

Figure 2.3: Frequency of pasture measurement during spring in a 2018 survey of 500 New Zealand dairy farmers. Adapted from B. Dela Rue, personal communication, January 24, 2022.

Correct pasture allocation can improve production and profitability (Fulkerson *et al.*, 2005; Beukes *et al.*, 2018; Irvine & Turner, 2018). For instance, Fulkerson *et al.* (2005) demonstrated that accurate feed allocation could increase production by around 10% when comparing cows grazing perennial ryegrass or kikuyu (*Pennisetum clandestinum*) pastures in Australia. They attribute the increase in production to keeping pastures in a growing state by targeting the correct residuals. However, the primary benefit was identified as the ability to increase pasture use that would otherwise have been wasted due to over-allocation.

Meanwhile, Beukes *et al.* (2018), using the DairyNZ Whole Farm Model, a farm systems research tool, found that using the knowledge gained from regular monitoring of herbage mass could increase per hectare production by 5-6% and farm profit by 15-19% in an 'average' year (Figure 2.4). The increase in production and profit is primarily due to more accurate feed allocation. Based on a milk price of \$6.33/kg milksolids (fat + protein) 'imperfect knowledge' (i.e., herbage mass estimated with an average error of 15%) increased farm operating profit by \$385/ha compared with 'low knowledge' (i.e., herbage mass is unknown). 'Perfect knowledge' (i.e., herbage mass is known with perfect accuracy) increased farm operating profit by another \$155/ha. Similarly, an eighteen-month on-farm study conducted in Tasmania, Australia, with four farmers estimated that regular pasture measurement could improve profitability by between \$90 and \$550/ha. In this trial, the farmers received weekly pasture data during the spring, summer and autumn periods as measured by technical officers employed by the Tasmanian Institute of Agriculture using a rising plate meter. When the cows were not lactating during the winter, pasture measurements were reduced to fortnightly (Irvine & Turner, 2018).

		Measure & Manage Pasture	
		No	**Yes**
Inputs	**High**	Milksolids (kg/ha) - 1,990 Profits (per hectare) - \$3,565	Milksolids (kg/ha) - 2,097 **(+5%)** Profits (per hectare) - \$4,119 **(+15%)**
	Medium	Milksolids (kg/ha) - 1,210 Profits (per hectare) - \$2,652	Milksolids (kg/ha) - 1,283 **(+6%)** Profits (per hectare) - \$3,177**(+19%)**

Figure 2.4: Effect of pasture measurement on production per hectare and farm profitability in an 'average' year for two farm systems, medium and high input, based on a study by Beukes *et al.* (2018).

As there may be considerable variation between individual paddocks on-farm (Table 2.2), it is unlikely that estimating paddock performance without physical measurements is the best way. For example, in three studies conducted across New Zealand, differences of up to 125% or 10.7 tDM/ha between individual paddocks on-farm have been recorded (Clark *et al.*, 2010; Yule *et al.*, 2013; Kerr *et al.*, 2015). Some of the differences within farms may be partly explained by the different soil types found across the property, impacting water holding capacity and nutrient status. However, care is needed when interpreting results across years due to the interactions between the soil and weather conditions each year (Blackmore *et al.*, 2003; Clark *et al.*, 2010).

Table 2.2: Individual paddock annual dry matter yield for several New Zealand studies.

Study	Region	Year	Yield tDM/ha	Pdk dif. tDM/ha	Measurement method	Notes
Clark *et al.* (2010)*	Waikato	2005-07	10.6-21.3	10.7	RPM	
Yule *et al.* (2013)	Taranaki	2009-13	8.0-18.0	10.0	C-Dax	
Kerr *et al.* (2015)	Canterbury	2012-13	9.3-15.1	5.8	'eyeometer'	Irrigated

* Average of two commercial farms

In the absence of adequate paddock records of pasture dry matter yield, many farmers may not be able to identify their top-performing paddocks relative to the lowest-performing ones. Consequently, the paddocks cropped or regrassed may not necessarily be the poorest performing paddocks on-farm. Therefore, it is beneficial for farmers to conduct regular pasture measurements since they provide a good starting point to identify any pasture performance issues (Yule & Atmore, 2006; Stevens & Knowles, 2011). Once identified, the reasons for the low dry matter yield can be investigated, including variations in soil type, drainage and fertility issues, a difference in pasture species, or insect damage (Yule & Atmore, 2006; Kerr & Montgomery, 2017).

If the cause of the low dry matter yield is identified as the pasture species, pasture renewal may be an option. Pasture renewal can increase total dry matter yield, pasture feed value, pasture utilisation, and animal performance (Kerr *et al.*, 2015; Tozer *et al.*, 2015), potentially leading to increased farm profitability (Table 2.3). However, the extent of these benefits will be determined by the overall management of the new pastures. For example, in one study, Glassey *et al.* (2010) reported a net advantage of pasture renewal at 1.7 tDM/ha/year and increased metabolisable energy of 0.5 MJME/kgDM on average. Similarly, over three years of comparing renewed and old pastures in the Waikato and

Bay of Plenty regions, Tozer *et al.* (2015) reported a yield advantage of renewed pastures at 1.5, 1.8 and 1.9 tDM/ha, respectively.

Table 2.3: Cost of new pasture and possible returns at increases of 1, 2, and 3 tDM/ha/year over four years. Adapted from P. Hames, personal communication, June 4, 2021.

Extra grown (tDM/ha/year)		**1**	**2**	**3**
	Extra growth over four years	4.00	8.00	12.00
DM yield tDM/ha	DM lost during renewal	1.50	1.50	1.50
	Net increase in yield (a)	2.50	6.50	10.50
Renewal costs[1]		$1,105	$1,105	$1,105
Cost c/kgDM		44	17	11
Extra kgMS[2]	Increase in dry matter yield	169	440	711
Extra kgMS[3]	Additional kgMS from higher MJME	336	336	336
Total extra kg MS over 4 years		**505**	**776**	**1047**
Income extra kgMS @ $6/kg		$3,031	$4,656	$6,281
Marginal cost extra kgMS @$1.50/kgMS		$758	$1,164	$1,570
Net increase income before renewal costs		$2,274	$3,492	$4,710
Return on investment (%)		106	216	326
Return on investment annualised (%)		**20**	**33**	**44**

[1] Appendix 1 $/ha.

[2] Net increase(a) pasture utilisation 80%, average MJME 11.0, conversion 130 MJME/kgMS.

[3] 14 tDM/ha/year pasture utilisation 80%, increase MJME 0.6 /kgDM, conversion 80 MJME/kgMS.

Since farm profitability is positively correlated with pasture eaten, as described above, there is likely to be value from the regular measurement of herbage mass and the recording of grazing events, as successfully demonstrated on Niaruo Dairies, an 85-hectare dairy farm situated in Taranaki, New Zealand. Over four years, farm management has increased average pasture production from 12.9 tDM/ha to 18.6 tDM/ha using technology such as the C-Dax pasture meter to conduct weekly farm walks and all paddock soil sampling (Yule *et al.*, 2013). Pasture utilisation has also increased from a historical average of about 75% to 85% (Yule *et al.*, 2010). Although the farm walk took about 1.25 hours every week to complete, it has enabled better farm management decisions to be made at all levels, strategic, tactical, and operational (Yule *et al.*, 2010).

Table 2.4 presents a breakdown of how Niaruo Dairies uses the pasture walk information at each management level.

Table 2.4: How Niaruo Dairies uses the pasture walk information at each of the three primary management levels, strategic, tactical, and operational. From Yule *et al.* (2010).

Management level	Management decisions
Strategic	
Total farm production per year – tDM/ha/year	Used to measure pasture performance annually.
Individual paddock performance – tDM/year	Lowest performing paddocks investigated and identified as possible cropping paddocks next rotation
Tactical	
Average pasture cover at measurement	Used to calculate desired pre-grazing cover
Average weekly pasture growth position	Use a feed wedge to check the current feed
Operational	
Paddock growth rates	Uses the currently available pasture cover in individual paddocks and predicted growth rate
Pasture demand	Calculate actual daily pasture intake

2.3 Pasture measurement methods

In farm practice, pasture measurement is traditionally carried out using visual assessment or technology such as the RPM, capacitance probe or sward stick (Dalley *et al.*, 2009). However, these methods are time and labour intensive, become tedious when used regularly, and are subject to operator error (Clark *et al.*, 2006; Dalley *et al.*, 2009). Recent developments in pasture measurement include the C-Dax tow behind pasture meter, the Grasshopper RPM, Pasture Reader, satellite imagery, the Farmote system, and the C-Dax pasture robot. These methods will be discussed more fully in the following section.

2.3.1 Visual measurement

Visual measurement or scoring of pastures is the most common method of pasture assessment on-farm because of its convenience and ease of use, although it can be highly subjective (L'Huillier & Thomson, 1988; Murphy *et al.*, 2021a). Nevertheless, when performed by a person experienced in visual pasture assessment, it can be reasonably accurate (Parker, 1973; L'Huillier & Thomson, 1988; O'Donovan *et al.*, 2002). However, variation may occur during the season due to pasture species, amount of dead matter present, and dry matter percentage (Parker, 1973). Therefore, while this is a quick and easy, non-destructive method of pasture assessment, operators need adequate training. They must also make regular visual calibrations using a RPM or other pasture assessment method such as cutting and weighing to ensure that paddocks are not under or overscored (O'Donovan *et al.*, 2002; Ali *et al.*, 2016; Murphy *et al.*, 2021a).

2.3.2 Sward stick

The sward stick is another simple but effective tool to measure pasture height (Figure 2.5). It is designed to fit in the user's pocket, is waterproof, and is a quick and easy tool to aid feed budgeting decisions featuring pasture dry matter estimates for different growth periods (Beef + Lamb New Zealand, 2017; Farmax, n.d.). To use, farmers need to take a minimum of six measurements per paddock by measuring the height of the tallest clover plants or the average ryegrass height, thus determining the average sward height (Farmax, n.d.). While the sward stick is characterised for different growing periods, there may be times when it is appropriate to use measures from another period. For example, in a dry autumn where the pasture contains mainly dead material and minimal green leaf, it may be appropriate to use the summer measurement rather than the autumn measurement (Beef + Lamb New Zealand, 2017; Farmax, n.d.). In addition, the sward stick is an ideal tool to check whether a user's 'eyeometer' matches their visual estimate of dry matter yield (Farmax, n.d.).

Figure 2.5: A sward stick example. From Farmax (n.d.).

2.3.3 Rising plate meter

After visual measurement, the RPM (Figure 2.6, left) is the most common method used on New Zealand dairy farms for pasture assessment. The RPM consists of a steel plate and a one-meter shaft and when lowered to ground level, the steel plate will rise relative to grass height, providing an estimate of the compressed pasture height (McSweeney *et al.*, 2019). The compressed pasture height is measured in clicks, with each click equal to 0.5 cm, so eight clicks on the RPM are equivalent to a compressed pasture height of 4 cm (DairyNZ, 2008; McSweeney *et al.*, 2019; Murphy *et al.*, 2021a). Several formulas are available to convert compressed pasture height into an estimate of kgDM/ha. The most common is the meter reading (pasture height) x 140 + 500. Nevertheless, to account for differences in dry matter or the growth rate of the pasture, the multiplier (140) or the adder (+ 500) may be adjusted for specific periods. For example, during periods of fast growth or low pasture dry matter, a multiplier of 115 can be used. In dry conditions or times of slow growth, a multiplier of 185 may be used (DairyNZ, 2008; Platemeters, 2021). However, most farmers use a multiplier of 140 year-round (DairyNZ, 2008).

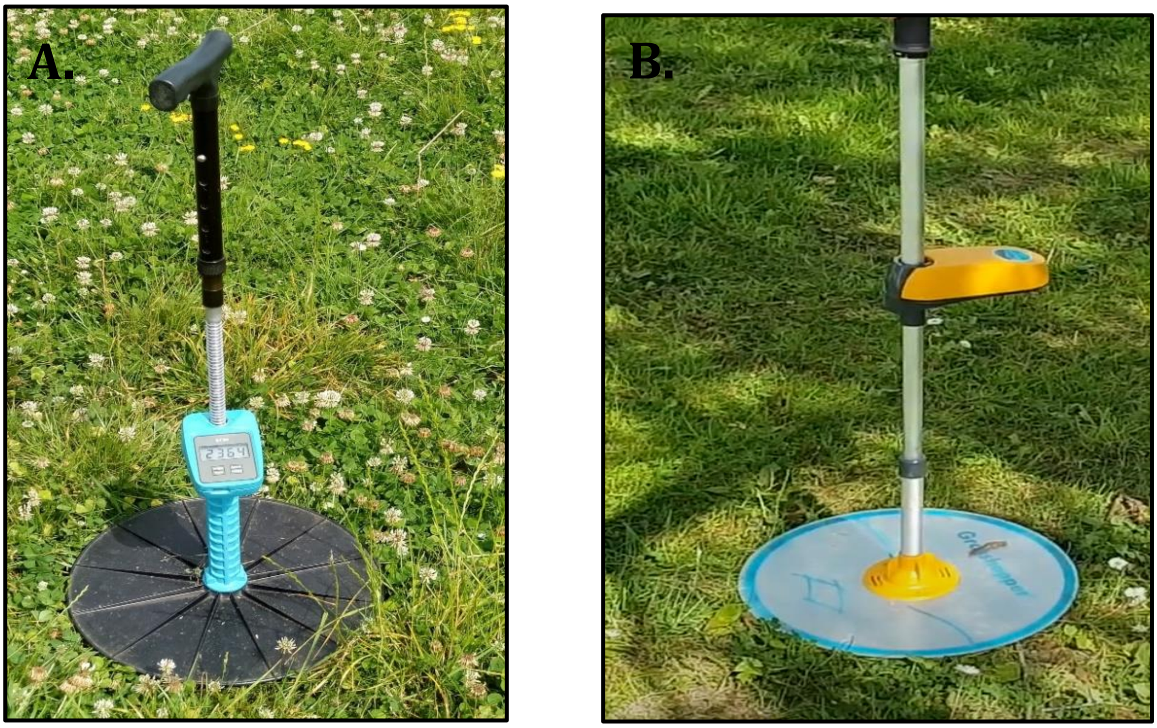

Figure 2.6: Photos showing the traditional electronic RPM (A) and the Grasshopper RPM (B). Photos by (A.) W. Hofmann and (B.) B. O' Brien, personal communication, January 26, 2022.

A recent update to the RPM led to the development of the Grasshopper (Figure 2.6, right). Developed by True North Technologies in partnership with Teagasc, Moorepark, Ireland, the Grasshopper is a modified version of the traditional RPM, which uses a GPS integrated ultrasonic sensor to record the height of the rising plate (Claffey, 2018; McSweeney *et al.*, 2019; Murphy *et al.*, 2021b). It also incorporates GPS for automatic paddock recognition and Bluetooth functionally for automatic data recording to a smartphone (Figure 2.7). Furthermore, this data is automatically uploaded to Pasturebase Ireland (PBI) to establish a performance history at a paddock and farm level (Macdonald, 2017; Claffey, 2018; McSweeney *et al.*, 2019; Maher *et al.*, 2021b). In a recent study, the Grasshopper proved to be more accurate than the traditional RPM (McSweeney *et al.*, 2019).

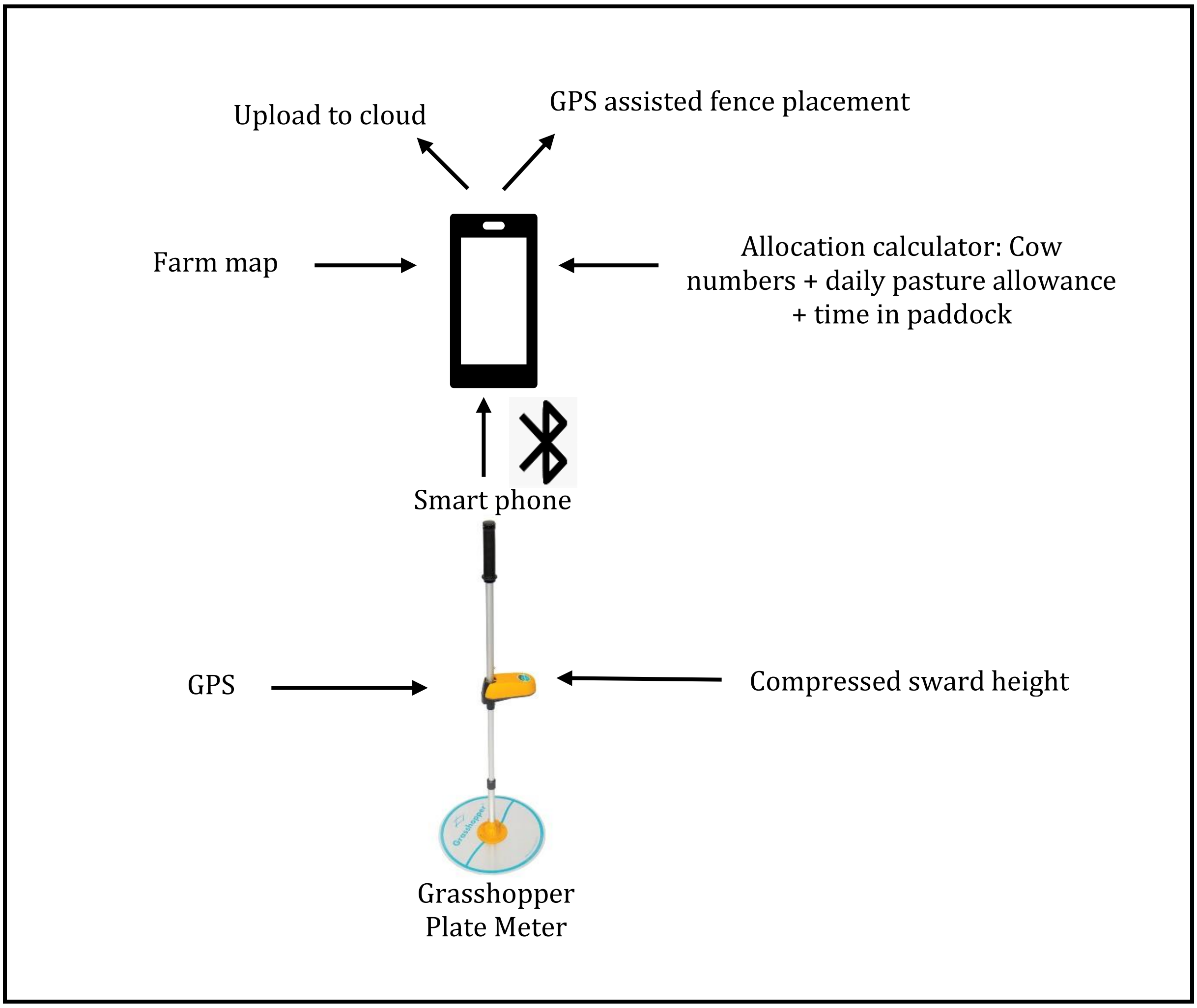

Figure 2.7: The wireless communication process between the Grasshopper Rising Plate Meter, GPS, and smartphone devices. Adapted from McSweeney *et al.* (2019, p. 280).

Nonetheless, the RPM has some disadvantages, including operator variability, reading accuracy on rolling contour or pugged pastures and changeability in pastures due to factors such as animal grazing, dung pats and pasture species (Lile *et al.*, 2001; Matthew, 2015; Murphy *et al.*, 2020; Murphy *et al.*, 2021a). These factors all contribute to measurement error. For example, in a study undertaken in Ireland using perennial ryegrass and white clover pastures, Murphy *et al.* (2021a) found that the RPM could estimate compressed herbage height to within 5% of actual if a minimum of 24 RPM measurements per hectare were taken in a random stratified manner. Similarly, in a study at Camden, Australia, using annual ryegrass, Gargiulo *et al.* (2020) reported a measurement error of 5% when using a RPM to estimate pasture dry matter after taking approximately 60 RPM readings per hectare. However, Murphy *et al.* (2021a) suggest that a 5% measurement error can be achieved by taking between 24-40 RPM readings per hectare. Their study found no evidence that more readings per hectare will ensure greater accuracy.

2.3.4 Quadrat cuts

Quadrat cuts (Figure 2.8) consist of placing a quadrat, usually 0.1 or 0.25 m^2, on the ground and cutting any herbage within the quadrat to a predetermined level, followed by washing to remove dung and dirt, drying and weighing to calculate dry matter yield (Dalley *et al.*, 2009; Beef + Lamb New Zealand, 2017). Quadrat cuts are considered the gold standard method of herbage mass estimation due to their accuracy (Dalley *et al.*, 2009; Murphy *et al.*, 2021a). However, this approach has several drawbacks, including being a destructive method of herbage assessment and that many samples are needed to account for paddock variability. Additionally, this method can be time-consuming if many samples are required (Ali *et al.*, 2016; Murphy *et al.*, 2021a). For these reasons, quadrat cuts are usually kept for research purposes (Bryan *et al.*, 1990; Murphy *et al.*, 2021a).

Figure 2.8: A quadrat and electric handpiece used to perform quadrat cuts. From Hofmann (2009, p. 25).

2.3.5 Capacitance probe

The use of capacitance probes (Figure 2.9) such as the GrassMaster II (Novel Ways Ltd) and the Pas-T-PLUS (TechniPharm) is another method used on-farm to measure pasture dry matter yields. Capacitance probes measure the difference in dielectric constant between air and the herbage to measure sward capacitance, thus indicating surface area. Pasture mass can then be estimated using inbuilt calibration equations (Currie *et al.*, 1987; Sanderson *et al.*, 2001; Novel Ways, 2015; Beef + Lamb New Zealand, 2017; Sharpe & Rayburn, 2019). The capacitance probe gave mixed results in studies, with Bryan et al. (1990) reporting that the capacitance probe showed promise as a herbage mass measurement tool. In contrast, Sanderson *et al.* (2001) suggested that this method was inaccurate for estimating herbage mass. O'Donovan *et al.* (2002), comparing four methods of herbage measurement (visual estimate, RPM, sward stick, and capacitance probe), also concluded that the capacitance probe was an inaccurate method of herbage assessment. In their study, the visual estimate was the most accurate method of herbage assessment (193 kgDM/ha residual s.d.). The least accurate was the capacitance probe (458 kgDM/ha residual s.d.).

Figure 2.9: The Pas-T-Plus capacitance probe for pasture measurement. From TechniPharm (2012, p. 3 & 8). Reprinted with permission.

2.3.6 C-Dax tow-behind pasture meter and pasture robot

The C-Dax tow behind pasture meter is a more recent development for pasture measurement (Figure 2.10, right). Developed at Massey University's Centre for Precision Agriculture in the early 2000s, it provides a quick and reliable measure of pasture cover. Towed behind a quad bike or other vehicle, it uses a series of interrupted light beams and high-speed electronic sensors to estimate pasture dry matter yield(Dalley *et al.*, 2009; Matthew, 2015). When operating at field speeds of around 20 km/hr, the C-Dax tow behind pasture meter can measure pasture height approximately 200 times per second or every 0.027 m (Yule & Atmore, 2006; Lawrence *et al.*, 2007; Dalley *et al.*, 2009). Thus, over a distance of 500 m, up to 18,500 readings may be taken compared to approximately 250 readings if using a RPM (C-Dax, 2021). Once taken, these measurements are then averaged to provide a pasture cover estimate on either a paddock or farm level scale (Dalley *et al.*, 2009).

The main advantages of the C-Dax tow behind pasture meter over other methods are that it is quicker, provides accurate information, and is less prone to operator error as the readings are independent of the operator (Yule & Atmore, 2006; Dalley *et al.*, 2009; C-Dax, 2021). It may also be linked to benchmarking and feed budgeting software, enabling timely decisions to be made at the farm level. Newer models may also be equipped with GPS to map pasture production and provide automatic paddock recognition (Yule & Atmore, 2006; Yule *et al.*, 2010).

Figure 2.10: C-Dax pasture robot (left) and tow-behind pasture meter (right). Photos by W. Hofmann.

A new development by C-Dax for pasture measurement is the pasture robot (Figure 2.10, left), developed in partnership with Massey University, New Zealand. The robot has been designed to measure pasture cover automatically using 3D cameras and GPS to navigate and 18 light bars to measure grass length as it drives over it (Gill, 2021; Massey Ventures, n.d.). The robot is currently undergoing field testing and is expected to be commercialised shortly.

2.3.7 Pasture Reader

The Pasture Reader (Figure 2.11), developed at Ellinbank in Australia, is a recent pasture measurement tool (Dairy Australia, 2014). Unlike the C-Dax pasture meter, which is towed behind the quad bike, the Pasture Reader is mounted to the front of an ATV or other suitable vehicle(Dalley *et al.*, 2009). This technology has also been adapted to fit onto mowers allowing farmers to measure the dry matter as the mower passes over it before the grass is cut (McCullough, 2018). It uses sonar (sound) technology, like that found in fish finders and other equipment (Dalley *et al.*, 2009), to measure the distance from the sensor to the top of the grass, assuming the ground is a known distance from the sensor (Legg & Bradley, 2019). Thus, pasture height can be obtained in centimetres and converted into kilograms of dry matter using a series of calibration equations developed for the Pasture Reader.

Figure 2.11: Pasture Reader mounted on the front of an ATV. From Naroaka Enterprises (2021).

The main advantages of the Pasture Reader are similar to that of the C-Dax pasture meter in that it is quicker than conventional methods of measuring pasture dry matter and that it takes multiple measurements per second, thus improving the accuracy (Dalley *et al.*, 2009; Dairy Australia, 2014). Furthermore, it can be permanently connected to the bike, making it easy for farmers to take pre and post grazing measurements to ensure the correct feed allocation. A downside to the Pasture Reader is that once the unit has been zeroed (i.e., to start measuring), the unit must remain stable. Anything that changes the suspension weight or causes the vehicle to tilt or bounce, such as a change in rider position, dogs jumping off, or driving over pugged ground, will alter the distance between the sensor and the ground and cause the readings to be inaccurate (Dalley *et al.*, 2009; Legg & Bradley, 2019).

2.3.8 Satellite imagery

After extensive field trials in both New Zealand and Australia, it is now possible to use satellite imagery to provide an estimate of pasture cover on a farm level (Clark *et al.*, 2006; Mata *et al.*, 2007; Dalley *et al.*, 2009; Mata *et al.*, 2011). The use of the Normalised Difference Vegetation Index (NDVI) is one of the main factors that make it possible to use satellite images to measure pasture dry matter. The principle of the NDVI index is that different plant materials have different reflective characteristics making it possible to determine if vegetation is present by evaluating the ratio between red and near-infrared wavelengths. Plants absorb red wavelengths and reflect wavelengths in the near-infrared range (Clark *et al.*, 2006; Dalley *et al.*, 2009; Shalloo *et al.*, 2018; Shalloo *et al.*, 2021; Stevens *et al.*, 2021). However, although satellite images can be used to measure pasture cover, several factors can influence the readings, including satellite position, cloud cover, and atmospheric conditions (Shalloo *et al.*, 2018; Woodward *et al.*, 2019; Shalloo *et al.*, 2021). Variation in pasture growth stages and botanical composition will also affect the accuracy of these images and pasture dry matter estimates. As the NDVI reaches 1, its upper limit, the saturation point is reached, lowering the prediction accuracy. Saturation point occurs for pastures at around 2,500-3,000 kgDM/ha (Wagenaar & de Ridder, 1986; Anderson & McNaughton, 2018; Anderson *et al.*, 2020; Pasture.io, 2021a; Stevens *et al.*, 2021).

In New Zealand, pasture cover can be measured by satellite through SPACE (Satellite Pasture and Cover Evaluation - Figure 2.12). This technology utilises Planet's constellation of Dove satellites comprising over 130 satellites and field analysis software from Farmshots to provide an estimate of pasture cover by using algorithms to convert an NDVI reading to an estimate of pasture biomass (Macdonald, 2017; Ritchey, 2017; Anderson *et al.*, 2020). SPACE is available through Livestock Improvement Corporation (LIC) as a subscription-only service. The actual price varies by farm size, with packages starting at approximately $1,250 per annum for a 50-hectare farm (Table 2.5). If satellite images are unavailable for any reason, a pasture growth forecast model (PGF) has been incorporated into SPACE to improve data frequency (Anderson *et al.*, 2020; LIC, 2021).

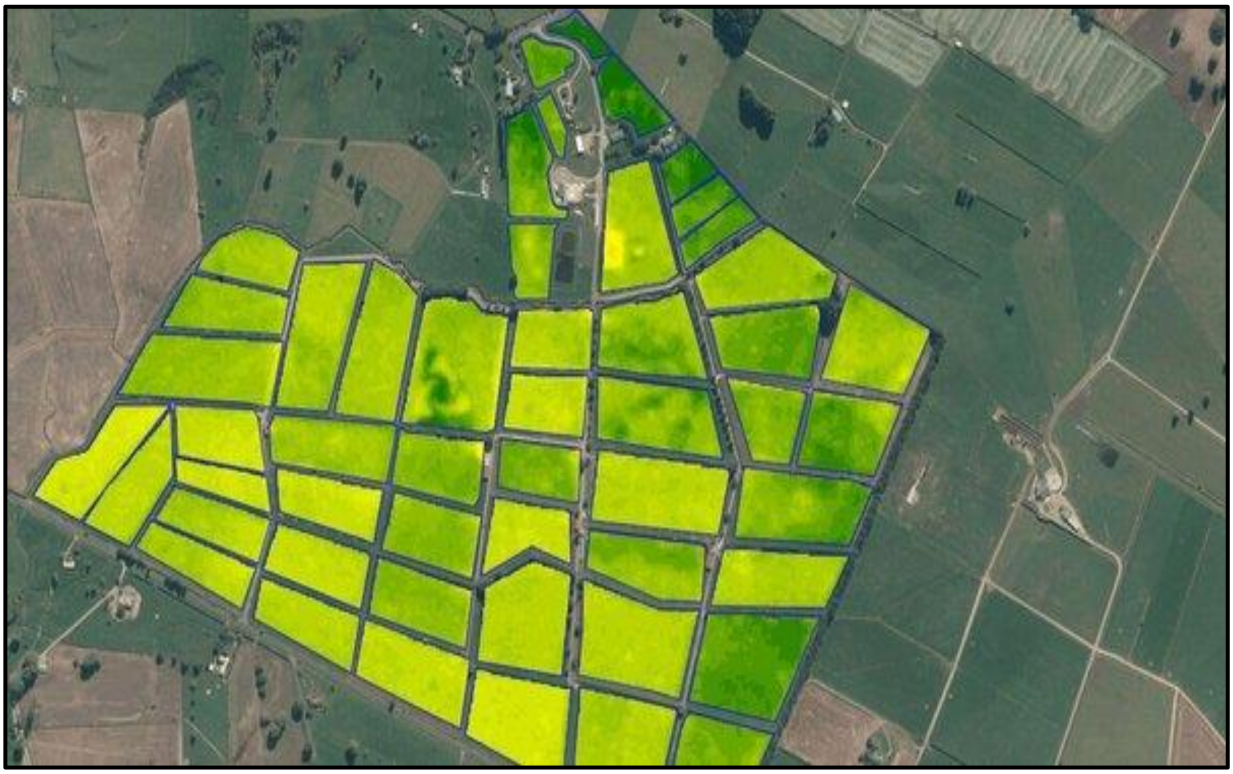

Figure 2.12: Satellite image showing varying amounts of grass represented by colour with dark green suggesting plenty of grass and yellow implying lower pasture covers. From G. Anderson, personal communication, September 2, 2021.

Table 2.5: Cost of the SPACE service from the 1st of June 2022. Adapted from LIC (2021).

Farm size (ha)	Price (per annum)
0-50	$1,253
51-80	$1,840
81-100	$2,438
101-150	$2,737
151-200	$3,036
201-300	$3,335
301-400	$3,634
401+	$3,634 + 1.15 /ha

2.3.9 Pasture growth models

Various pasture growth models have been developed and trialled over the years for New Zealand and Irish conditions, including the Pasture Quality model (Woodward, 2001), AgPasture (Li *et al.*, 2011), Pasture Growth Simulation Using Smalltalk (PGSUS) (Romera *et al.*, 2010; Romera *et al.*, 2013), and the Moorepark St Gilles Grass Growth (MoST) model

(Ruelle *et al.*, 2018; Ruelle *et al.*, 2019; Maher *et al.*, 2021a). Based on climatic conditions, farm management decisions such as nitrogen fertiliser application and irrigation use, and data from farm walks, pasture growth models aim to improve the on-farm decision-making process by modelling the expected pasture production (Woodward, 2001; Romera *et al.*, 2010; Li *et al.*, 2011; Romera *et al.*, 2013; Ruelle *et al.*, 2019). Although these models have shown promise as a potential tool for predicting pasture growth, there use is not widespread among farmers. For example, the PGSUS model showed great potential in a farmer trial and could predict herbage mass. However, farmers must enter grazing information daily for the PGSUS model to function effectively, which proved a challenge for the trial farmers (Romera *et al.*, 2013). Given that the participating farmers thought that the time needed to run the model was acceptable, Romera *et al.* (2013) felt that the farmer's routine had to change concerning the recording of grazing information.

Developed for Irish grazing systems by Moorepark, the MoSt model has proven reasonably accurate at the farm level but less accurate for individual paddocks in early studies (Ruelle *et al.*, 2019). The model can predict farm grass growth by working at the farm and paddock level after considering soil type, meteorological data, and farm management decisions like nitrogen usage (Ruelle *et al.*, 2018; Ruelle *et al.*, 2019; Maher *et al.*, 2021a). While it may not identify the absolute value, it can identify trends such as increasing or decreasing pasture growth rates, which is valuable information for short-term feed budgeting decisions (Ruelle *et al.*, 2018). Eventually, if the trial succeeds, the MoST model will be incorporated into decision support tools in Ireland, such as PBI (Ruelle *et al.*, 2019).

2.3.10 Farmote system

The Farmote system is a more modern innovation aimed at helping farmers make better pasture management decisions on-farm. The system combines multispectral satellite imagery with remote monitoring systems (motes) to create a more inclusive picture of pasture performance, enabling more informed decisions to be made (Milsom *et al.*, 2019; Rural News Group, 2019; Farmote Systems, n.d.). Solar-powered motes (Figure 2.13) are placed in selected locations on-farm and measure pasture height, atmospheric conditions, and the soil environment, i.e., soil moisture. This information is then cross-referenced with multispectral satellite imagery before being uploaded to the company's website. It is subsequently accessible to farmers or other stakeholders (Rural News Group, 2019;

Stevens *et al.*, 2021; Farmote Systems, n.d.). Each mote can monitor approximately ten hectares (Rural News Group, 2019).

In a preliminary investigation of the Farmote system at Lincoln University, New Zealand, in 2018, there was a strong correlation (R^2 = 0.93) between the Farmote derived data and collected herbage samples for pure ryegrass swards. However, the correlation was weaker for mixed ryegrass white clover swards (R^2 = 0.68) (Milsom *et al.*, 2019). Nevertheless, the authors concluded that the Farmote system had potential over traditional methods such as the RPM, including labour and time savings. Nonetheless, further work was needed to develop specific calibrations to account for pasture type and environmental effects.

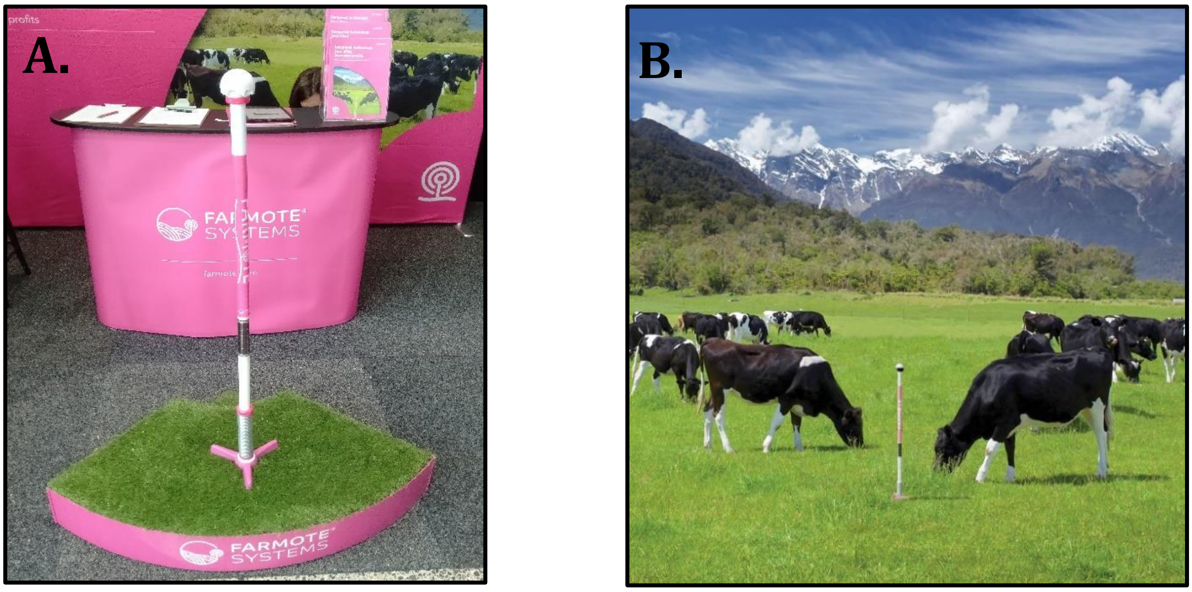

Figure 2.13: Sensor probe (mote) for the Farmote system. Photos by (A.) W. Hofmann and (B.) R. Barton, personal communication, June 1, 2021.

2.3.11 Selection of pasture assessment method

Since there are numerous methods available for pasture assessment, it can be difficult for users to decide which tool is right for them. Considerations include farm size, labour availability, accuracy required, purchase cost, and ongoing maintenance costs. However, with all these considerations in mind, the user can then decide what method is suitable for them, their farm and their unique needs, which may not be the same as their neighbour (Pasture.io, 2021b).

Figure 2.14 summarises the cost and effort associated with different pasture assessment methods. Among the methods included, the satellite-based assessment method is the most cost-effective in monetary and labour terms simply because there are no ongoing maintenance costs nor time spent in the field collecting dry matter paddock records. Data analysis is also relatively simple and may require only a few clicks on a smartphone or computer (Pasture.io, 2021b). However, using the RPM can take considerable time and energy to complete a farm walk (farm size dependent), followed by additional time to analyse the data (Clark *et al.*, 2006; Dalley *et al.*, 2009).

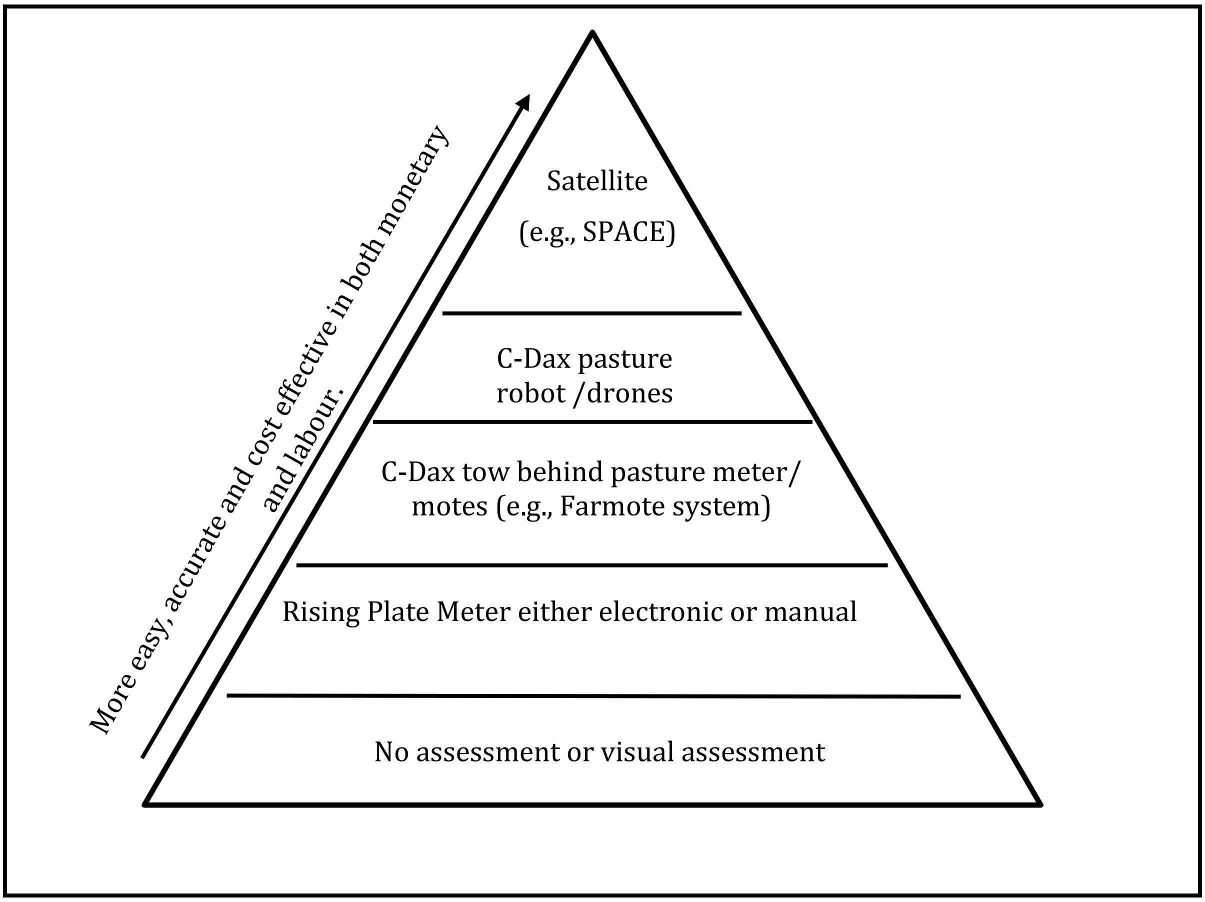

Figure 2.14: The monetary and labour cost required for various pasture measurement tools. Adapted from Pasture.io (2021b).

Dalley *et al.* (2009) evaluated a range of different pasture measurement tools for several criteria, including speed, ease of use, accuracy, and cost for many of the measurement aids described above, as displayed in Table 2.6.

Table 2.6: Evaluation rankings for current and developing pasture assessment techniques. From Dalley et al. (2009, p. 151). Reprinted with permission.

	Rising Plate Meter	Visual	Laneway drive-by	Sward Stick	C-Dax Rapid Pasture Meter	Automatic Pasture Reader	Spectral Satellite	Radar
Speed	√	√	√√√	√	√√	√√	?	?
Ease of use	√√	√√	√√√	√√	√√√	√√√	?	?
Accuracy	√√	√√	X	√√	√√	?	√	√
Ability to calibrate	√√	√√	X	√√	√√	?	√	√
Representative of paddock	√	√	X	√	√√√ *	√√	√√√	√√√
Cost	√	√	N/A	√	√√	√√	?	?
Insensitivity to weather	√	√√	√√	√	√√√	?	√	√√
Consistency between operators	√	√	√	√√	√√√	√√√	N/A	N/A
Portability	√√√	√√√	X	√√√	√√	√√	?	?
Pasture friendly	√√	√√	√√	√√	√	√	√√√	√√√
Hazard rating	√	√	√√√	√	√√	√√	N/A	N/A

√ Low √√ Medium √√√ High X Not suitable ? Currently unknown N/A Not applicable * If used with GPS and mapping software

2.4 On-farm technology

The total number of dairy herds in New Zealand has declined in the past ten years, while the average herd size has increased (LIC & DairyNZ, 2020). This has led to greater technology adoption, such as automatic cup removers (ACR), teat sprayers, drafting systems, and milk recording systems, as farmers seek to improve labour efficiency, productivity or operate more sustainably (Edwards *et al.*, 2015; Dela Rue *et al.*, 2020). In a 2018 survey of 500 New Zealand dairy farmers looking at technology adoption, 39% had ACRs installed, 29% had automatic teat spraying, and 24% had automatic drafting systems (Figure 2.15). Additionally, 8% of farms surveyed had electronic milk meters, 7% automatic animal weighing and 3% automatic heat detection systems (Dela Rue *et al.*, 2020). As technology evolves and the cost decreases, more farmers are likely to install new technologies on-farm if they can deliver value to their farm business (Edwards *et al.*, 2015; Dela Rue *et al.*, 2020). Technology adoption is likely to be the greatest on larger farms, as Gargiulo *et al.* (2018) showed. In this study, farms with more than 500 cows adopted 2-5 times more technologies such as ACRs and electronic identification than those with smaller herds.

Milk Vat Monitoring Systems (MVMS) such as Halo and Levno are examples of a technology found on many New Zealand dairy farms. Recently installed by Fonterra on its suppliers' farms, these systems provide a wealth of information, including milk temperature, milking start and stop times, and milk volume. Primarily, the installation aims to improve the efficiency of Fonterra and maintain milk quality. However, this data may have other uses at the farm level. For example, it may be possible to utilise further the information collected by these MVMS and compare milk production with the paddock recently grazed. Rationally, paddocks that produce the highest milk volumes are likely to grow higher-quality pastures; therefore, they may be grazed more often than paddocks with lower performance. Thus, leveraging data that is already collected would provide farmers with valuable information on the productivity of their paddocks and may guide other farm decisions, such as regrassing and fertiliser application.

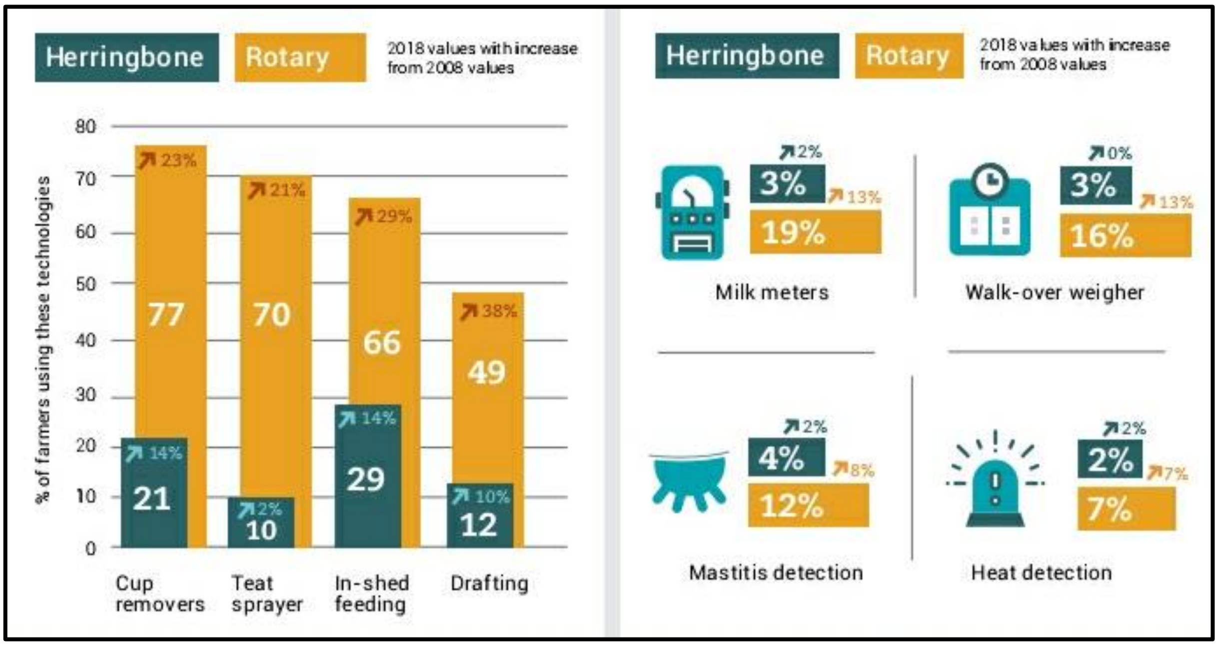

Figure 2.15: Summary of technology in the farm dairy from 2008-2018. From Dela Rue (2018, p. 9). Reprinted with permission.

2.5 Recording paddock grazing events

Some New Zealand dairy farmers record pasture covers as part of their regular farm walks to enable feeding and farm management decisions to be made (Stevens & Knowles, 2011). However, these records may not necessarily be kept electronically or on paper after making immediate decisions (Stevens & Knowles, 2011; Woodward *et al.*, 2019; Eastwood *et al.*, 2020). In one study, 42% of farmers kept electronic records of their pasture data, a third temporarily recorded pasture covers either in their head or on a whiteboard, and 23% recorded the data on paper (Dela Rue & Eastwood, 2018; Eastwood *et al.*, 2020). Electronic ways of recording the data included spreadsheets, mobile phone apps, and decision support software such as LIC Minda Land and Feed, Pasture Coach and FarmIQ in New Zealand, or PBI in the case of Irish farmers (Kerr *et al.*, 2015; Hammond, 2017). These software programmes are usually internet-based and involve the user inputting information such as fertiliser and irrigation applied and grazing information to build up a paddock history to enable better decisions (Hanrahan *et al.*, 2017; O'Leary & O'Donovan, 2019). PBI is currently one of the most effective pasture decision support tools (Kerr *et al.*, 2015; Woodward *et al.*, 2019).

PBI is an internet-based grassland management program that helps farmers get more from their pasture (Hanrahan *et al.*, 2017; O'Leary & O'Donovan, 2019). In 2018 PBI merged with AgriNet Grass to create one grassland management programme for Irish farmers (Cummins, 2018). In 2020 approximately 3,664 Irish farmers were using PBI, completing an average of 19 pasture measurements per year (Maher *et al.*, 2021b). To ensure that PBI functions effectively, farmers are encouraged to enter information about individual paddocks, such as plant cultivar, sowing date, fertiliser applications, pasture cover records, and grazing information. Some useful short-term statistics are available from this data, such as a feed wedge, average farm cover, and growth rate. In the medium term, if farmers have entered 25-30 pasture covers throughout the year, PBI will calculate the total amount of dry matter grown in each paddock. In response, farmers can investigate lower-performing paddocks and take corrective action if necessary, such as fertiliser application or reseeding. Finally, in the long term, with regular paddock data provided by farmers, PBI can calculate the dry matter yield expected in an average year which may guide future stocking decisions (O'Leary & O'Donovan, 2019).

Several platemeters (i.e., the Grasshopper and Jenquip EC20) are available that automatically link to the PBI database making pasture measuring and recording simpler for the farmer. Furthermore, on-farm links have been established with other service providers such as milk processors to add extra value to data that is already being recorded. For example, daily milk data is sent directly to PBI, allowing farmers to view current cow production (i.e., milk litres and kilograms milksolids) and the inputs (i.e., grass and meal) and outputs (i.e., kilograms milksolids) (Maher *et al.*, 2021b).

2.6 Calculating pasture harvested

Two main methods can be used to calculate the amount of pasture consumed: the disappearance and back-calculation methods. The disappearance method is based on the pre and post grazing covers with the difference between the two assumed to be the pasture eaten (Lile *et al.*, 2001). However, while this method is a quick and easy way to calculate pasture harvested, it is not always accurate. Firstly, measurement error can occur due to either operator error or variations in the pasture sward due to factors such as sward composition, animal grazing, and season (Murphy *et al.*, 2020; Murphy *et al.*, 2021a). Secondly, it involves measuring pasture cover when the cows enter and leave a particular paddock, which is not always practical. Finally, given that many farmers only conduct a farm walk once every seven to ten days, there is the potential for regrowth between the measurement period and the cows entering or exiting a particular paddock, consequently providing a less accurate measure of pasture disappearance (Yule & Atmore, 2006).

The second widely used method is the back-calculation technique, an indirect method of estimating how much pasture must have been consumed given the production level. Metabolisable energy (MJME) requirements for animal maintenance, liveweight change, pregnancy, and lactation have been well documented (Holmes *et al.*, 2002; Nicol & Brookes, 2007; DairyNZ, 2017). Therefore, it is possible to calculate an animal's energy requirements for a given level of production and period and estimate pasture harvested after subtracting any energy supplied by purchased feed using the published equations (Brookes & Holmes, 1987). In simple terms, *MJME pasture = Total MJME required – MJME purchased supplements.*

2.7 Global Positioning Systems

2.7.1 The GPS

The United States Department of Defence developed the GPS (initially known as NAVSTAR) in 1973 for the military. However, until 2000 it was only available for military use and was not publicly available (Turner *et al.*, 2000; Yahya & Kamarudin, 2008; Maddison & Mhurchu, 2009; Joshi *et al.*, 2019). The GPS is one of several Global Navigation Satellite Systems (GNSS) in operation the others being GLONASS (Russia), Galileo (European Union) and NAVIC (India) (Joshi *et al.*, 2019). There are three major components to the GPS: the control segment, the space division, and user devices, e.g., mobile phones and fitness trackers (Turner *et al.*, 2000; Yahya & Kamarudin, 2008; Pullen, 2015).

The control segment consists of around thirty terrestrial control stations in various locations worldwide that track and communicate with GPS satellites in orbit (Pullen, 2015), monitoring essential information including health, status, time, and location (Turner *et al.*, 2000). The second part is the space division, consisting of 24-32 satellites orbiting the earth at an altitude of 20,000 km, transmitting signals to GPS receivers (Turner *et al.*, 2000; Pullen, 2015; Joshi *et al.*, 2019). A minimum of four satellites may always be observed anywhere on earth (Turner *et al.*, 2000; Joshi *et al.*, 2019). The final segment includes GPS-enabled devices, including cars, mobile phones, and fitness devices (Maddison & Mhurchu, 2009; Pullen, 2015). A user's speed, position, and elevation can be determined within 5-10 m using trilateration, a mathematical technique (Maddison &

Mhurchu, 2009; Joshi *et al.*, 2019). While the maintenance of the GPS network costs around two million USD per day, it is free for users to use the system if they have a suitable GPS device (Turner *et al.*, 2000; Joshi *et al.*, 2019).

2.7.2 GPS and the agriculture sector

There has been a rapid increase in GPS usage in the agriculture sector since the early 2000s, such as crop yield mapping and variable fertiliser and seed placement (Trotter, 2019). Nonetheless, this technology has not been widely used on livestock on commercial farms until recently due to the cost. However, some studies have been done on the potential of this technology for the grazing livestock sector. These studies examined various factors ranging from grazing and feeding behaviour, urination events, virtual fencing and recording paddock grazing events (Draganova & Yule, 2008; Trotter *et al.*, 2009; Betteridge *et al.*, 2010; Draganova *et al.*, 2010; Trotter *et al.*, 2010; Haultain, 2014; Draganova *et al.*, 2016; Campbell *et al.*, 2019; Woodward *et al.*, 2019).

With the rapid development in the Internet of Things (IoT) applications, new networks such as LoRa (Figure 2.16) and SigFox have been developed since early 2010. The existing networks (e.g., cellular) were unsuited to many IoT applications, which require low power consumption, low data rate, and the ability to transmit data over long distances. While the cellular network (e.g., 2G, 3G and 4G) can provide extensive coverage in many areas, it consumes a lot of energy (Mekki *et al.*, 2019; Dos Reis *et al.*, 2021). LoRa developed in 2009 by Cycleo, a French company, is a long-range, low data rate, wireless communication system with minimal power consumption which uses the unlicensed radio spectrum (ISM band) to communicate (Abdullahi *et al.*, 2019; Mekki *et al.*, 2019; Behjati *et al.*, 2021). The LoRa network can reach 2-5 km in urban areas and 15-20 km in rural areas (Abdullahi *et al.*, 2019; Behjati *et al.*, 2021; Dos Reis *et al.*, 2021). The Sigfox technology was developed in 2010 in Toulouse, France, by Sigfox. Like LoRa, Sigfox uses unlicensed ISM bands to communicate and has a range of up to 10 km in urban areas and 40 km in rural areas (Mekki *et al.*, 2019; Behjati *et al.*, 2021). Several GPS capable devices using a range of networks are currently available for cattle as either ear tags or collars, as shown in Table 2.7 and Figure 2.17 based on an internet search by the author.

Due to the increasing availability of long-range wide-area networks like LoRa and Sigfox and the developing IoT market, Tobin *et al.* (2021) considered the potential of GPS tracking systems and accelerometers for detecting water system failures. The authors randomly selected cows from a 120-cow herd and fitted them with either GPS devices (10 in 2018 and 23 in 2019) or accelerometers (7 in 2018 and 10 in 2019). Water system failure was simulated by blocking access to the only available water source over four hours on several occasions in 2018 and 2019. During the simulated water system failure days, movement intensity was significantly greater ($P = 0.03$) than on the control days as measured by the accelerometers. Likewise, during simulated water system failure, the cows remained closer to the water source (< 150 m) than on control days, where they typically drank and then moved away from the water source. Thus, the authors concluded that GPS devices, either with or without accelerometer capability, could be used as a tool to detect water system failures.

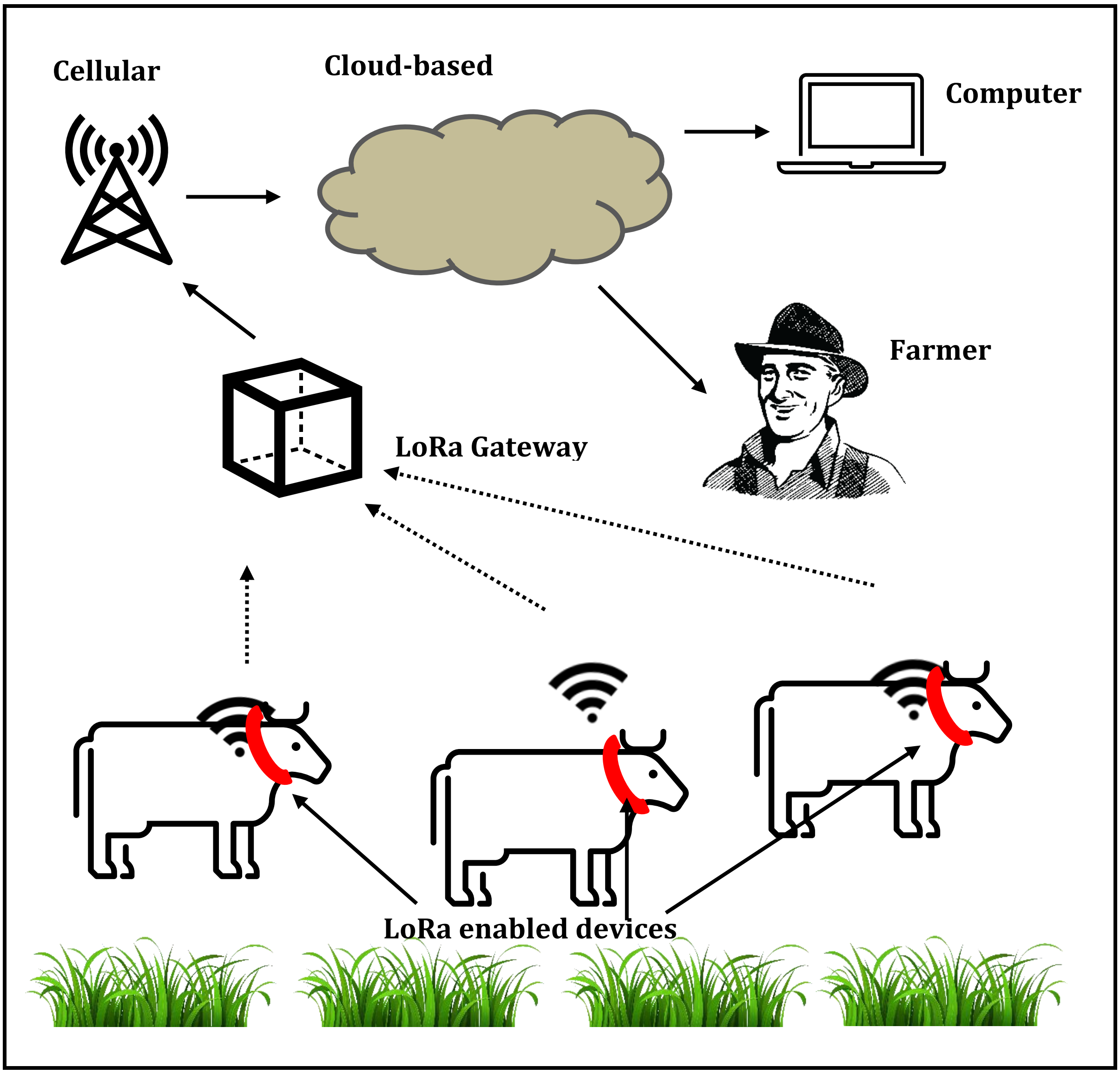

Figure 2.16: Diagrammatic representation of how a LoRa network operates. Adapted from Abdullahi *et al.* (2019, p. 152).

Several virtual fencing options have limited commercial release or are under development, including Halter, eShepherd, Vence, and Nofence. Virtual fencing involves controlling an animal's location without using fixed fencing, which is achieved by the animal wearing a collar or neckband embedded with a GPS receiver (Umstatter, 2011; Lomax *et al.*, 2018). From this, the farmer can assign a grazing zone to the animal through a cellular or LoRa network (Dos Reis *et al.*, 2021; Stevens *et al.*, 2021). An animal will receive an audio alert at the virtual boundary to prevent livestock from leaving the given area. If the animal continues to advance, it will receive an electric pulse (Lomax *et al.*, 2018; Campbell *et al.*, 2019; Robinson, 2020; Stevens *et al.*, 2021).

In a study on animal welfare issues associated with virtual fencing systems, Campbell *et al.* (2019) concluded that they were comparable to the standard electric fence tape after comparing the two methods using 12-14 month steers in Australia. Similarly, Verdon *et al.* (2021) concluded there were no animal health and welfare concerns with virtual fencing systems after conducting a short-term study using dairy cows and the eShepherd system. Nonetheless, there were some indications of increased stress with the virtual fence system, although this did not affect milk production. The main advantages of such a system include reduced labour requirements, improved pasture management and utilisation, and the ability to exclude livestock from areas where fencing may be costly or simply not practical such as waterways (Lee *et al.*, 2018; Stevens *et al.*, 2021).

Table 2.7: GPS ear tag and collar options currently on the market or expected to be soon.

Brand	Type	Network	Product stage	Country
mOOvement	Tag	LoRaWAN	Commercially available	Australia
Agtech	Tag	LoRa	Commercially available	Australia
ProTag – Massey University	Tag	LoRaWAN	Development stage	New Zealand
Ceres	Tag	Direct to satellite	Commercially available	Australia
Smart Paddock - Bluebell	Tag	LoRaWAN	Commercially available	Australia
Roper	Tag	LoRa	Development stage	United States
Kraal	Tag	LoRa	Commercially available	
GlobalSat*	Tag	LoRaWAN & Sigfox	Commercially available	Taiwan
GSatRancher	Tag	Direct to satellite	Commercially available	United States
Smarter Technologies	Collar	Orion data network	Commercially available	United Kingdom
digitanimal	Collar	Sigfox or GSM	Commercially available	United Kingdom
digital matter - Oyster2	Collar	Cellular	Commercially available	
Halter	Collar	LoRa	Limited commercial release	New Zealand
eShepherd	Collar	LoRa	Beta testing, expected release 2022	Australia
Vence	Collar	LoRa	Limited commercial release	United States
Nofence	Collar	Cellular 2G network	Limited commercial release	Norway
SODAQ	Collar	LoRaWAN	Commercially available	Netherlands

* Also available as a collar version

 mOOvement*	 Agtech*
 digitanimal*	 Oyster2*
 Ceres	 eShepherd

Figure 2.17: Examples of currently available GPS ear tags and collars. *Used in this study. Photos by W. Hofmann.

Earlier work was conducted using GPS devices to calculate pasture growth and record paddock grazing events (Haultain, 2014). As part of this study, dairy cows on a Waikato farm were fitted with collars containing GPS trackers to record their daily movements. The GPS location information was then used in conjunction with milk production data to score the paddocks from highest performing to lowest, providing valuable information to farmers and enabling them to schedule their regrassing and fertiliser programs accordingly. It showed that GPS devices could automate the recording of paddock grazing events on New Zealand dairy farms. However, it did not become commonly used. A primary reason was probably the cost of the GPS units and the lack of integration with computer software at that time.

Liu *et al.* (2015) also used GPS devices to identify areas visited by grazing livestock and group movement characteristics. This study conducted in 2011 involved two different groups comprising either 8 or 24 beef cows on intensively managed pastures and corn residue being monitored by GPS collars logging a position every four minutes. Spatial occupancy was one aspect of this study and involved comparing the results between subgroups and the entire group. They concluded that the number of animals that would need to be fitted with GPS devices in a group would depend on the specific use of the collected data. For example, a small subset group may be adequate for identifying areas visited by cattle, such as a farm paddock. However, suppose the aim is to correlate group movements or spatial occupancy with other factors such as environmental conditions. In that case, it is recommended that a larger subset group size (i.e., at least 75% of animals in a herd are fitted with GPS devices) is used, helping to achieve better accuracy of group movement and spatial occupancy.

McGranahan *et al.* (2018) used GPS devices to determine how closely animals fitted with GPS devices cluster together using both sheep and cattle on rangeland in North Dakota, United States, over several one-week periods. Additionally, they examined the effect of the fix rate, the frequency at which a GPS position is logged, on the ability to estimate patch selection. The fix rates tested were one position every 5 or 10 minutes and burst logging, where positions are recorded at 20-second intervals for 5 or 10 minutes per hour followed by a sleep period. They found that sheep in the same pasture fitted with GPS devices were within 42 m of each other on average, while the cattle remained within 76 m of each other on average. If the aim is to estimate patch use and the spatial distribution of grazing livestock herds, they concluded that a minimum of two collars programmed with burst logging capacity should be used. The use of burst logging will also help extend the battery life of the devices.

Finally, Woodward *et al.* (2019) looked at the possibility of combining satellite imagery and GPS data to automatically estimate pasture mass and growth and paddock grazing events on a Waikato dairy farm over 123 days. GPS collars recording an animal's location approximately once per hour were placed on thirteen cows within a dairy herd of 380 cows. This data was used with satellite images supplied via the LIC SPACE programme. A calibration approach was required because satellite data was only available for sixteen dates during the study because of weather conditions. Nonetheless, this study successfully demonstrated that satellite images could be combined with GPS technologies such as cow collars to help improve the decision-making process around pasture management on dairy farms. Furthermore, this process could be automated, except for a few minor procedures such as fitting the GPS devices and changing batteries as required.

Several companies have recently released GPS ear tags commercially, including mOOvement and Agtech. Packages start from around 60 NZD per tag and 2,000 NZD for a LoRa base station for the Agtech product (C. Brand, personal communication, September 30, 2021) and 60 NZD per tag and 1,400 NZD for a LoRa base station for the mOOvement product (mOOvement, 2021b). These tags are solar-powered, reusable, lightweight (30-37 grams), and have an expected lifespan of about five years (Meat & Livestock Australia, 2019; mOOvement, 2021b). Some tag brands can also record the ambient air temperature, such as the Agtech product (Meat & Livestock Australia, 2019). Furthermore, direct to satellite solar-powered GPS ear tags are now commercially available, including the Ceres tag developed in Australia and the GSatRancher developed in the United States (CSIRO, 2020; Global Satellite Engineering, 2022). The main benefit of these tags is that no on-farm infrastructure is needed because the tags link directly to low earth orbit satellites with all the data stored in the cloud. Additionally, they last the animal's lifetime (around ten years) without requiring a battery change (CSIRO, 2020; Frost, 2020; Ceres Tag, 2021). However, the cost of these tags is considerably more, with the Ceres tag costing approximately 240 NZD per tag. Additionally, it also requires a specialised tag applicator at the cost of around 720 NZD, although this is a one-off cost (Ceres Tag, 2021).

Although these tags are primarily designed to help extensive farmers like those in the Australian outback to track their livestock in real-time, they may have other uses on-farm.

Examples include vehicle monitoring, placement evidence for effluent and irrigation applications, and identification of preferential grazing areas or where water troughs may be needed (Trotter *et al.*, 2010; Meat & Livestock Australia, 2019). They also present an opportunity to automate the daily recording of pastures grazed by the dairy herd replacing the various methods currently used, such as notebooks, diaries, and whiteboards, as Haultain (2014) and Woodward *et al.* (2019) showed. This would be a beneficial option on large farms that run multiple herds for most of the year.

2.8 Research needs

This chapter has highlighted the importance of pasture measurement on dairy farms from a farm productivity and profitability perspective and discussed the various methods currently available to measure pasture dry matter yields, including the RPM, satellite imagery, quadrat cuts, and capacitance probes. While the evidence is clear that regular pasture measurement and recording can increase farm productivity and profitability, recent studies have shown that the proportion of New Zealand and Irish dairy farmers regularly measuring pasture dry matter and recording grazing events is hugely variable. This may be due to the cost, time requirements, and accuracy of some of the available methods. Consequently, research is ongoing to either improve the existing methods of pasture assessment or find new innovative ways to measure pasture dry matter and record grazing events so farmers can maximise their pasture utilisation, their cheapest feed source.

With the recent release of the next-generation GPS devices, e.g. mOOvement and Agtech solar-powered ear tags, it is worth revisiting the earlier work of Haultain (2014) and Woodward *et al.* (2019). They considered GPS technology as a tool to automate the recording of paddock grazing events and estimate pasture mass. Both studies successfully showed that it was possible to record paddock grazing events using GPS technologies. However, it did not become commonplace on dairy farms, possibly due to the cost of the GPS devices and the lack of integration with computer software packages. This problem has been solved with GPS devices available from around 60 NZD /tag with much-improved computer connectivity. Therefore, their experiences provide the background to the present study, which aims to determine the accuracy and precision of the current generation of GPS-enabled devices and establish if they can be used to determine the area allocated and record grazing events automatically. This study also aims to identify the number of GPS devices required per herd and the fix rate needed to achieve the above objective.

Chapter 3

Device static testing

3.1 Introduction

The objective of this chapter was to determine the accuracy and precision of a range of GPS devices presently available for livestock use. This data could subsequently be used to establish if they can aid the decision-making process on-farm, particularly around pasture management. For GPS measurements, accuracy is defined as how far the logged location is from the true position. In contrast, precision refers to how tightly the logged positions from one GPS device are clustered together (Menditto *et al.*, 2007; McGranahan *et al.*, 2018; Davies, 2020). Figure 3.1 visually summarises the difference between accuracy and precision.

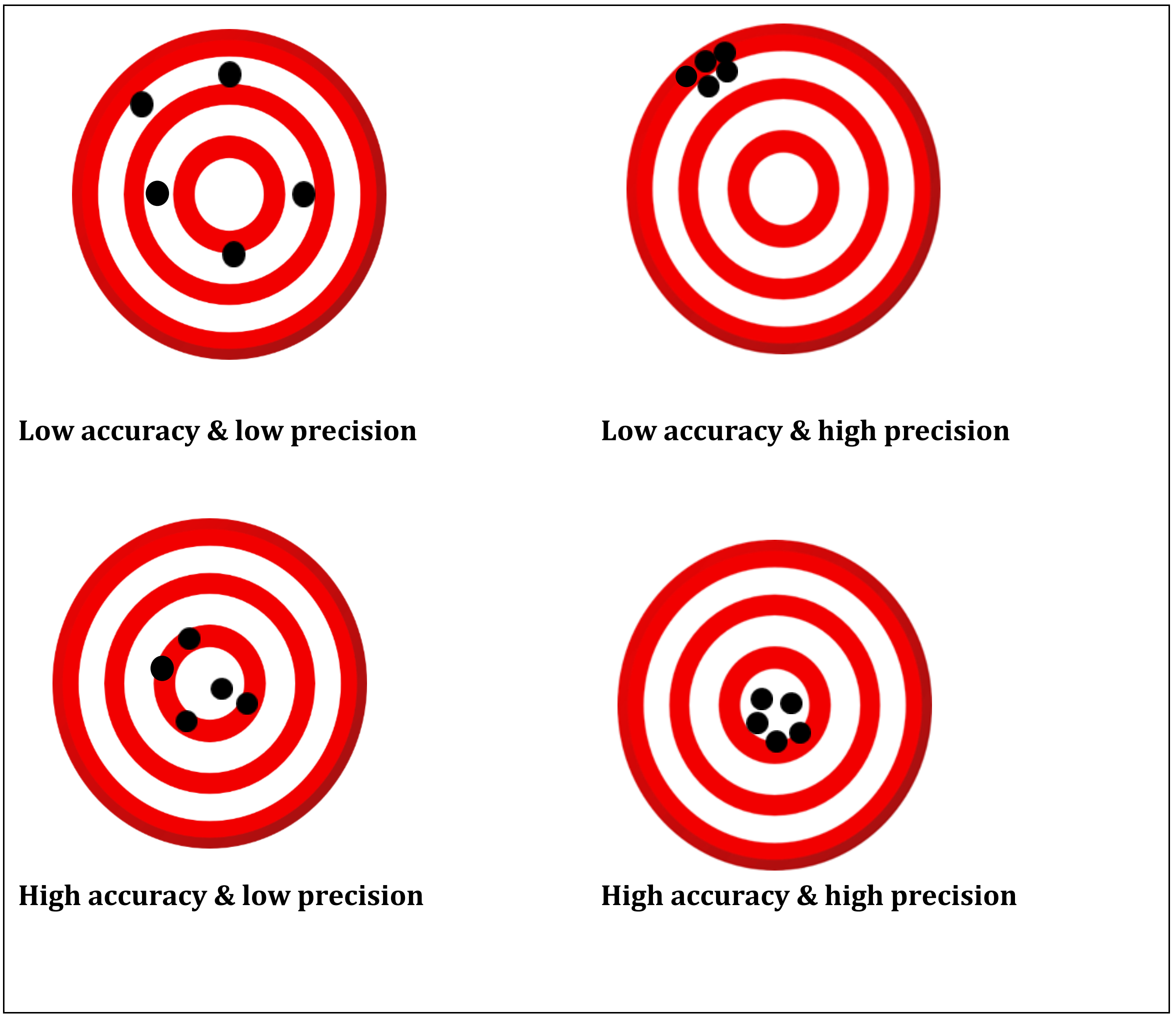

Figure 3.1: Diagrammatic representation of the difference between accuracy and precision. Adapted from Davies (2020).

This chapter first describes the static testing methodology used to calculate both the location error (accuracy) and the Circular Error Probable (CEP, precision) to determine the accuracy and precision of a range of commercially available GPS devices. The location error is the distance between the true position of an object (e.g., a GPS device) and that estimated by a GPS position fix (Swain *et al.*, 2008; Swain *et al.*, 2011; Morris & Conner, 2017). In contrast, the CEP is a circular radius containing a stated percentile of points around an actual location (Moen *et al.*, 1997; Rempel & Rodgers, 1997; Turner *et al.*, 2000; Haultain, 2014; Morris & Conner, 2017). It is used to measure the GPS positional accuracy or impact accuracy of a projectile (Zhang & An, 2012). The 95% CEP may also be termed the horizontal 95% accuracy (R95) (Agouridis *et al.*, 2004). Following a discussion of the methodology used, the results are presented, and the practical implications for on-farm use are discussed.

3.2 Methodology

Static testing was necessary to determine the accuracy and precision of each GPS device used in this study before its use on livestock. The devices tested were Agtech and mOOvement solar-powered ear tags and Oyster2 tracking devices. Agtech and mOOvement ear tags are reusable, lightweight (30-37 grams), and have an estimated lifespan of about five years. (Meat & Livestock Australia, 2019; mOOvement, 2021b). They use the LoRa network to get the data from the ear tag to the individual base station before using the 4G cellular network or Wi-Fi to transfer the data to the cloud (Vogels, 2020). Oyster2 are general all-purpose GPS tracking devices weighing approximately 194 grams. They are powered by three long-life AA batteries and use the 4G cellular network (Digital Matter, 2021). Table 3.1 summarises each device, including the network used and the individual fix rate of each device, defined as how often it records a GPS position.

Table 3.1: Summary of GPS devices used in this study, including the network used, fix rate, type, and the number of devices tested.

Device	Network	Fix rate	Type	Number devices
mOOvement	LoRa/Wi-Fi	2 hourly	Tag	22
Agtech	LoRa/4G	Hourly	Tag	11
Oyster2	Cellular 4G	Hourly	Collar	2

Testing took place at DairyNZ's Scott Farm (Figure 3.2), Newstead, New Zealand (37°46'7"S, 175°21'59"E) for six days between the 17th and 22nd of March 2021 for the Agtech and mOOvement devices (Figure 3.3). Subsequently, two Oyster2 devices were static tested for seven days from the 23rd to the 30th of June 2021 (Figure 3.4). During testing, while the possibility of any interference between devices was minimal as they were recording GPS coordinates at different times to other devices to minimise any possibility of interference between each device, they were affixed at 10 cm intervals onto a wooden board. All devices were installed and tested in one location on Scott Farm to reduce spatial variability in terms of precision and accuracy and satellite visibility affecting the results. Satellite visibility may become a problem if a GPS device cannot receive an uninterrupted signal from at least four GPS satellites at any given time, which may occur if vegetation or artificial structures such as walls and buildings are in the way (Yahya & Kamarudin, 2008). Here they remained and generated data for the duration of the respective static test period.

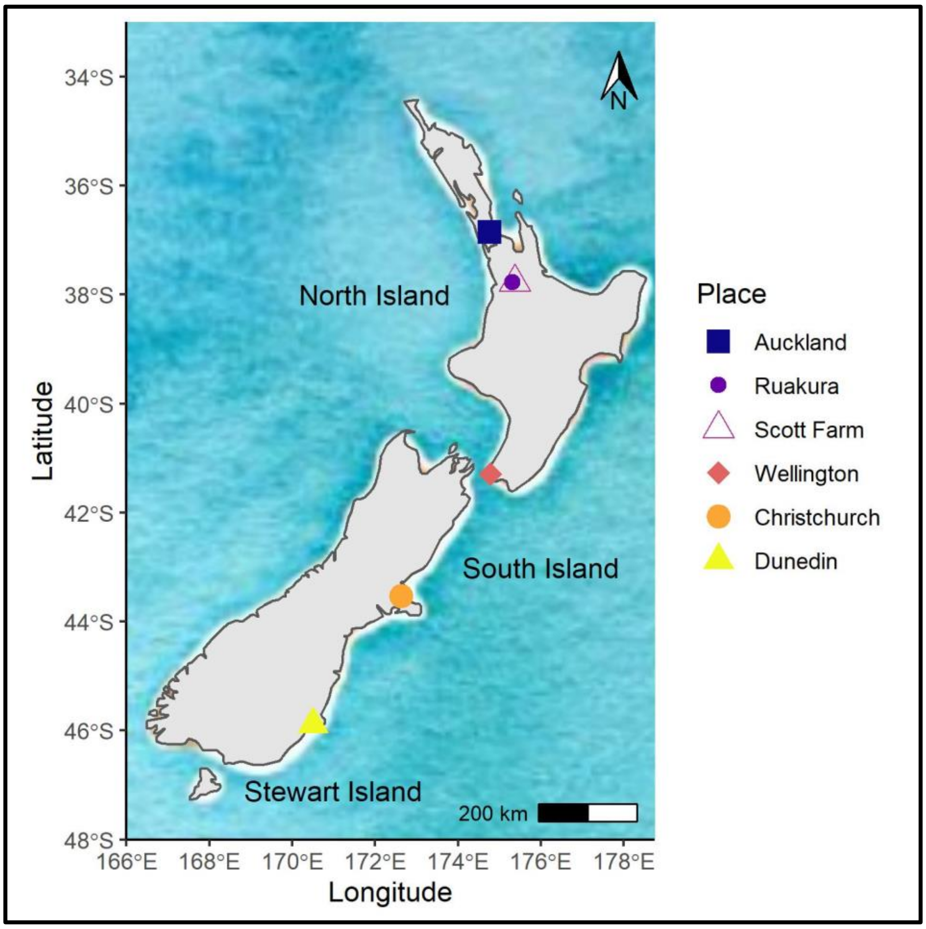

Figure 3.2: Map of New Zealand showing the location of both Scott Farm and the Ruakura weather station.

Figure 3.3: Static testing set-up of the devices with the Agtech tags shown on the left and the mOOvement Tags on the right between the 17th and the 22nd of March 2021. Photos by W. Hofmann.

Figure 3.4: Oyster2 4G devices during static testing between the 23rd and the 30th of June 2021. Photo by W. Hofmann.

During the static test period, the wooden board to which the GPS devices were attached was situated on the top of two wooden posts forming a part of a conventional electric fence (Figure 3.5). This trial site was selected because it was easily accessible and central to the Wi-Fi connection needed to operate the mOOvement LoRa base station. Previously Agouridis *et al.* (2004) undertook a static test by placing 15 GPS collars adjacent to a five strand electric fence (5,500 V) to determine if the electric fence affected collar performance and location accuracy, given that it is a common feature on-farm. For an in-depth comparison, the collars were placed against various fence features, including wooden and steel posts, gates, and wire. While the location error was 50% greater than the same collars tested in an open field, this was equivalent to an additional error of less than 1 m. Therefore, based on the study by Agouridis *et al.* (2004), it is unlikely that the electric fence would have had a substantial impact on the static test results of this study.

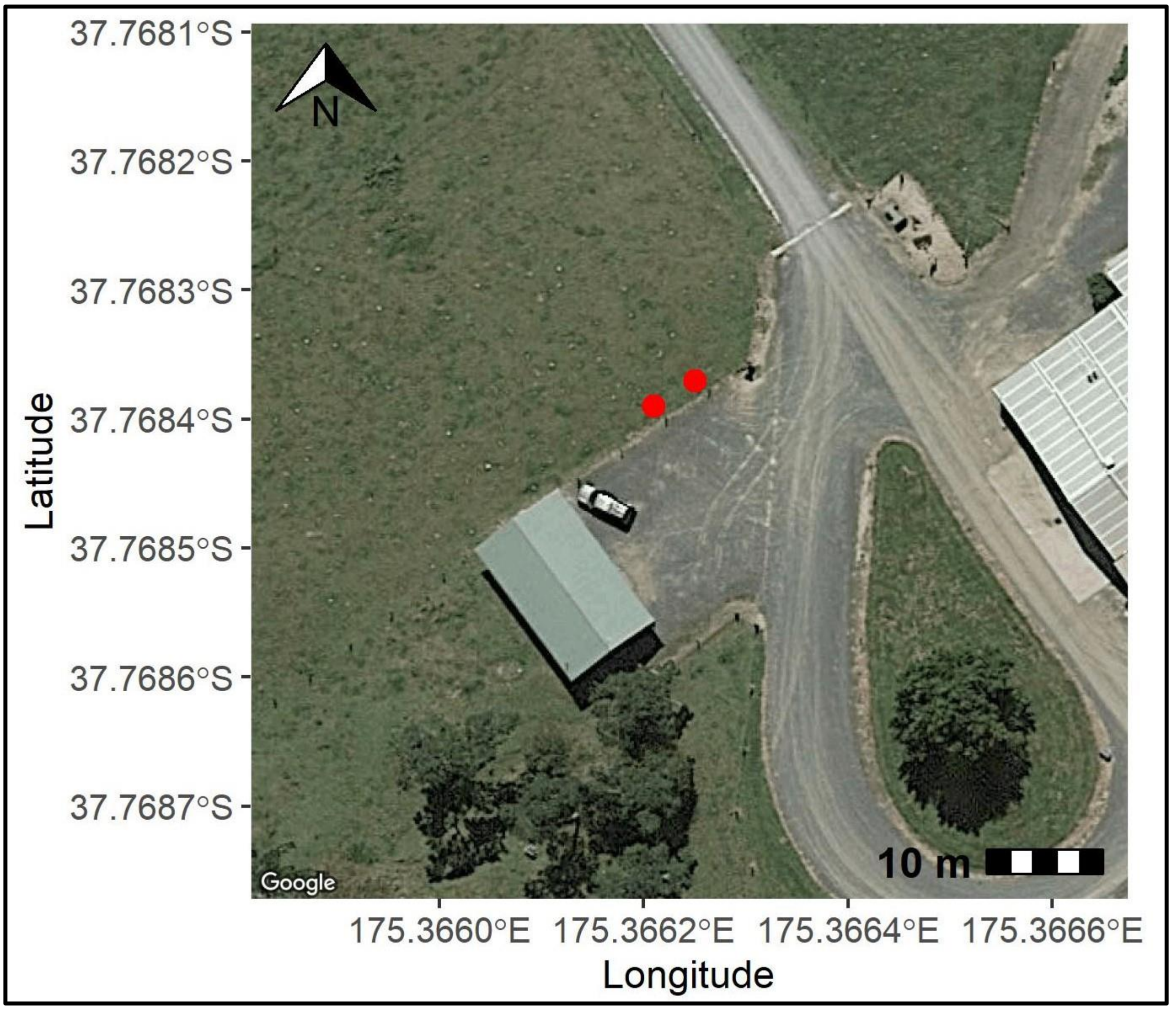

Figure 3.5: Aerial overview of the Scott Farm static testing test site. The wooden board holding the GPS devices was positioned between the two red points.

Both the mOOvement and Agtech devices use the LoRa network to communicate the GPS coordinates of the individual ear tags. LoRa is a long-range wireless communication system that can transmit data over long distances. It uses the unlicensed radio spectrum (ISM band) for communication, and it is capable of low data rates and minimal energy consumption (Abdullahi *et al.*, 2019; Mekki *et al.*, 2019). For this study, the mOOvement base station could receive tag signals within a maximum range of approximately 8-10 km radius around the LoRa antenna, according to the manufacturer's website (mOOvement, 2021a). In contrast, the Agtech base station can receive tag GPS signals within a maximum 10-15 km radius around the base station (C. Brand, personal communication, August 31, 2021). However, it is essential to note that the range of the individual base stations was not tested as part of this study.

The essential components of the mOOvement and Agtech ear tags include a GPS chip, a LoRa antenna and a solar panel and charger as the power source (Vogels, 2020; C. Brand, personal communication, August 31, 2021). Each ear tag receives GPS coordinates from passing satellites based on the ear tag's fix rate, which was either hourly (Agtech) or two hourly (mOOvement) in this study. Once received by the LoRa enabled device, these GPS coordinates are then sent to the base station using the LoRa network. They are then uploaded to the cloud using the cellular network or Wi-Fi, where they are stored and become available to the end-user to either download or view using the internet or phone applications (Vogels, 2020). Refer to Figure 2.16 for a diagrammatic representation of how the devices work.

The LoRa base stations for the Agtech and mOOvement tags were installed within approximately 10 m of the wooden board holding the devices. The base station for the mOOvement tags was mains powered and connected to Wi-Fi. In contrast, the Agtech base station was solar-powered and supported by the 4G cellular network (Figure 3.6). The Oyster2 devices did not require a base station. Instead, each device contained a 4G SIM (Subscriber Identification Module) card commonly used in mobile phones and other cellular devices connected to the Spark NZ Ltd network to transmit the data to the cloud. It was then available for viewing on the Telematics Guru website, or it could be downloaded in Microsoft Excel format.

For this study, the device manufacturer's default settings were used for the fix rate. The Agtech and Oyster2 devices recorded a GPS position approximately once per hour and the mOOvement devices about once every two hours. Fix rate is defined as the frequency at which an individual device records a GPS location (Swain *et al.*, 2008; Haultain, 2014). The individual data points of each GPS unit were then compared with the actual position of each device using the following two-step process. First, a Real-Time Kinematic device (Model: Trimble R6 RTK - Figure 3.7) with an accuracy of 3 cm (G. Rennie, personal communication, July 7, 2021) was used to identify the GPS coordinates for the start and end of the wooden board. Then, from these two points, the coordinates for each device were calculated.

Figure 3.6: Experimental configuration of the Agtech base station (A) and mOOvement base station (B) during the static testing period. Note the two small antennae on the Agtech base station, increasing cellular coverage and aiding data transfer between the devices and the base station. Obscured from photo A is a solar panel that was facing north to power the Agtech base station. Photos by W. Hofmann.

Figure 3.7: Trimble R6 RTK set-up used to accurately identify (within 3 cm) the GPS coordinates for the start and end of the wooden plank holding the GPS devices during the static testing process. Photo by W. Hofmann.

3.3 Statistical analysis

Statistical analysis of the GPS data was performed using the software packages RStudio (Version 1.4.1106) and R (Version 4.1.0 "Camp Pontanezen") (R Core Team, 2021) to find the location error and the CEP of each device and device group during the testing period. The distance between the true and logged points (i.e., the location error, accuracy calculation) was calculated using the *distHaversine* function in the *geosphere* package for R (Hijmans *et al.*, 2019). It uses the 'haversine method' to calculate the shortest distance between two points. Meanwhile, the CEP (precision calculation) was calculated using the *getCEP* function in the *shotGroups* package for R to calculate the distance containing a stated percentile of points around the true location, the GPS device's proper position, at the 50% and 95% levels (Wollschlaeger, 2021). The R *ggsignif* package was used to calculate any statistically significant differences between groups and between devices within a group (Ahlmann-Eltze & PatiI, 2021). Other essential packages used included *lubridate* (Spinu, 2021) to ensure that the dates were in a suitable format for data analysis and *tidyverse*, which contains the core packages for the successful operation of RStudio (Wickham, 2021).

3.4 Results and discussion

The weather was primarily fine and clear during the initial test period (17^{th} to the 22^{nd} of March 2021), as reported by the National Institute of Water and Atmospheric Research (NIWA) at the nearby Ruakura weather station (37° 46' 26'' S, 175° 18' 19'' E, see Figure 3.2 for location map). However, during the second test period in June (23^{rd} to the 30^{th} of June 2021), a range of weather conditions was observed, including rain, thick cloud or fog, clear days, and winter frosts (NIWA, 2021).

The Agtech and mOOvement data were downloaded from the cloud and stored on the DairyNZ Snowflake cloud service following the static test period. Snowflake is a cloud-based payment data storage system developed in 2012 that enables users to store and analyse data using cloud-based hardware and software (Ryan, 2019). Later, the data was imported into RStudio via an API (Application Programming Interface). This software intermediary allows computer software to communicate to different programs, in this case, the Snowflake Server and RStudio. In contrast, the Oyster2 data was imported into

RStudio using a Microsoft Excel spreadsheet downloaded from the Telematics Guru website and the *readxl* package for R (Bryan, 2019).

The data was then reviewed, and any tags that did not record GPS data points for all the static test period were deemed defective and were removed from any further data analysis. Essential information collected by the devices included the position (latitude and longitude in WGS84 format), date and time of each observation, temperature, and battery condition. WGS84, or the World Geodetic System, is the standard reference system for GPS systems. It comprises four parts, the reference ellipsoid, a standard coordinate system, altitude data, and a geoid and is usually accurate to within 2 cm (GISGeography, 2021). After removing the defective tags described above, the location error and CEP were calculated for each device type (Agtech, mOOvement, and Oyster2) and each tag or collar.

Figure 3.8 to Figure 3.10 provide a visual summary of the GPS points recorded by each device type and devices within that type during the test period. Note that Figure 3.9 shows a much larger area than Figures 3.8 and 3.10 due to the greater variation in the fixes returned by the mOOvement devices than the Agtech and Oyster2 devices.

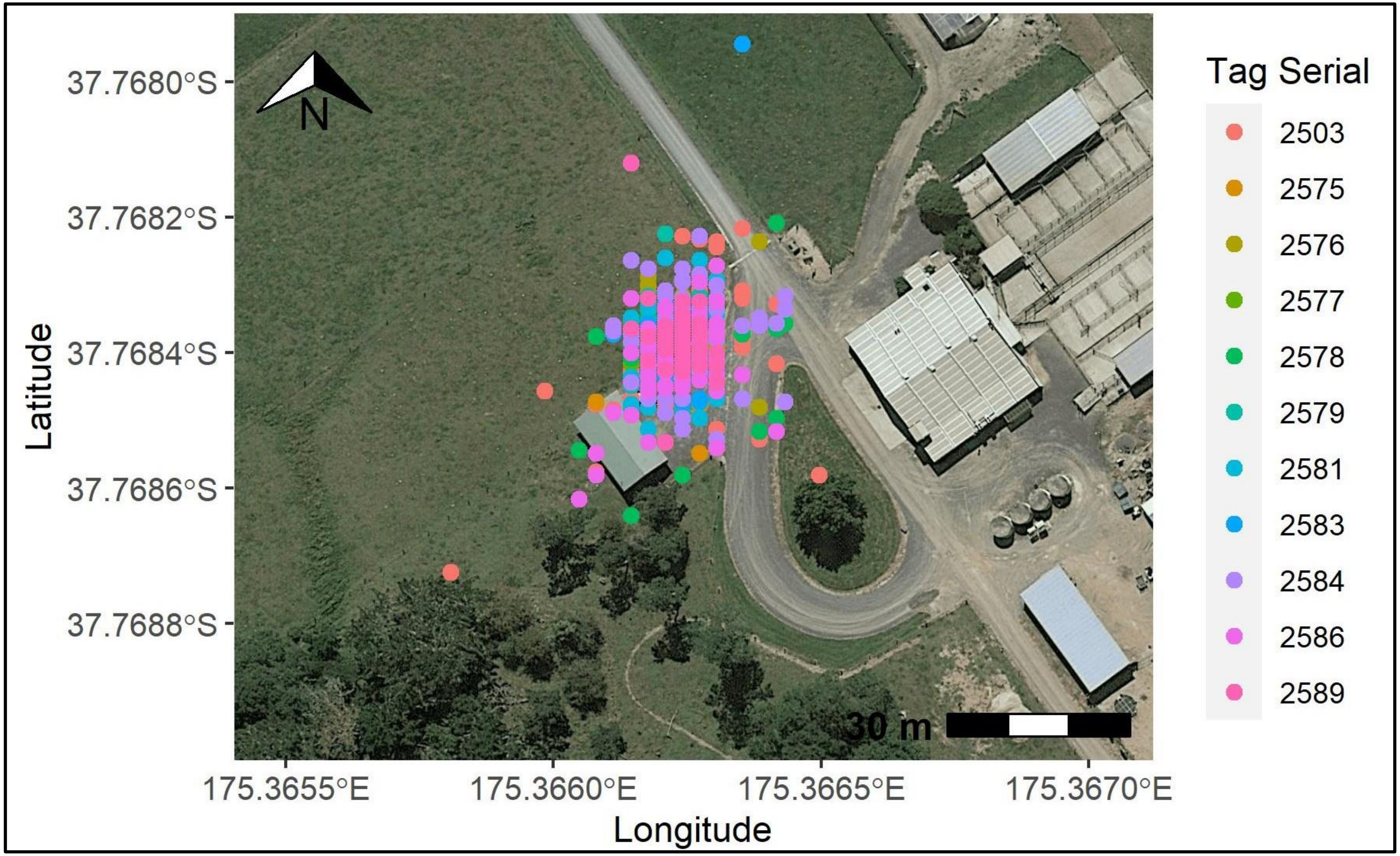

Figure 3.8: Summary of GPS location fixes for the 11 Agtech devices during the static test period at Scott Farm from the 17th to the 22nd of March 2021. Background image sourced from Google Maps as part of the ggmap package in R.

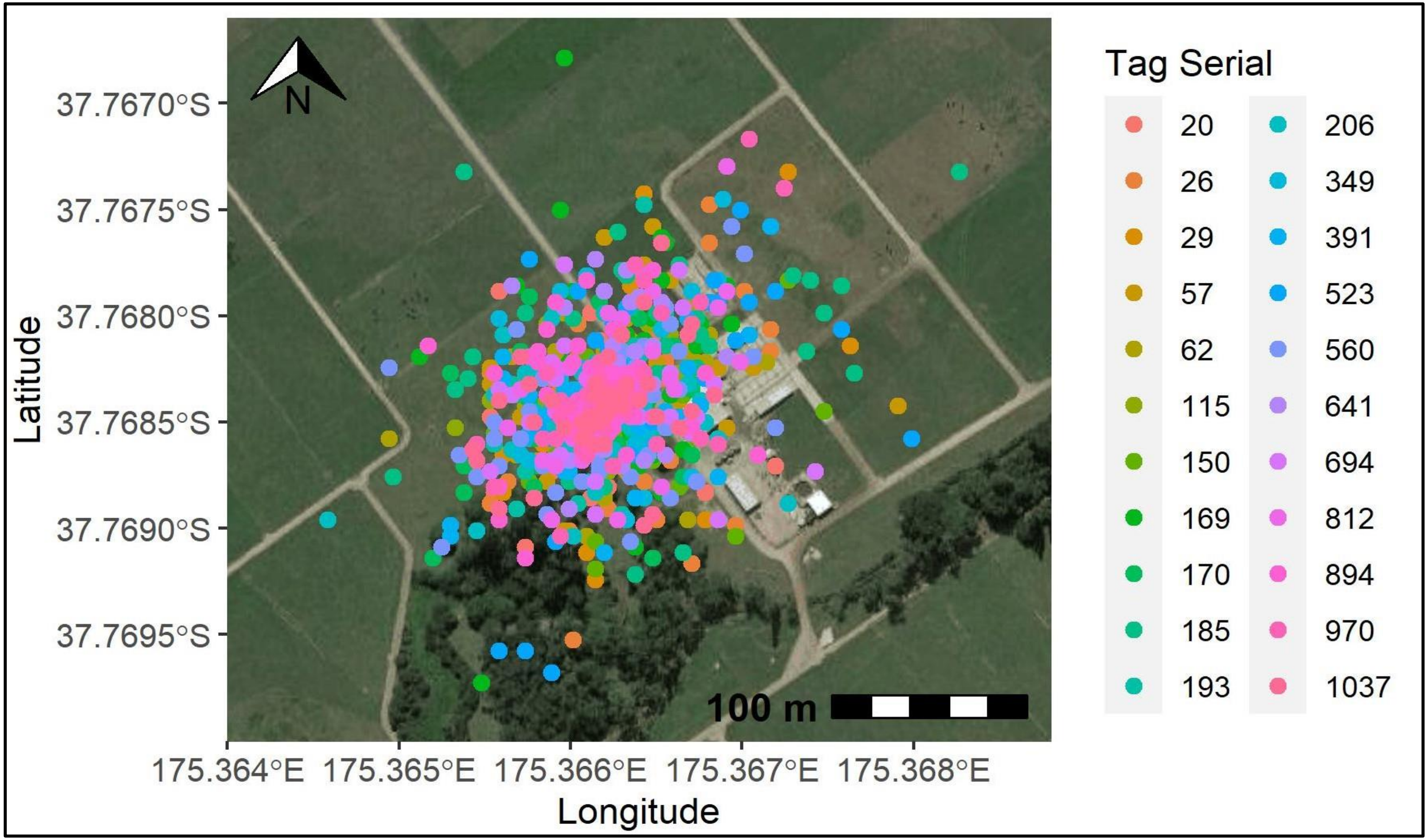

Figure 3.9: Summary of GPS location fixes for the 22 mOOvement devices during the static test period at Scott Farm from the 17th to the 22nd of March 2021. Background image sourced from Google Maps as part of the ggmap package in R.

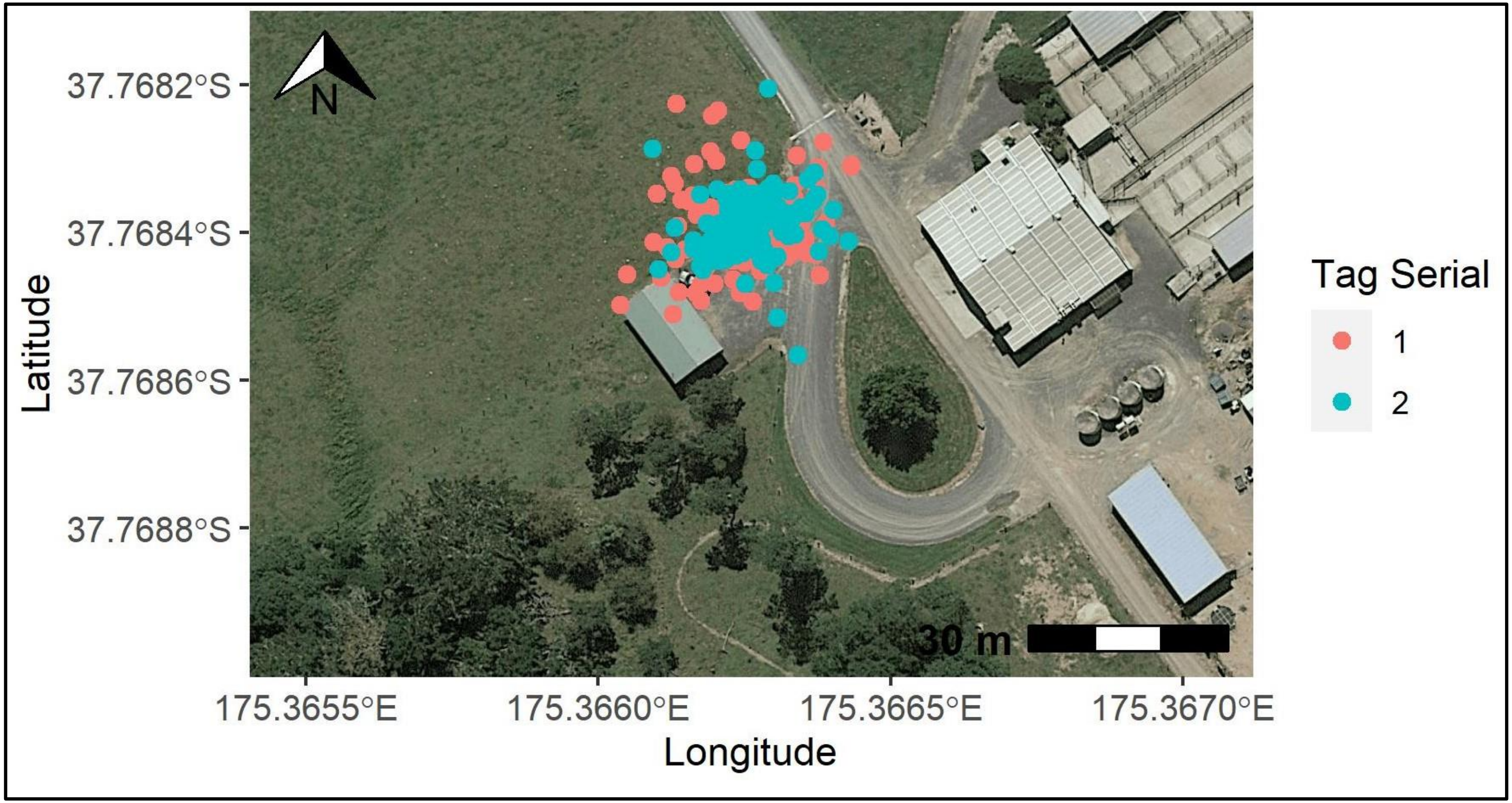

Figure 3.10: Summary of GPS location fixes during the static test period for two Oyster2 devices at Scott Farm from the 23rd to the 30th of June 2021. Background image sourced from Google Maps as part of the ggmap package in R.

3.4.1 Accuracy calculation: The location error

Across the two static test periods, 2,684 observations were recorded: 1,109 observations from the 11 Agtech GPS devices, 1,208 observations from the 22 mOOvement devices, and 367 observations from the two Oyster2 devices. The Agtech devices returned a mean location error (MLE), the difference between the true and projected location, of 5.4 m (± 6.7 m), a median location error of 4.0 m, and a range of 0.3-166.8 m. For the Agtech treatment, 65.2% of all the observations were within 5 m of the true position, 89.7% within 10 m and 98.2% within 20 m. This compares with a MLE of 34.2 m (± 31.0 m), a median location error of 24.5 m and a range of 0.3-213.2 m for the mOOvement devices. Of all mOOvement observations, 8.9% were within 5 m of the true position, 23.8% within 10 m, 43.8% within 20 m and 56.5% within 30m.

The Oyster2 tracking devices returned a MLE of 5.7 m (± 4.2 m), a median location error of 4.5 m and a range of 0.2-22.4 m for the two devices tested. Of all Oyster2 observations, 56.1% were within 5 m of the true position, 85.6% within 10 m and 99.2% within 20 m. There was no statistically significant difference in location error between the Agtech and Oyster2 device groups. However, when both device groups were compared against the mOOvement group, the result was statistically highly significant ($P < 0.001$).

Table 3.2 below presents a complete summary of the results for location error, including the median and lower and upper quartile for each device group.

Table 3.2: Mean, lower quartile (LQ), median (Med), and upper quartile (UQ) of location error (m) from three brands of GPS devices.

Device	Mean ± SD	LQ	Med	UQ	No. Devices	No. Obs	Test Date
Agtech	5.4 ± 6.7	2.6	4.0	6.4	11	1,109	17th - 22nd March
mOOvement	34.2 ± 31.0	10.6	24.5	49.5	22	1,208	17th - 22nd March
Oyster2	5.7 ± 4.2	2.8	4.5	8.0	2	367	23rd – 30th June

3.4.2 Location error of individual devices

Variation in location error between individual GPS devices of the same type was observed in this study. For the Agtech group, the MLE ranged from 3.8-7.8 m between devices and 20.2-46.7 m for the mOOvement devices. The MLE for the two Oyster2 devices was 4.9 m and 6.5 m.

The best four devices in the Agtech group had a MLE of 4.3 m (± 2.8 m), while the bottom four had a MLE of 6.5 m (± 9.5 m). It is a difference of 2.2 m (+51.1%) and a statistically highly significant ($P < 0.001$) result. In contrast, the top four devices in the mOOvement group returned a MLE of 24.8 m (± 21.9 m) and the bottom four a MLE of 44.9 m (± 39.4 m), a difference of 20.1 m (+81%). Again, the difference between the top-performing and lowest-performing devices was statistically highly significant ($P < 0.001$). However, while differences between devices of the same type were observed in this study under normal operating conditions, there is always likely to be some variation between devices of the same type (Agouridis *et al.*, 2004). Figure 3.11 to Figure 3.13 summarise the location error for all device types and devices within that type.

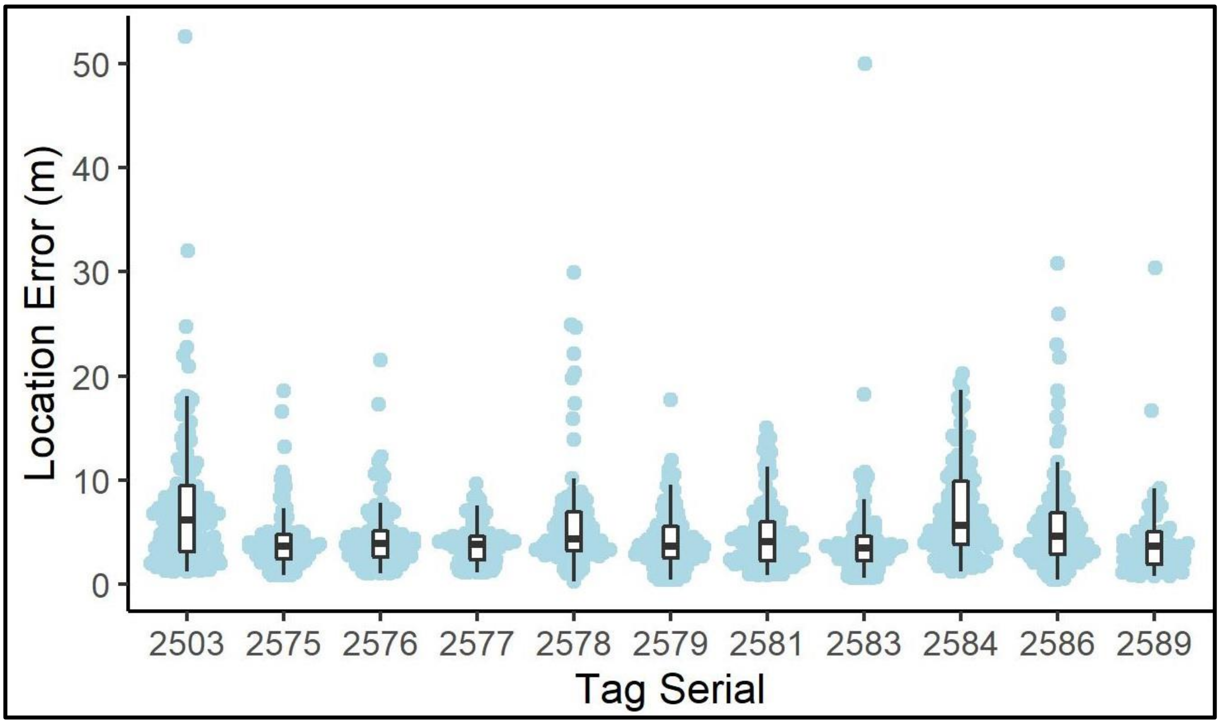

Figure 3.11: Location error (m) for each Agtech device during the static test period from the 17th to the 22nd of March 2021 at Scott Farm. NB: Points above 50 m are not shown on the graph.

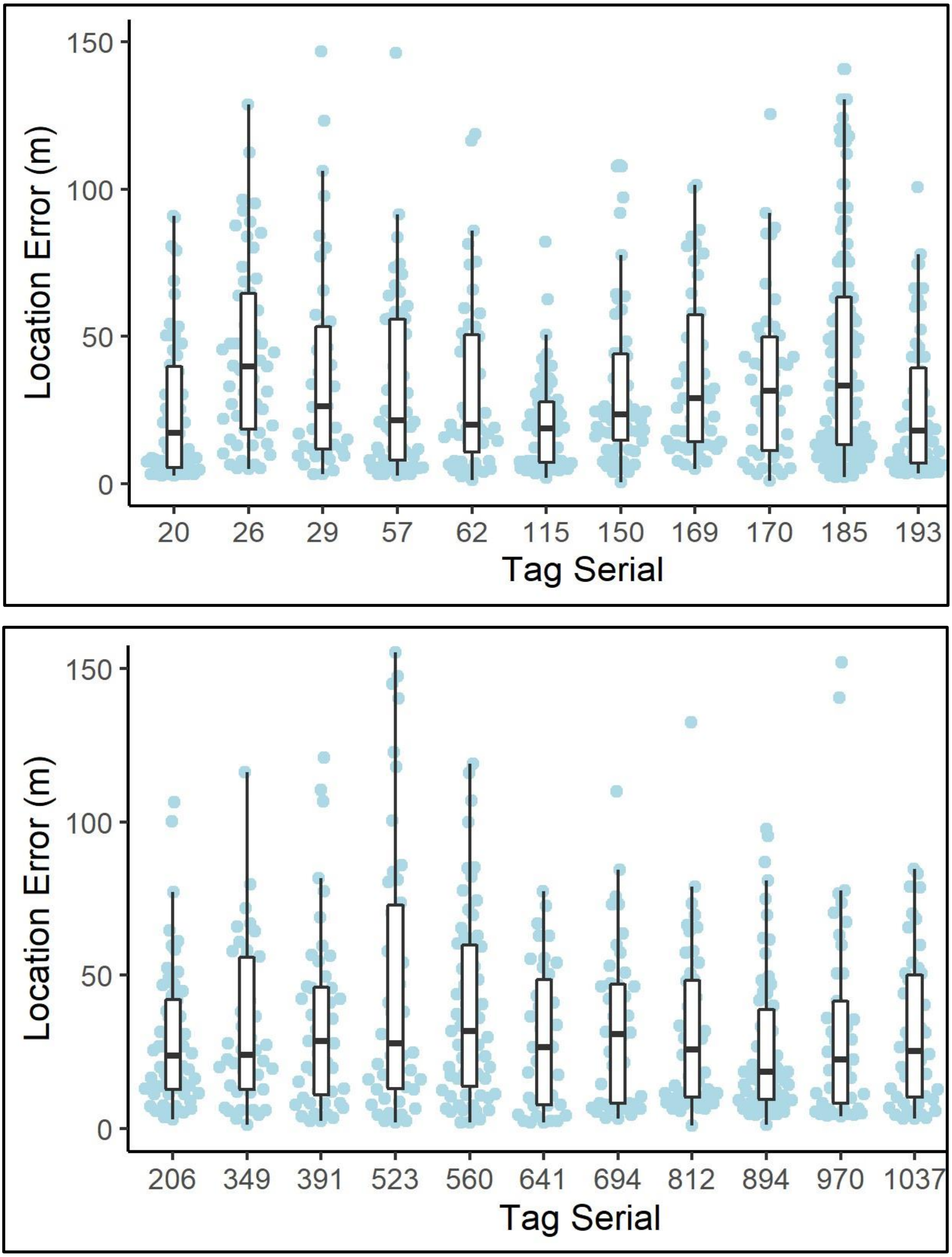

Figure 3.12: Location error (m) for each mOOvement device during the static test period from the 17th to the 22nd of March 2021 at Scott Farm. NB: Points above 150 m are not shown on graphs.

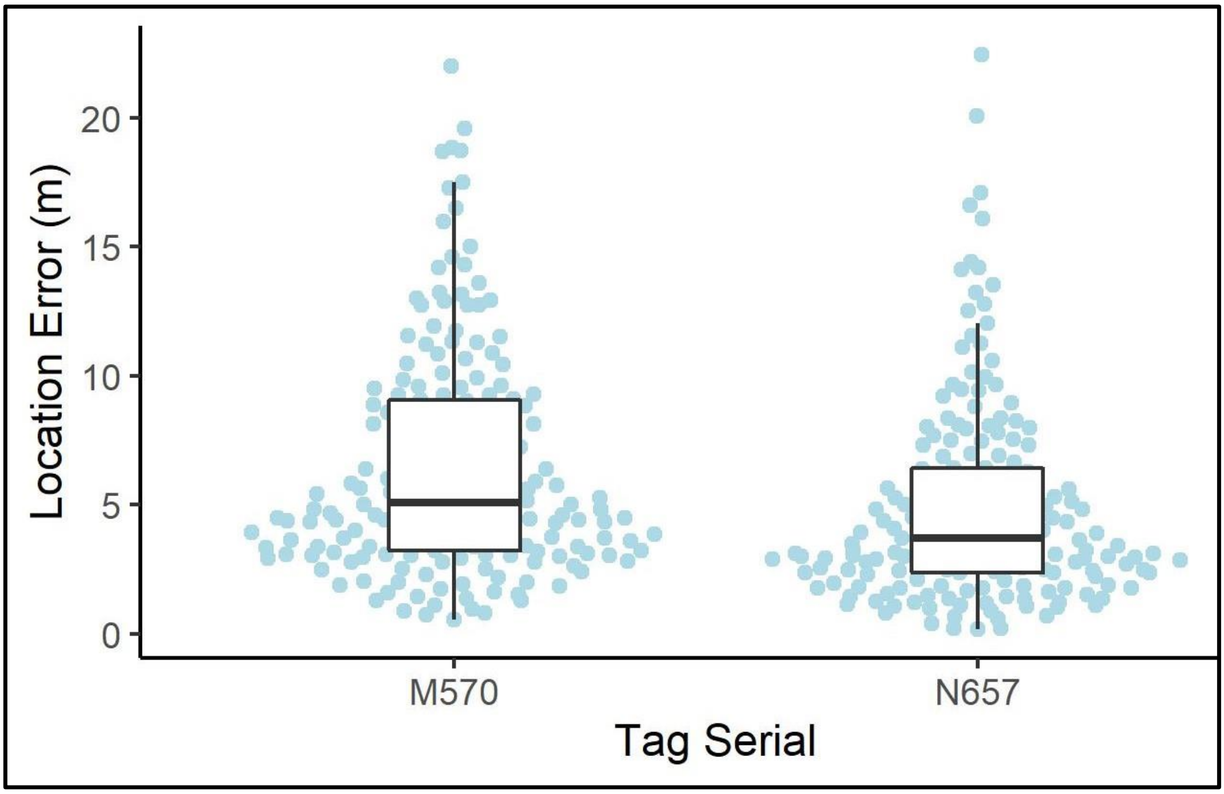

Figure 3.13: Location error (m) for each Oyster2 device during the static test period from the 23rd to the 30th of June 2021 at Scott Farm.

3.4.3 Location error and time of day

There appears to be no change in location error on a day-to-day basis. Changes within a day may be due to changes in the satellite position or availability (Figure 3.14 & Figure 3.15). Furthermore, the observed location error differences do not appear to be related to the battery voltage of the solar-powered GPS devices (Agtech) (Figure 3.16). Although Haultain (2014) reported reduced accuracy at certain times of the day, such as in the afternoon and early evening, this was not evident in this study. This may be due to the higher number of satellites available in 2021 compared with 2013, resulting in improved GPS accuracy. Nevertheless, the location errors recorded in this study (except for the mOOvement devices) are within the range reported by previous studies and the normal accuracy range expected for GPS devices of being within 5-10 m of the actual point (Agouridis *et al.*, 2004; Swain *et al.*, 2011; Morris & Conner, 2017).

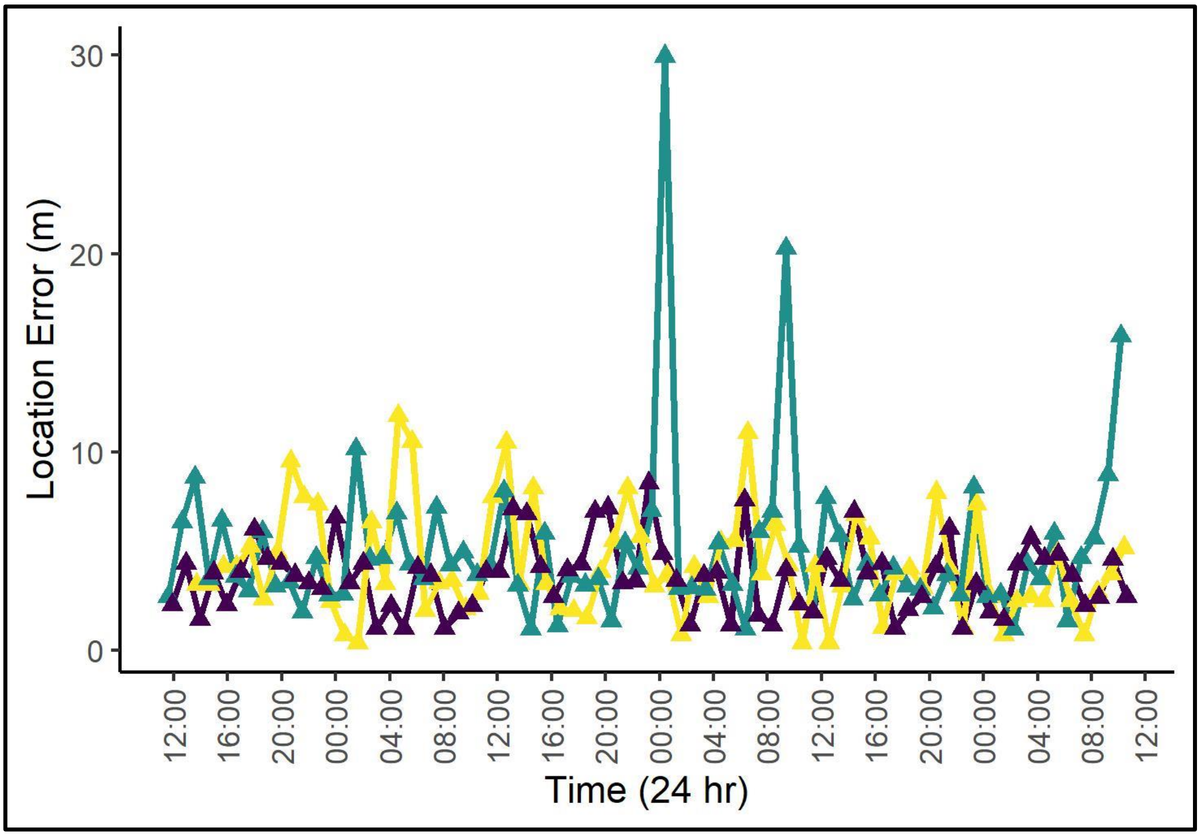

Figure 3.14: Location error (m) throughout the day for three Agtech GPS devices for three days during the March static test period. Each coloured line represents one device.

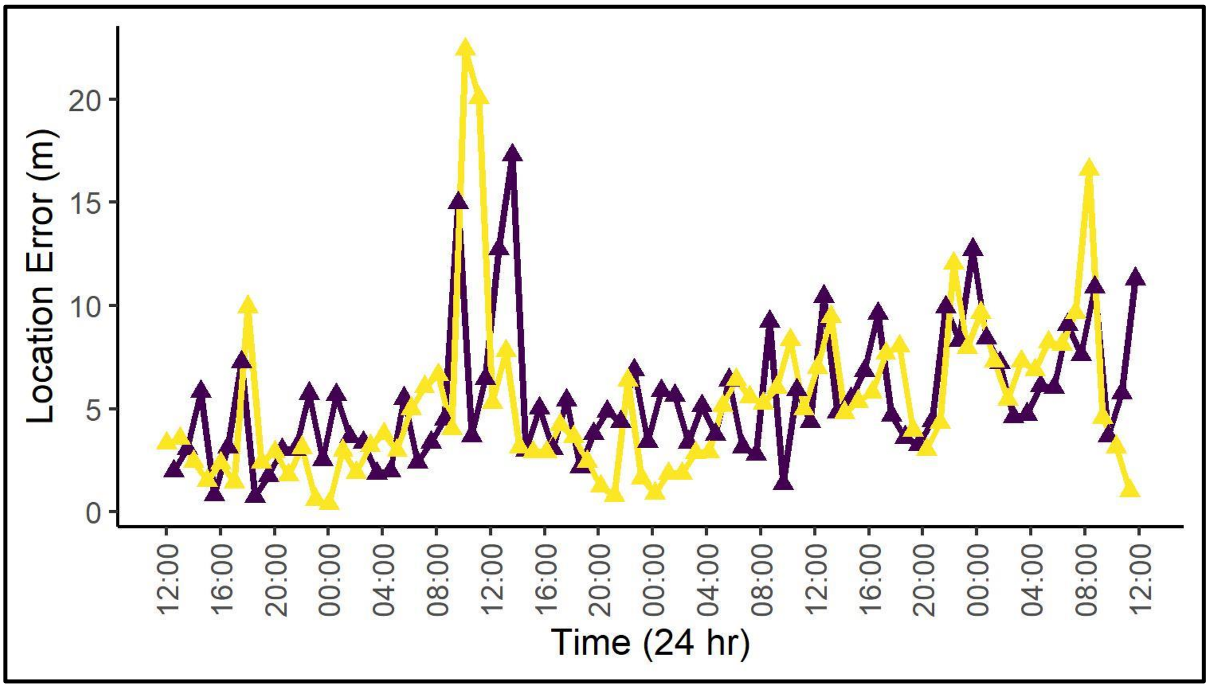

Figure 3.15: Location error (m) throughout the day for three days for both Oyster2 devices tested during the June static testing period.

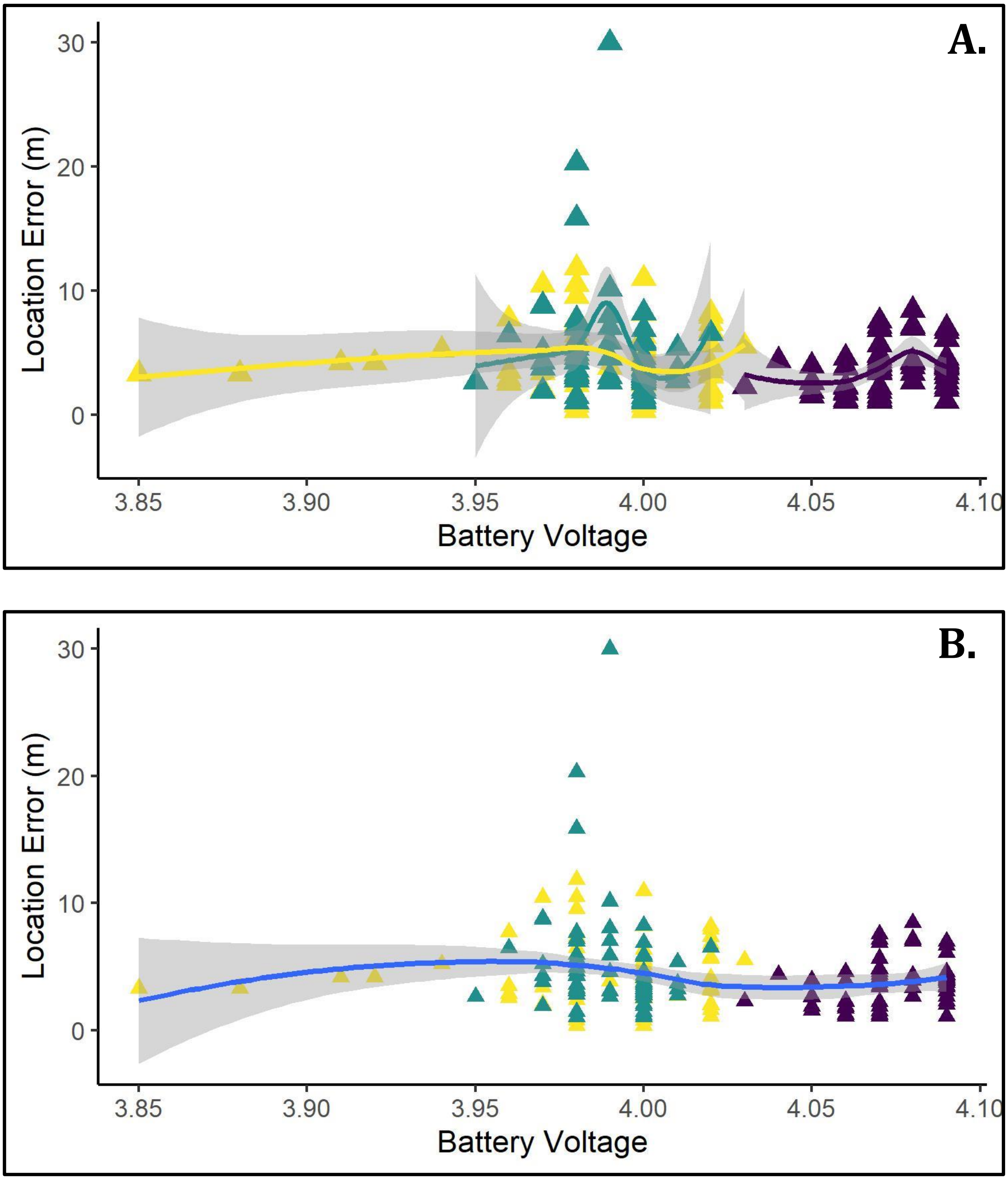

Figure 3.16: Effect of battery voltage (A & B) on location error (m) for the same devices reported in Figure 3.14.

3.4.4 Precision calculation: The CEP

The CEP is the expected distance at which a percentage of the GPS observations are expected to land (Moen *et al.*, 2001). For example, if a GPS device had a 95% CEP of 10 m, this means that 95% of all observations are expected to be within 10 m of the true location or target. The Agtech treatment returned a mean 50% CEP of 6.1 m (± 2.5 m) and a mean 95% CEP of 13.9 m (± 7.3 m). In contrast, the mOOvement treatment recorded a mean 50% CEP of 35.4 m (± 7.3 m) and a mean 95% CEP of 77.6 m (± 16.7 m).

For the Oyster2 devices, a mean 50% CEP of 5.7 m (± 1.0 m) and a mean 95% CEP of 11.9 m (± 2.0 m) were returned. Table 3.3 summarises both the 50% CEP and 95% CEP for all device types.

Table 3.3: Mean Circular Error Probable (CEP) at 50% and 95% for three types of GPS devices recorded during the static test period.

Device	Mean 50% CEP ± SD (m)	Mean 95% CEP ± SD (m)
Agtech	6.1 ± 2.5	13.9 ± 7.3
mOOvement	35.4 ± 7.3	77.6 ± 16.7
Oyster2	5.7 ± 1.0	11.9 ± 2.0

3.4.5 CEP of individual devices

For the individual Agtech devices, the 95% CEP ranged from 7.0-33.7 m (Figure 3.17). In addition, 27.3% of the devices tested had a 95% CEP of less than 10 m, and 81.8% of devices had a 95% CEP of less than 15 m. For individual mOOvement devices, the 95% CEP ranged from 44.1-114.2 m (Figure 3.18). Meanwhile, the two Oyster 2 devices returned a 95% CEP of 10.4 m and 13.3 m.

The best four devices in the Agtech group returned a mean 95% CEP of 8.8 m, while the bottom four had a mean 95% CEP of 20.0 m, a difference of 11.2 m (+127.3%). In contrast, the top four devices in the mOOvement group returned a mean 95% CEP of 55.1 m and the bottom four a mean 95% CEP of 103.9 m, a difference of 48.8 m (+88.6%). While there were differences in the 95% CEP between devices of the same type, they can be expected in the ordinary course of operation of the devices.

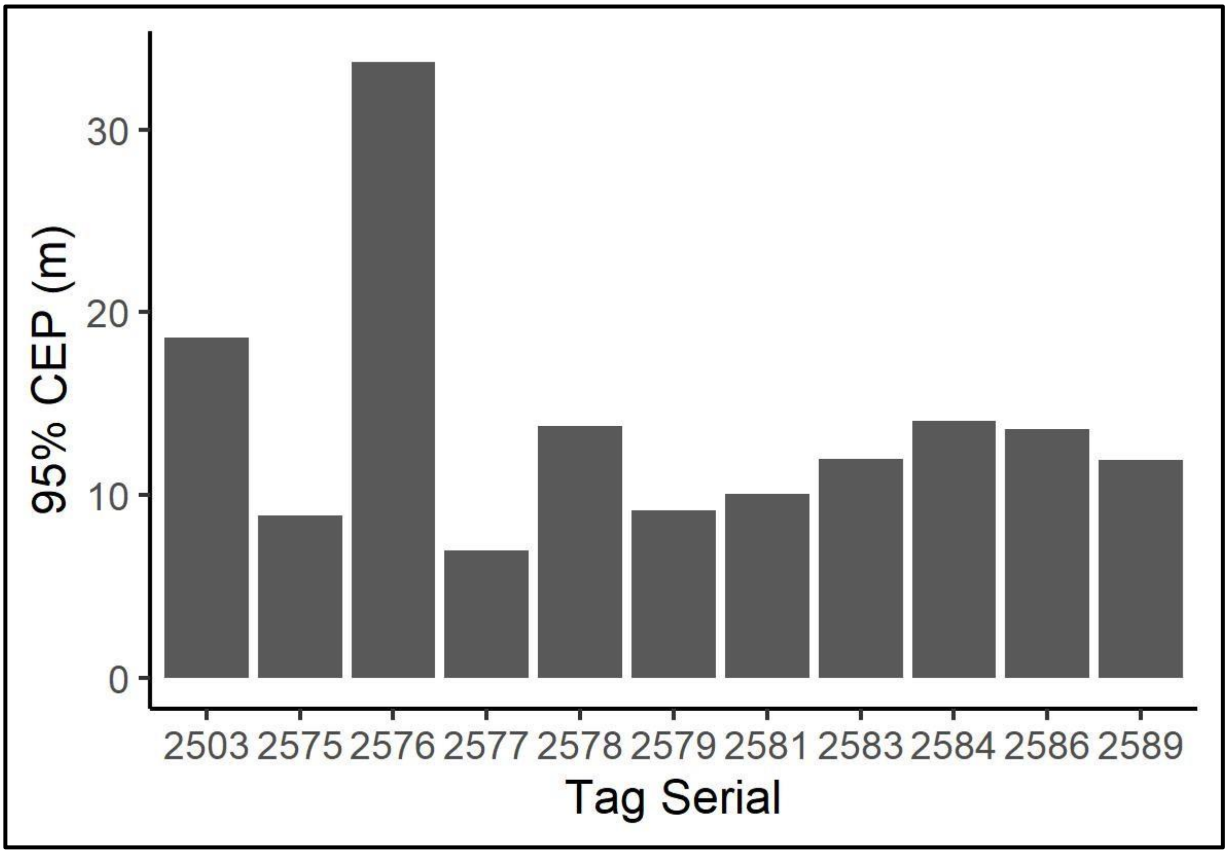

Figure 3.17: 95% CEP (m) for the individual devices in the Agtech group during the static test period at Scott Farm from the 17th to the 22nd of March 2021.

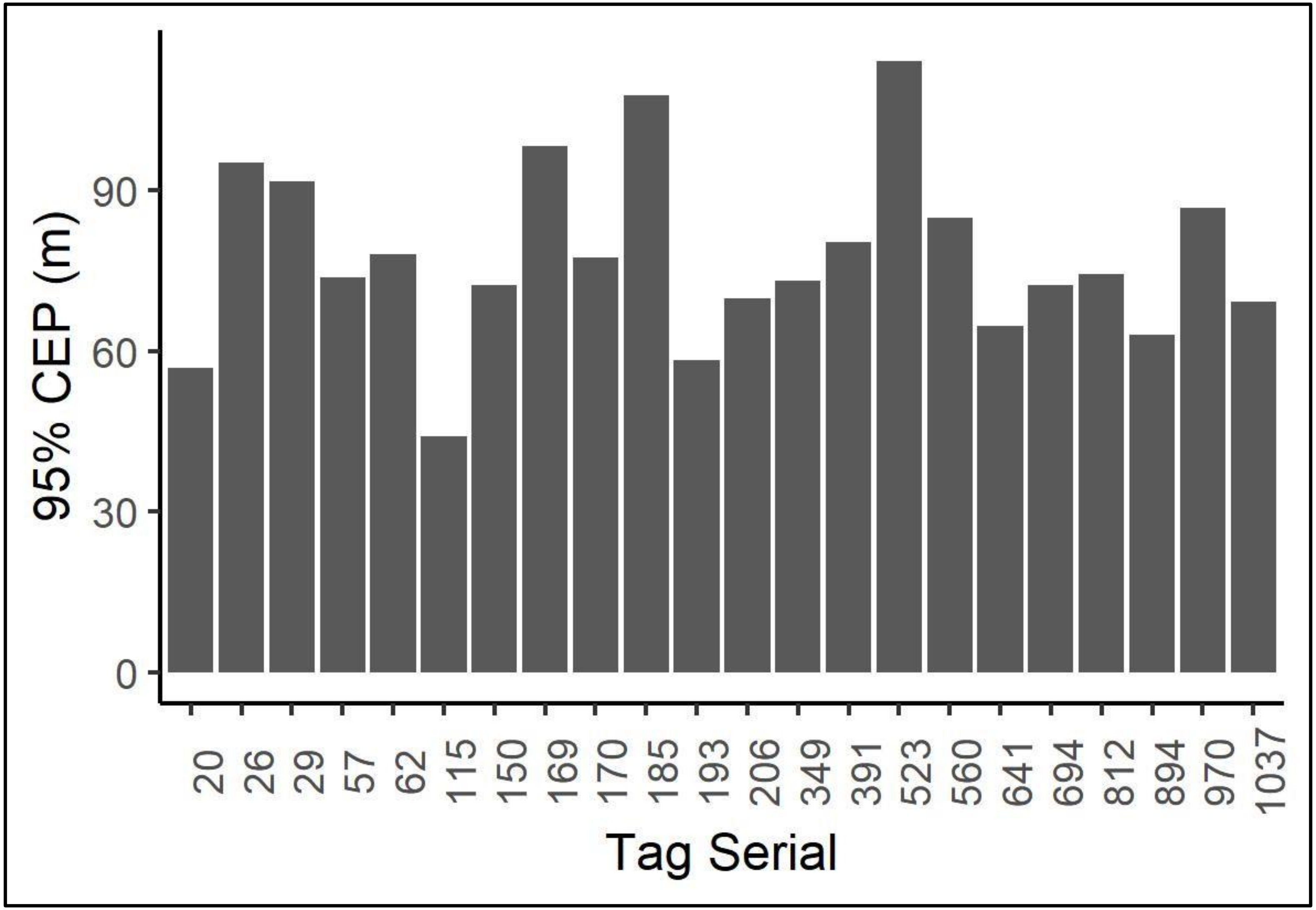

Figure 3.18: 95% CEP (m) for the individual devices in the mOOvement group during the static test period at Scott Farm from the 17th to the 22nd of March 2021.

3.5 General discussion

A primary aim of this research is to assess whether the current generation of GPS devices can be used to determine which paddock was recently grazed or is currently being grazed by a dairy herd. Therefore, the location error and CEP should be minimised to identify the paddocks correctly. A similar experiment that included static testing of 20 GPS collars designed and built by Massey University and suitable for use on cattle was conducted by Haultain (2014). The static test component comprised four treatment groups of five collars based on the individual fix rate of the device, either once per minute, once every 15 minutes, once every half hour or hourly. In this study, the four best-performing devices had a location error of 2.4 m (± 1.4 m) and a 95% CEP of 5 m, while the four worst-performing devices had a location error of 3.0 m (± 1.4 m) and a 95% CEP of 5.5 m, an improvement on the results of the current study.

Several key findings of the Haultain (2014) study are relevant to the current study, including the CEP of GPS devices required to identify grazed paddocks and the effect of paddock shape and size on the ability to identify the correct paddock. For example, the author (i.e., Haultain 2014) reported reduced paddock identification accuracy for paddocks smaller than 0.5 ha compared with paddocks larger than 1 ha. Fortunately, although some dairy farms may have paddocks smaller than 0.5 ha, these are rare and usually used for calf rearing or to keep sick cows close to the milking shed rather than being grazed by the milking herd.

Haultain (2014) recommended a 95% CEP of 6 m for GPS devices to identify paddocks less than 1.5 ha in size correctly. However, for paddocks larger than 1.5 ha (a typical paddock size on many New Zealand dairy farms), a 95% CEP of 9 m was suggested. In this study, the Agtech devices had a mean 95% CEP of 13.9, and the Oyster2 devices had a mean 95% CEP of 11.9 m. The mOOvement devices recorded a mean 95% CEP of 77.6 m. All of these are outside the suggested range. Therefore, according to Haultain (2014), neither type of device will correctly identify the paddock being grazed, which was one of the main objectives of this study. Chapter 4 will further explore this issue and report their ability to identify the paddock grazed in a commercial dairy situation.

While Haultain (2014) emphasised the 95% CEP precision levels required, the accuracy is equally if not more important as the CEP is purely a measure of how tightly GPS positions from one device are clustered together (McGranahan *et al.*, 2018). However, cows wearing GPS devices are likely scattered around the grazing area in a practical farm-based situation, which may be a two or three-hectare paddock depending on herd size. Therefore, accuracy may be more critical (McGranahan *et al.*, 2018). Furthermore, multiple GPS positions provided by an animal wearing a GPS device while grazing should provide a good indication of its current grazing area and provide increased accuracy of the GPS points recorded by each device. However, given the MLE for the mOOvement devices of 34.2 m, they are unlikely to be suitable for the automatic identification of the grazing area on a dairy farm due to poor accuracy with the manufacturer's default settings.

Another crucial factor required to correctly identify the paddock grazed by the dairy herd or other livestock using GPS devices is the fix rate of individual devices. For example, Swain *et al.* (2008) reported that at a one-hour fix rate which is the fix rate of both the Agtech and Oyster2 devices in this study, the probability of accurately predicting patch selection defined as the area currently being grazed is only around 30% within 10,000 m^2 (1 ha). On smaller farms, this may be a typical paddock size. Therefore, as paddock size or the area allocated decreases, the number of devices, device accuracy/precision, and fix rate of individual devices must increase to accurately predict herd locations (Swain *et al.*, 2008; Haultain, 2014). According to Haultain (2014), at least three GPS fixes are required per paddock to identify paddocks below 0.5 ha.

In this study, the Agtech and mOOvement devices were spaced 10 cm apart during the static testing period, which was closer than the spacing used by Agouridis *et al.* (2004) and Haultain (2014). In their studies, the GPS devices were placed either 1 m or 3 m apart during the static testing process to eliminate any possible interference between them and prevent satellite visibility from biasing the results. However, while there was only 10 cm between GPS devices in this study, there was no apparent evidence of interference between the devices.

3.6 Conclusion

This study has provided much-needed information on the location accuracy and precision of a range of commercially available GPS devices under New Zealand conditions. A key finding was that the location error of around 5.5 m was similar between both battery-powered (Oyster2) and solar-powered devices (Agtech) and within the range reported by previous studies (Agouridis *et al.*, 2004; Swain *et al.*, 2011; Haultain, 2014; Morris & Conner, 2017). In contrast, the MLE for the mOOvement devices of 34.2 m fell outside the expected range of 5-10 m and is inconsistent with the previous studies above. While significant differences ($P < 0.001$) between devices of the same type were observed for location error, this was not apparent for CEP. However, under typical operating conditions, differences between devices can be expected. What effect this will have on identifying grazed areas accurately by cattle tagged with GPS devices remains unknown. Individual differences between device types and devices within a type, along with the higher 95% CEP level found for the devices reported in this study compared with Haultain (2014), will be the focus of Chapter 4. This chapter will aim to understand how these tags perform under normal farming conditions, particularly concerning identifying both the paddock and the grazed area within that paddock.

Chapter 4

Automatic paddock identification

4.1 Introduction

Previous work by Haultain (2014) and Woodward *et al.* (2019) on Waikato dairy farms has demonstrated that commercially available GPS devices can identify the paddock grazed in near real-time. These GPS devices are either made for general use, such as vehicle tracking or specifically for use on cattle. However, such devices are not currently being used on commercial dairy farms in New Zealand for this purpose, possibly due to the lack of computer integration and the cost of earlier devices. Recently, several companies, including both Agtech and mOOvement, have released solar-powered GPS ear tags to the market. These tags are available at a lower cost. They can also be better integrated into recording systems and used by decision support systems, usually computer software developed to support and aid the user in decision-making (Taechatanasat & Armstrong, 2014). This chapter applies the findings of previous studies (including the study described in Chapter 3) to a commercial dairy farm situated in the Canterbury region of New Zealand. It aims to quantify how well these devices perform under real-world farming conditions. Of particular interest is whether these devices can accurately identify the grazed paddock and area allocated. Following a discussion of the methodology used, the results are presented and discussed.

4.2 Methodology

The trial was conducted on a 400-cow commercial dairy farm in Fernside, Canterbury, New Zealand (Figure 4.1). The farmers (husband and wife partnership) participated in the Irrigation Insight programme, a five-year industry-led programme examining the effect of improved weather and drainage forecasts on on-farm water management (Srinivasan *et al.*, 2019). The programme's overall aim was to provide farmers and growers with the tools to appropriately manage their irrigation needs by applying water at the correct rate and time, therefore being economically sound and environmentally responsible (Fear *et al.*, 2018; Srinivasan *et al.*, 2019).

The trial property is situated at 38 metres above sea level and covers approximately 115 hectares, of which 110 hectares are effective. It is subdivided into 45 paddocks ranging from 1.7 to 3.4 hectares. In the 2020/21 season, the farm produced 179,000 kgMS (447 kgMS/cow) from 400 cows peak milked. These are run as one herd plus a treatment herd for penicillin and lame cows. The farm receives an average rainfall of 650 mm per annum. Consequently, irrigation is applied from December to May via a sprinkler system if sufficient water is available from the Cust Water Users' Group, which extracts water from the Cust Main Drain. A typical South Island dairy farming system is used on the property with all cows grazed off for six weeks from early June to Mid-July and calves from December once they have attained 100 kg. They then return at approximately 22 months as in-calf heifers.

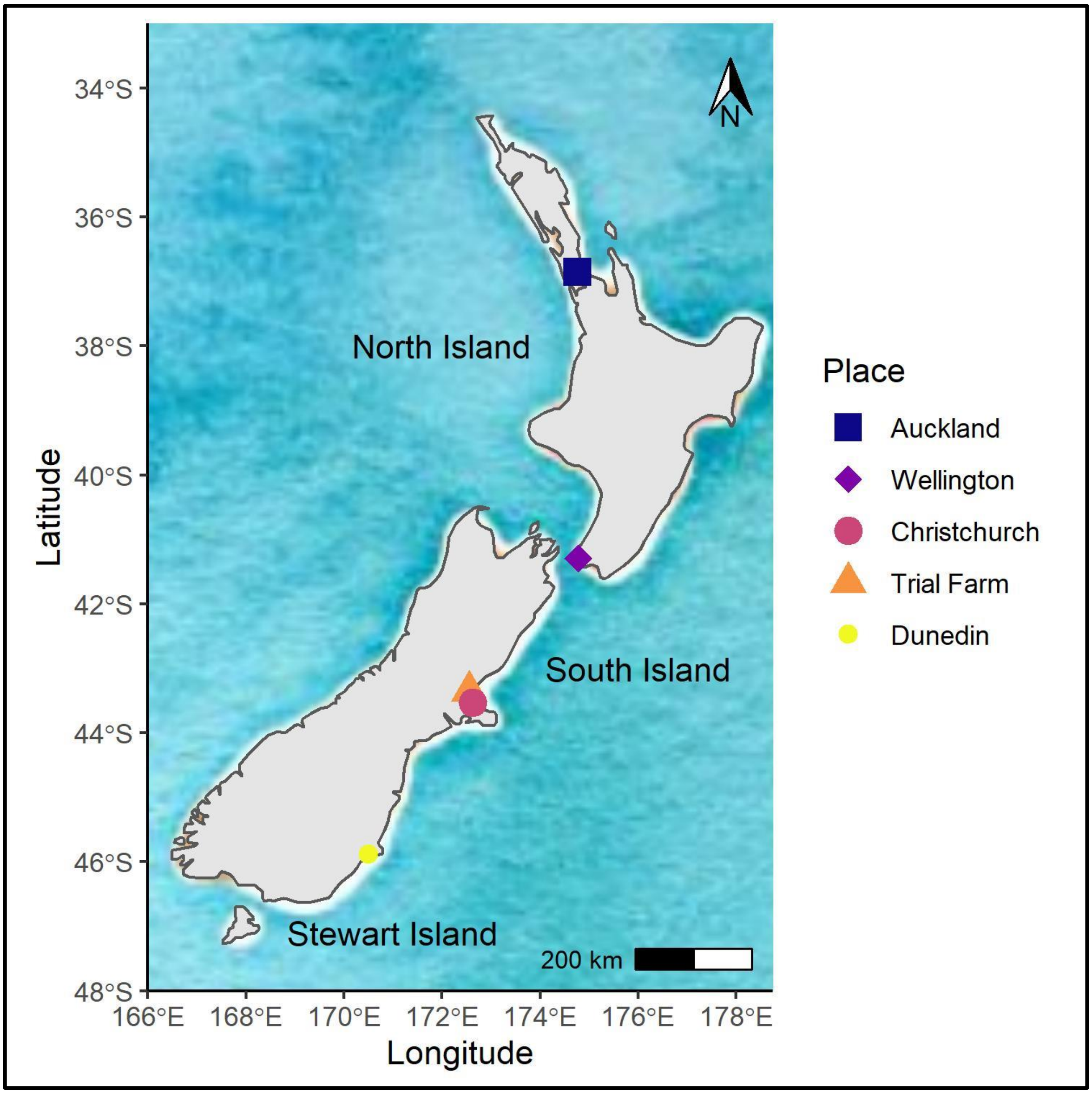

Figure 4.1: Location of the trial property in the Canterbury region of New Zealand.

Three types of GPS devices were tested, including the Agtech and mOOvement devices described in Chapter 3 and digitanimal cow collars (Figure 4.2). The digitanimal collars are specifically designed for animals, including cattle, and provide activity tracking and animal location data. They are lightweight devices weighing 265 g and measuring 4.1 x 3.0 x 1.9 inches. The digitanimal collars use the Sigfox network to transfer the data from the cow to the cloud before it is available for viewing (digitanimal, 2021). Like the LoRa network that the Agtech and mOOvement devices use, Sigfox is another low-power wide-area network (LPWAN). However, while the Agtech and mOOvement devices use a combination of the LoRa (data from the GPS devices to the base station) and cellular network (data from the base station to the cloud), the Sigfox network provides the ability to transmit data directly to the cloud. Developed in 2010 in Toulouse, France, Sigfox offers benefits over conventional cellular-based technology, including longer battery life, transmission range, and cost (Mekki *et al.*, 2019; Woodward *et al.*, 2019). In addition, Sigfox coverage is now available in most regions of New Zealand (Woodward *et al.*, 2019). A summary of the devices is provided in Table 4.1.

Table 4.1: Summary of GPS devices used in this study, including the network used, fix rate, type, number of devices tested, and test dates.

Device	Network	Fix rate	Type	Number	Test dates
Agtech	LoRa/ 4G	Hourly	Tag	11	1/4 - 1/12/2021
mOOvement	LoRa/ 4G	Two-hourly	Tag	11	1/4 - 1/12/2021
digitanimal	Sigfox	Hourly	Collar	2	1/3 - 20/5/2021

Eleven cows (~2.8% of the milking herd) were randomly selected from the milking herd, and each fitted with both an Agtech and mOOvement solar-powered GPS ear tag (one in each ear). Static test results (reported in Chapter 3) indicated that interference between devices was not detected at 10 cm spacing, so this method was decided upon to minimise the number of cows required for the trial.

The LoRa base stations for the Agtech and mOOvement devices were installed near the cowshed for convenience and ease of access (Figure 4.3). The mOOvement base station was configured to use the Spark NZ Ltd 4G cellular network since Wi-Fi was unavailable at the test site compared with the static test component at Scott Farm, where the mOOvement base station used the Wi-Fi network (Chapter 3). Although the Agtech base station is solar-powered as it was designed to be used where power was not readily available, it may be worthwhile for the manufacturers to investigate a powered alternative for when mains power is readily available.

The Agtech and mOOvement devices were fitted to the cows from the 1st of April to the 1st of December 2021. In addition, two of the eleven cows (0.5% of the milking herd) were also fitted with digitanimal cow collars as part of the existing Irrigation Insight trial. The current trial included digitanimal devices for approximately three months, from the 1st of March to the 20th of May 2021. The devices were configured to record a GPS position hourly (Agtech and digitanimal) or two-hourly (mOOvement) based on the manufacturer's default settings. The GPS devices remained fitted to the same cows throughout the trial period irrespective of whether they remained in the milking herd or were drafted out into a secondary herd for medical treatment or another purpose.

Figure 4.2: GPS devices on cows during testing on a commercial dairy farm. The digitanimal collars are on the left and the Agtech tag (white tag) on the right. Photos by M. Srinivasan, personal communication, September 13, 2021, and P. Edwards, personal communication, December 10, 2021.

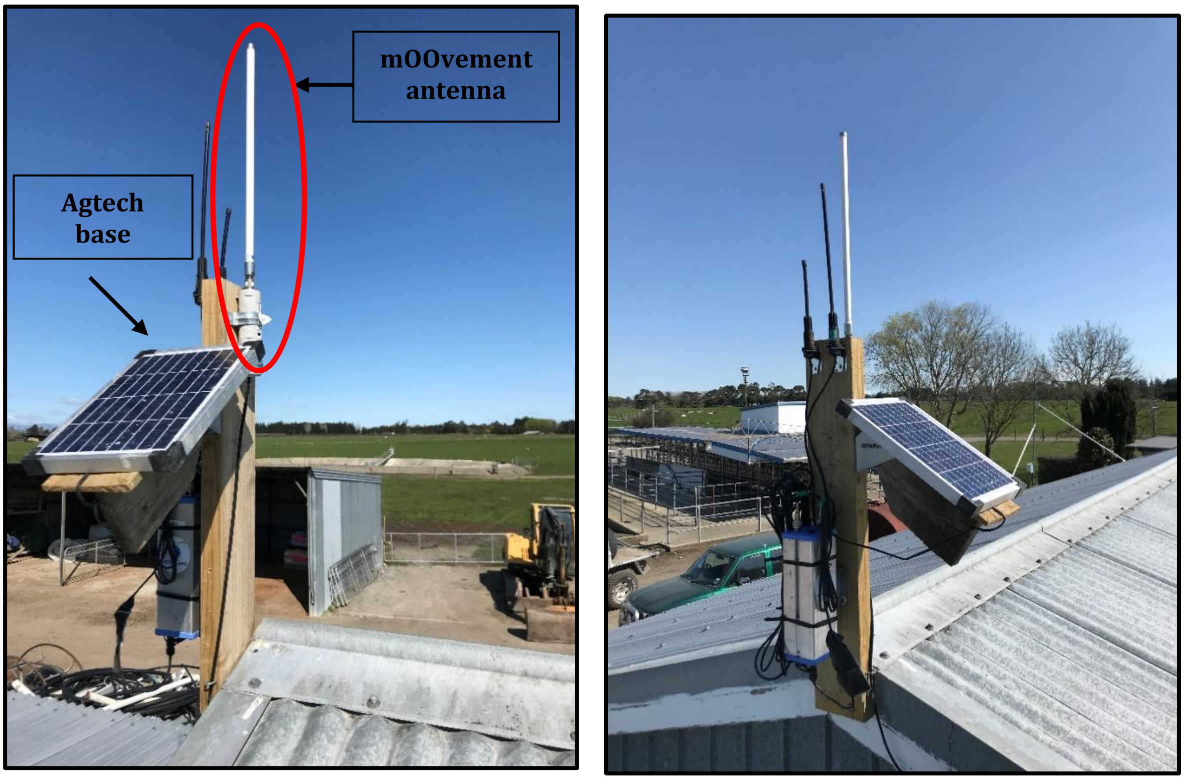

Figure 4.3: Experimental configuration of both the Agtech and mOOvement LoRa base stations during the testing period on a commercial dairy farm. Solar panel facing north to power the Agtech base station and the two black antennae to increase cellular coverage and aid the data transfer between the Agtech devices and the base station. The white antenna pictured is the mOOvement base station, which is mains powered and connected to a 4G modem (black cable running down inside of the post in the photo on the left) featuring a Spark NZ Ltd SIM card for cellular coverage and data transfer to the cloud. Photos by P. Edwards, personal communication, September 12, 2021.

4.3 Statistical analysis

RStudio (Version 1.4.1106) and R (Version 4.1.0 "Camp Pontanezen") were used in the statistical analysis of the GPS data (R Core Team, 2021). The *sf* (simple features) package for *R* allows spatial data to be explored (Pebesma, 2018; Pebesma, 2021) and was used to create a digital map of the paddock boundaries of the trial property. In combination with the GPS data, the paddock boundaries could be used to identify which paddocks had recently been grazed or were currently being grazed. The *sf* package was also used to estimate the size of the grazing break using convex hulls. The *ggmap* package for R was used to visualise the individual GPS data points on a satellite map (sourced from Google) with an outline of the trial property (Kahle, 2019). Other packages used included *tidyverse* to manipulate data frames (Wickham, 2021) and *lubridate* (Spinu, 2021) to ensure that dates and times were in a suitable format for analysis.

4.4 Results and discussion

A range of weather conditions was observed during the on-farm test period, including rain, clear days, and frost. During the first five months of 2021 to the 28th of May, only 103 mm of rainfall was recorded at nearby Ohoka, situated approximately 10 km from the trial property. However, the following 72 hours (29th – 31st May) saw a total of 168 mm of rainfall. The mean air temperature for February to September 2021 was approximately 12.2 °C, 0.7 °C warmer than average, while the mean max daily temperature was 17.8 °C, 1.0 °C warmer than average (Macara, NIWA personal communication, 2021).

The Agtech and mOOvement data were downloaded from their respective websites and stored on the DairyNZ Snowflake cloud service following the on-farm trial period. The data was later imported into RStudio via an API, a software intermediary that allows computer software to communicate to different programs, in this case, Snowflake and RStudio. The digitanimal data was supplied as a Microsoft Excel spreadsheet from a third party and imported into RStudio using the *readxl* package for R (Bryan, 2019). Essential information collected by the devices included the position (latitude and longitude), date and time of each observation, temperature, and battery condition.

4.4.1 Automatic paddock identification

Using a digital farm map of the property (Figure 4.4), it was possible to interpret the GPS data recorded by the devices to create a virtual record of the paddocks that had recently been grazed. In conjunction with the digital farm map of the paddock boundaries, the st_join function (part of the sf package(Pebesma, 2021)) in R was used to identify which GPS points were recorded in the allocated paddock and which were recorded elsewhere, e.g., at the cowshed or on the farm laneways. The data were then grouped by grazing break (either AM, between 6 am - 3 pm, or PM between 3 pm - 6 am the following day) and analysed for four days from the 5th to the 8th of April 2021. It was then compared with a list of paddocks grazed over this period by the trial farmers (Table 4.2). Figure 4.5 to Figure 4.7 visually present the raw data collected by each device and device type over this period.

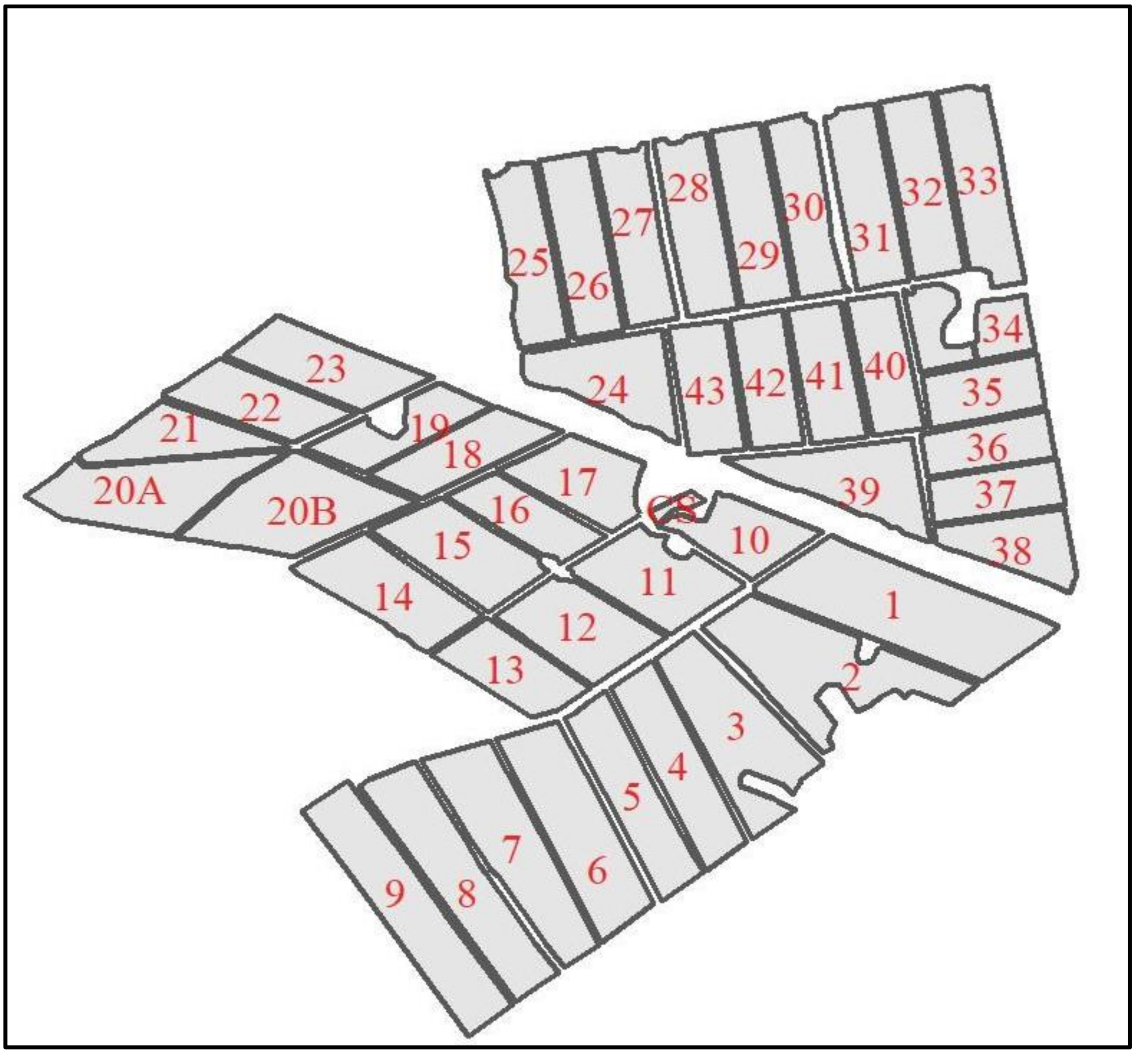

Figure 4.4: Farm paddock layout of the trial property with the cowshed shown as CS (between paddock 17 and paddock 10).

Table 4.2: Paddock grazings for the AM and PM periods on the trial property from the 5th to the 8th of April 2021.

Date	AM	PM
5/4	38	24
6/4	34	2
7/4	33	43
8/4	32	23

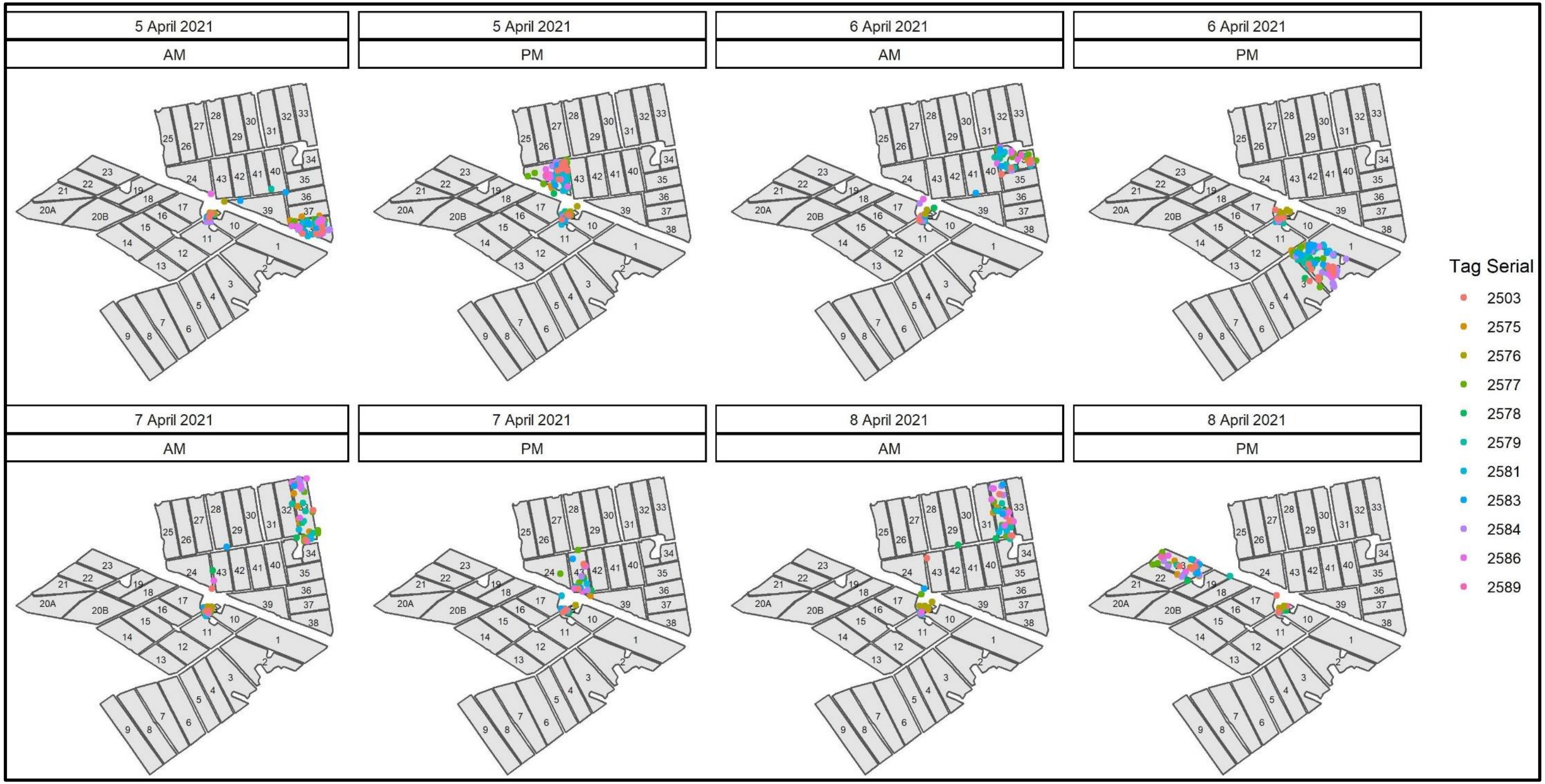

Figure 4.5: Summary of GPS location fixes for the 11 Agtech devices, and paddocks grazed over four days on a commercial dairy farm from the 5th to the 8th of April 2021 based on 6 am and 3 pm milking times.

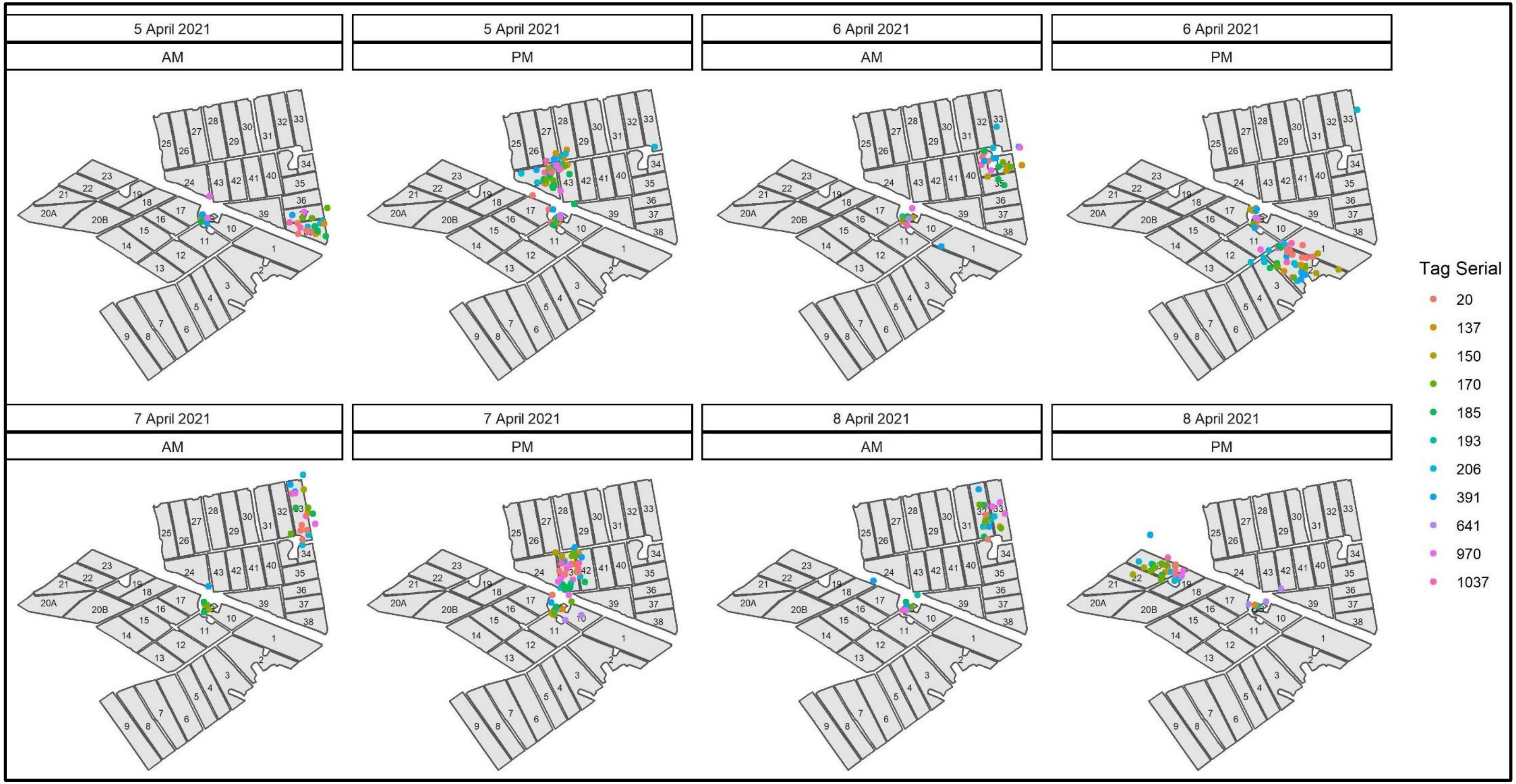

Figure 4.6: Summary of GPS location fixes for the 11 mOOvement devices, and paddocks grazed over four days on a commercial dairy farm from the 5th to the 8th of April 2021 based on milking times of 6 am and 3 pm.

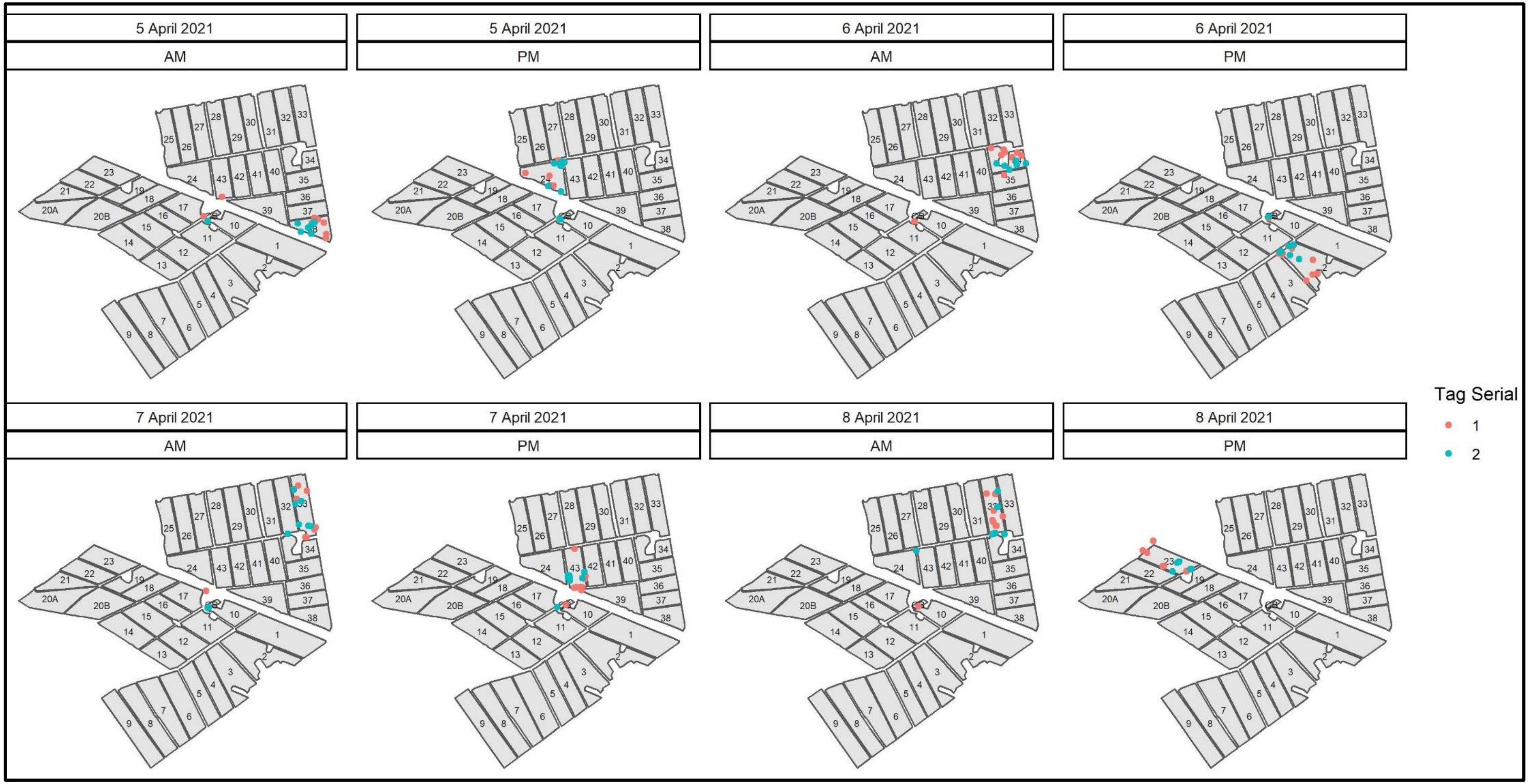

Figure 4.7: Summary of GPS location fixes for two digitanimal devices, and paddocks grazed over four days on a commercial dairy farm from the 5th to the 8th of April 2021 based on 6 am and 3 pm milking times.

Six hundred and nineteen observations were recorded from 11 Agtech devices during the four days. From these 619 hourly observations, 345 (55.7% of total observations) were recorded in the allocated paddock and 94 (15.2%) at the cowshed. The remaining 180 observations (29.1%) were recorded either on the laneways or in the incorrect paddock. For individual paddocks, the percentage of GPS observations in the allocated paddock ranged from 34.9% to 71.6% of total observations recorded while the dairy herd was in that paddock.

During the four days, 11 mOOvement devices recorded 364 observations recording an observation approximately once every two hours. One hundred and sixty observations (44%) were recorded in the allocated paddock, with another 28 (7.6%) recorded at the cowshed. The remaining 176 (48.4%) observations were recorded on the farm laneways or in the incorrect paddock. The percentage of GPS observations in the correct paddock ranged from 32.4% to 57.1% of the total observations recorded during that grazing period.

The two digitanimal devices recorded 158 observations in total over the four days. Of these 158 observations, 100 (63.3%) were recorded in the actual paddock grazed by the dairy herd and six (3.8%) were recorded at the cowshed. The remaining 52 observations (32.9%) were recorded on the farm laneways or in the incorrect paddock. The allocated paddock observations ranged from 50% to 76.5% of total observations for individual paddocks. Table 4.3 summarises the observations recorded in the allocated grazing break for each grazing period for each device type.

The *slice_max* function in R was used to select the rows with the highest percentage of observations for each grazing break (AM or PM). For the Agtech devices, the highest percentage of observations for each grazing break was in the actual paddock grazed for all eight occasions. Meanwhile, for both the mOOvement and digitanimal devices, the paddock with the highest percentage of observations was the correct paddock grazed for seven grazings out of the eight. For the remaining grazing, the percentage of observations recorded on the laneways or outside any paddock boundary on the trial property was equal to or greater than the actual paddock grazed.

Table 4.3: Number of GPS observations (*n*) recorded in the allocated paddock during each grazing period for three brands of GPS devices Agtech (11), mOOvement (11), and digitanimal (2). The numbers in parentheses represent the total number of devices for each type.

Paddock	Agtech		mOOvement		digitanimal		Grazing
	n	% total	*n*	% total	*n*	% total	period
2	79	55.6	28	40.6	17	68.0	PM
23	22	47.8	21	56.8	7	50.0	PM
24	101	71.6	26	37.1	19	73.1	PM
32	29	55.8	14	45.2	9	56.3	AM
33	22	34.9	15	48.4	10	58.8	AM
34	29	48.3	12	32.4	9	56.3	AM
38	47	57.3	20	57.1	13	76.5	AM
43	16	48.5	24	44.4	16	59.3	PM

The Agtech and mOOvement devices were primarily designed to help farmers keep track of their livestock over the vast areas found on Australian stations and American ranches. Nonetheless, this study shows that they can be used to identify grazed land areas on a much smaller scale (e.g., a paddock of 1.5-2.5 hectares) with some success. However, while the Agtech and digitanimal devices recorded around 30% of total observations over the four days in the incorrect area, the mOOvement devices recorded approximately half of all observations in the incorrect area. A key reason for the difference in observations in the incorrect area between device types is likely to be the location error of the individual device, with the mOOvement devices having a higher location error, as discussed in the static testing chapter (Chapter 3). Therefore, depending on the individual farm property and layout (i.e., paddock shape and size), the current mOOvement devices with the default settings may not be suitable if the main aim is to record the grazed paddock with the greatest possible confidence.

If the objective is to record the paddock grazed automatically using GPS devices, it is likely beneficial to use devices with a higher fix rate than this study. Nevertheless, the current study shows that devices with fix rates of either hourly (Agtech and digitanimal) or two-hourly (mOOvement) could identify the paddock grazed. A half-hourly fix rate (i.e., one observation every thirty minutes) means that more GPS observations will be recorded, therefore providing greater certainty that the identified paddock is correct. A half-hour fix rate effectively doubles the number of observations for the Agtech and digitanimal devices and quadruples the observations for the mOOvement devices. Although increasing the fix rate will increase paddock accuracy due to more observations, there will be a trade-off in battery life. Devices that run on internal batteries (e.g., digitanimal) will require more frequent changes. Similarly, solar-powered devices may require an additional power source (e.g., a backup battery) to meet the power demand of a higher fix rate, particularly if inclement weather prevents the charging of the batteries, such as that which may occur during the winter months.

Using the current generation of GPS devices, it is possible to automate the recording of paddocks grazed on a commercial dairy farm which could help farmers optimise grazing management and feed planning. For example, if paddock grazings are routinely recorded throughout the season, this information can help farm management decisions such as pasture renewal and fertiliser usage. In addition, farmers can target their resources more appropriately by building a performance history of individual paddocks over a year. Furthermore, this information could also be used as a data feed to other programmes which rely on paddock grazing information, such as feed budgeting software like Minda Land and Feed and Pasture Coach. Additional uses could be identifying preferential grazing areas or where additional water troughs may be required in individual paddocks and providing proof of grazing to milk processors for compliance or provenance purposes.

4.4.2 Estimate of the area allocated

A convex hull approach was used to estimate the grazing area of the dairy herd during each grazing allocation. This approach is commonly used in wildlife studies to identify the home range, which is the area an animal regularly occupies (Nilsen *et al.*, 2008; Quinton, 2016; Baíllo & Chacón, 2021). In this approach, the home range is assumed to be approximated by the smallest convex polygon (i.e., the convex hull) that contains the observed locations of the animal (Franzreb, 2006; Quinton, 2016; Baíllo & Chacón, 2021). An example of a convex hull is shown in Figure 4.8 using data gained from two digitanimal collars during one grazing break in paddock 38.

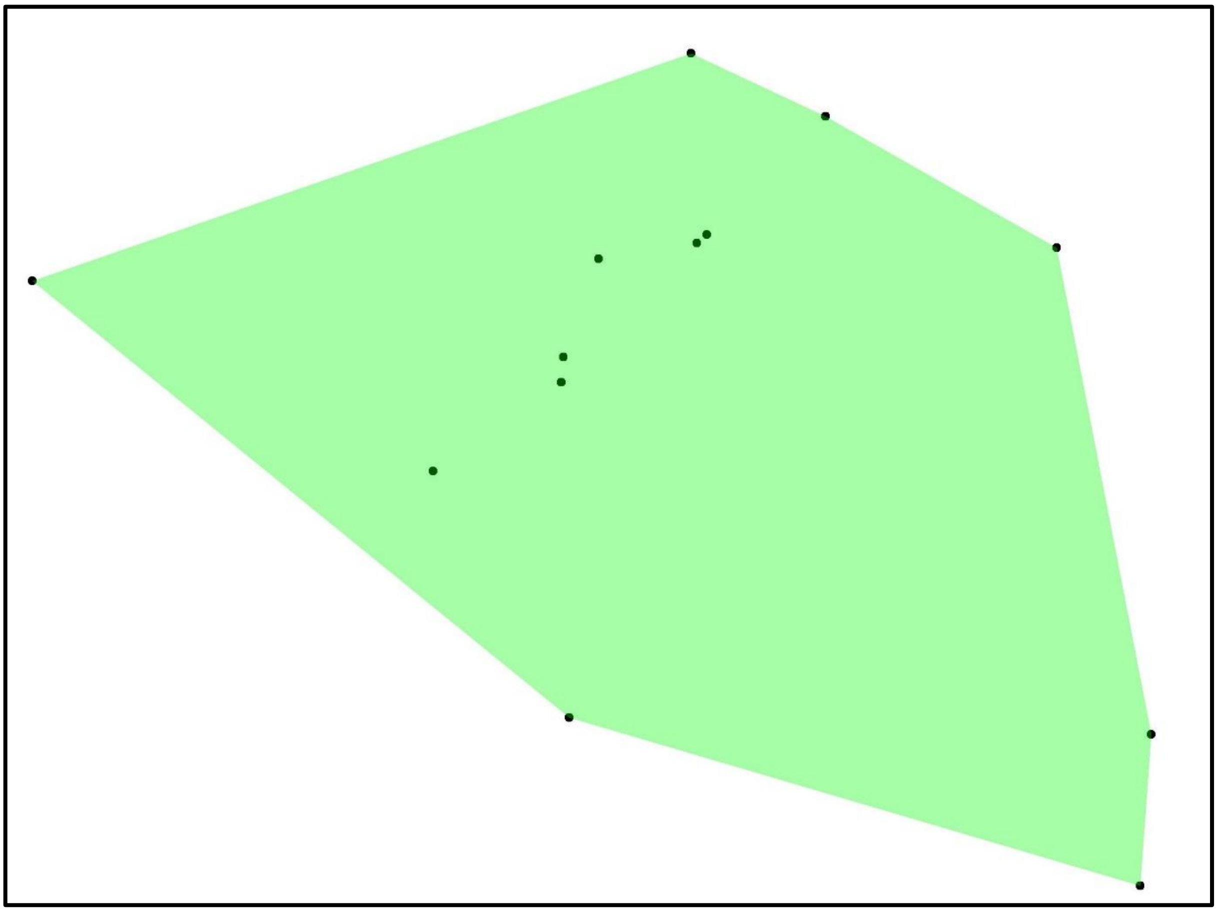

Figure 4.8: An example of a Minimum Convex Polygon (convex hull) based on GPS observations recorded by two cows wearing digitanimal collars for one grazing break (paddock 38).

Eight paddocks were grazed over four days in April. Using the *st_convex_hull* and *st_area* function in R (part of the *sf* package), it was possible to create a convex hull and estimate the grazing area using only the GPS observations recorded in the actual grazed paddock for each device type (refer to Table 4.3). When using the convex hull approach, the allocated area was underestimated most of the time, as expected (an overestimate is only possible when the paddock itself is not convex). The calculated grazing area ranged from 57.6% to 112.3% of the actual area for the Agtech devices and from 30.7% to 123.3% of the actual area for the mOOvement devices. For the digitanimal devices, the estimated area ranged from 25.5% to 64.8% of the actual area. Where paddock shape was irregular (i.e., not square or rectangle), this approach overestimated the allocated area for the Agtech and mOOvement devices but not the digitanimal devices. The latter may be due to only two devices being used compared with 11 devices for the Agtech and mOOvement devices, reducing the number of available points to create a convex hull. Table 4.4

summarises the calculated grazing area and the actual grazing area for the individual grazed paddocks.

If this method is used to estimate the grazing area, more GPS observations are required to obtain a more accurate representation of the grazed area. This could be achieved by having more animals fitted with GPS devices than this study used or using devices with higher fix rates. For example, instead of using devices recording a position approximately once per hour or once every two hours as used in this study, it may be appropriate to use devices recording a position once every 15-30 minutes if the aim is to estimate the area allocated. However, more devices will require a higher capital cost, while a higher fix rate will reduce the battery life of the devices. Therefore, there will always be a compromise between the number of devices used versus the selected fix rate.

Although the convex hull approach is relatively simple and easy to implement, it has limitations. The main limitations are that it is highly susceptible to outliers and tends to include areas that the animal does not utilise, leading to an overestimation of the occupied area (Burgman & Fox, 2003; Grueter *et al.*, 2009; Quinton, 2016). For example, the overestimation of the occupied area can be seen in Figure 4.9 to Figure 4.11. On several occasions, the allocated area has been overestimated due to the inclusion of land areas that do not form part of the actual paddock on the trial property, e.g., house sites. Franzreb (2006), investigating the home range of the red-cockaded woodpecker in South Carolina, also suggested that this method can overestimate the home range by including areas not visited by the target animal. Likewise, the convex hull method may overestimate the area with landscape changes or natural barriers such as rivers or steep terrain (Scull *et al.*, 2012).

Table 4.4: Estimate of grazing area versus paddock size using the convex hull method for three brands of GPS devices, Agtech (11), mOOvement (11), and digitanimal (2). Numbers in parentheses equals the number of devices. For simplicity, only four days (eight grazings) are shown below.

Paddock	Size (ha)	Area estimate (ha) - Agtech	Percent of actual	Area estimate (ha) - mOOvement	Percent of actual	Area estimate (ha) - digitanimal	Percent of actual
2	2.36	2.65	112.3	2.91	123.3	1.16	49.2
23	2.24	1.39	62.1	0.82	36.6	0.58	25.9
24	2.44	1.86	76.2	1.52	62.3	1.58	64.8
32	2.31	1.58	68.4	0.71	30.7	0.59	25.5
33	2.50	1.44	57.6	1.16	46.4	1.47	58.8
34	1.66	1.43	86.1	1.11	66.9	0.98	59.0
38	1.72	1.10	64.0	0.97	56.4	0.88	51.2
43	1.84	1.13	61.4	1.29	70.1	0.94	51.1

Figure 4.9: The estimated area grazed for eight grazing breaks (blue outline) based on the GPS fixes recorded within the allocated paddock (black outline) for 11 Agtech devices.

Figure 4.10: The estimated area grazed (blue outline) for eight grazing breaks based on the GPS fixes recorded within the allocated paddock (black outline) for 11 mOOvement devices.

Figure 4.11: The estimated area grazed (blue outline) for eight grazing breaks based on the GPS fixes recorded within the allocated paddock (black outline) for two digitanimal devices.

4.4.3 Positional fixes per device

The devices were configured to record a GPS position fix approximately once per hour (Agtech and digitanimal) or once every two hours (mOOvement). Differences between individual devices are shown in Figure 4.12 to Figure 4.14, which show the number of GPS position fixes per device within a device type daily for the test period described above. In theory, the mOOvement devices should return 12 fixes per day, and the Agtech and digitanimal devices should return 24 fixes per day. However, some individual devices recorded fixes at shorter or longer intervals than expected from the manufacturer's programmed fix rate. This may be due to the charge status of the device or connectivity to the base station or network.

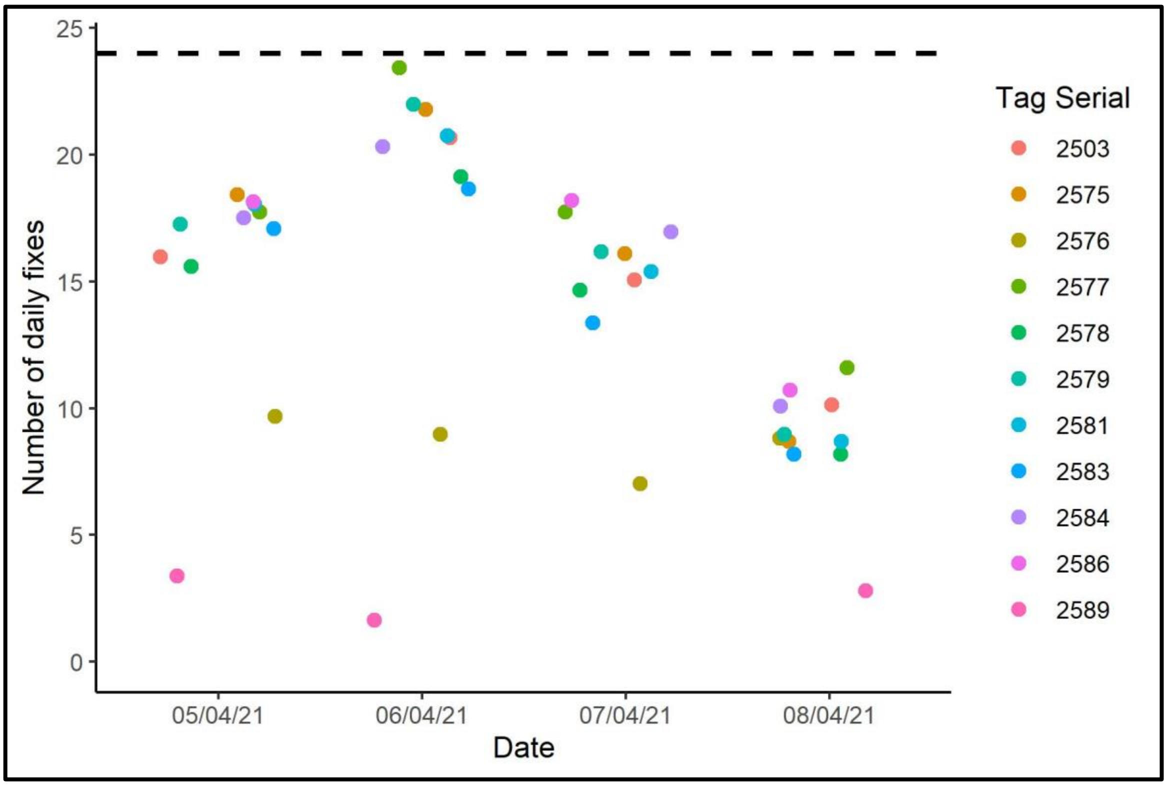

Figure 4.12: Number of pings (GPS fixes) per day for the test period from the 5th to the 8th of April 2021 for 11 Agtech devices. The horizontal dashed line represents the expected number of fixes per day for each device.

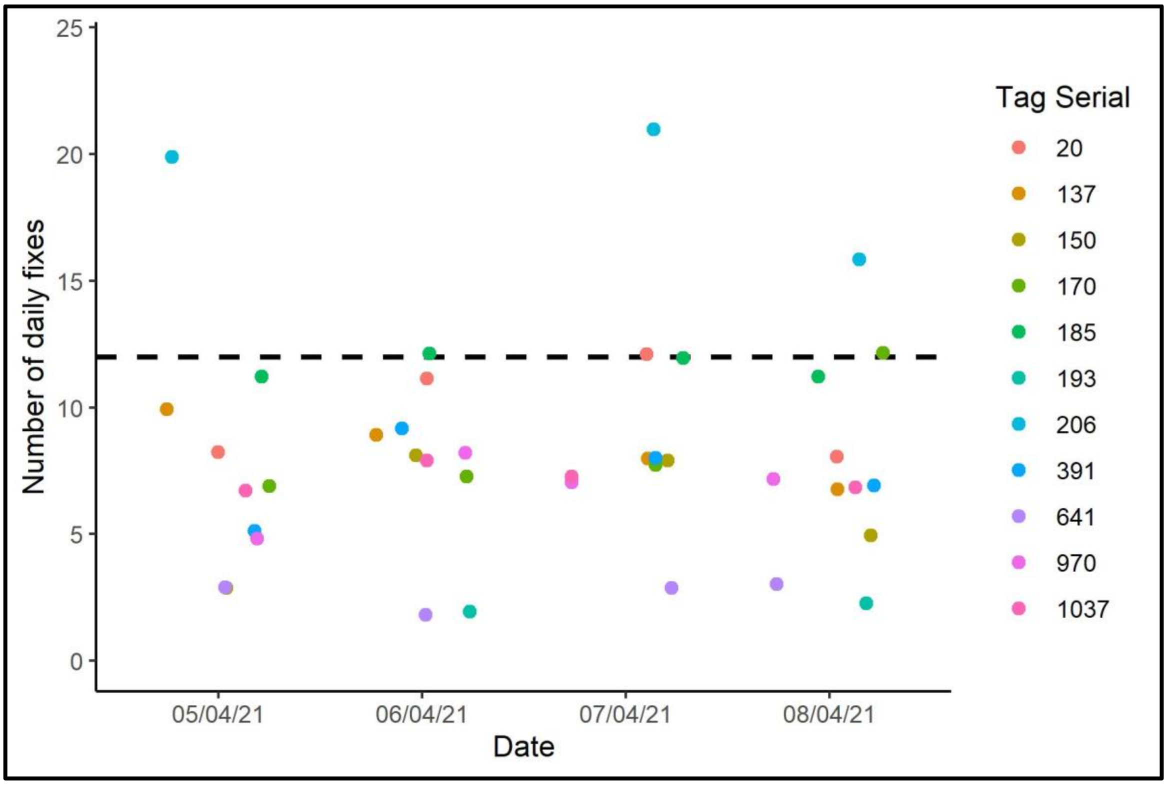

Figure 4.13: Number of pings (GPS fixes) per day for the test period from the 5th to the 8th of April 2021 for 11 mOOvement devices. The horizontal dashed line represents the expected number of fixes per day for each device.

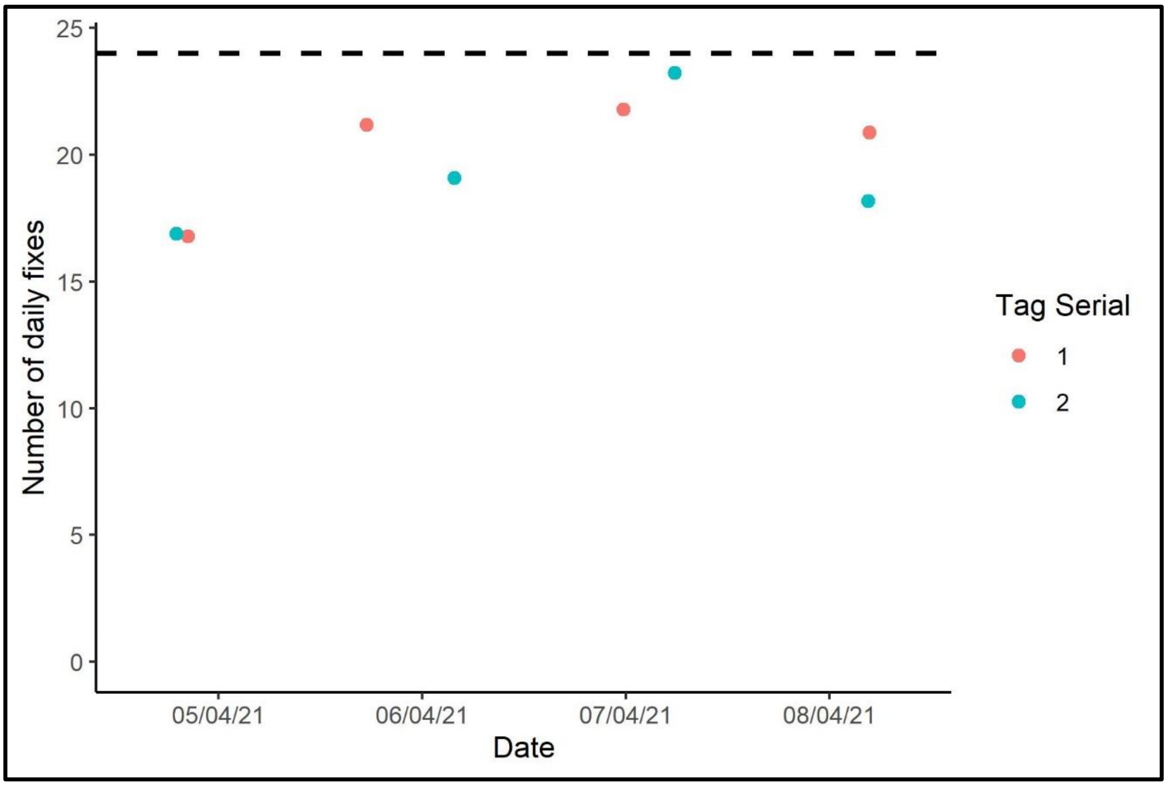

Figure 4.14: Number of pings (GPS fixes) per day for the test period from the 5th to the 8th of April 2021 for two digitanimal collars. The horizontal dashed line represents the expected number of fixes per day for each device.

The GPS fix rate is important because it dictates the battery life, the useful life of the unit, and the accuracy of the information provided (Haultain, 2014). For example, while a lower fix rate (i.e., increasing from hourly to two hourly) extends a unit's battery life and useful life, it also means that fewer GPS points are recorded. Therefore, it will be harder to determine the paddock or paddocks currently being grazed. The opposite also applies in that as the GPS fix rate increases (i.e., half-hourly instead of hourly), a decrease in battery life will occur. However, as more GPS points are recorded, it will be easier to determine the paddock or paddocks being grazed. Therefore, the end-user will have to balance the number of devices, the battery life, device accuracy, and the fix rate. Chapter 5 will further explore this issue.

4.4.4 Other on-farm considerations

This study has considered the use of GPS devices to record grazing events for a farming system that operated one main herd plus a treatment herd and offered one paddock per grazing period. However, many farming systems are used; therefore, other factors not explored in the current study also need to be considered and require further research.

Examples include using multiple herds on-farm or offering several paddocks (or parts of paddocks) during each grazing period. Furthermore, cows may be offered crops or supplements on a feed pad at certain times of the year, reducing the time available to graze the allocated paddock or paddocks. Likewise, a change in milking frequency from twice daily to once daily or sixteen hourly will also alter the time spent in the allocated paddock. Where grazing time is reduced, more devices or a higher fix rate are likely needed to provide sufficient confidence of the area grazed.

4.5 Conclusion

This study has successfully demonstrated that the current generation of commercially available GPS devices could be used to automate the recording of paddocks grazed in a dairy farming situation. In most cases, the percentage of observations in the correct paddock was around 50% of the total observations in each grazing period. This was sufficient to determine which paddock had been grazed by the dairy herd in most situations. However, if the overall aim is to identify the paddock grazed, it is suggested that the fix rate be increased from the hourly and two-hourly fixes used in this study. This will provide more GPS observations and should improve the number of observations in the correct paddock (depending on the location error of individual devices), thus providing greater certainty as to which paddock was grazed.

Likewise, an increase in the number of observations should provide a more accurate representation of the area grazed during each grazing period if using the convex hull method described above to determine the area grazed. The proposed system could be implemented relatively easily on-farm because the technology and data capability already exist. This system should require little human intervention other than fitting the devices, changing batteries, and installing and maintaining a base station if needed. While this study did not examine the number of devices and the ideal frequency at which individual devices record GPS points, Chapter 5 will investigate this further using a simulation exercise to identify the ideal number of devices required per herd and the required fix rate.

Chapter 5

Number of GPS devices per herd and the required fix rate

5.1 Introduction

Practical use of GPS devices to identify the paddock grazed and the area of pasture allocated requires several parameters to be optimised. These include the number of GPS devices required per herd, the fix rate of individual devices (how often a GPS location is recorded) and the number of location fixes required per paddock. For example, after undertaking a simulation exercise Haultain (2014) suggested that a minimum of three GPS devices per herd and at least three location fixes per paddock are needed to identify the paddock grazed correctly. Additionally, Haultain (2014) stated that the devices must have a tested accuracy of no more than ± 6-9 m 95% of the time, depending on paddock size. Similarly, Liu *et al.* (2015) thought that a small group subset (i.e., a subset of animals from a wider group, e.g., dairy or beef herd) would be sufficient to identify frequently visited areas such as grazing areas. McGranahan et al. (2018) likewise recommended using at least two to three GPS devices per herd to identify herd locations at the landscape level (e.g., area grazed) while considering potential equipment failure or animal mortality. However, if the intended aim is to correlate cattle locations with other environmental factors, Liu *et al.* (2015) suggested that at least 75% of a group have GPS devices for better accuracy.

Considering the current average herd size in New Zealand and the cost of currently available GPS devices, having 75% of the herd fitted with GPS devices is likely to be cost-prohibitive. Consequently, this chapter aims to clarify the number of GPS devices required per herd and the GPS fix rate needed to identify the grazed paddock and area allocated in a dairy farming situation. Following a discussion of the methodology used, the results are presented, and the implications for on-farm use are addressed.

5.2 Methodology

To achieve the objective of this chapter and identify both the number of devices and the fix rate required, the following approach was used. Firstly, random x and y variables (to represent longitude and latitude) were generated in RStudio between 0 and the long and short side of the paddock shape being tested. Following this, to allow for the device error, the rnorm function in R was used to generate a random number using a normal bell curve distribution based on the standard deviation of the individual device error for both the x and y variables. The x and y errors were then added to the previous x and y points to create the observed points. A similar process was used to estimate the area allocated using simulated observations in Section 5.2.2.

5.2.1 Number of devices and fix rate

Computer simulation of GPS fixes during a 6-hour daybreak was carried out 1,000 times using RStudio (Version 1.4.1106) and R (Version 4.1.0 "Camp Pontanezen") (R Core Team, 2021). The simulation aimed to calculate the number of GPS devices required and the fix rate needed to identify which paddock a herd of dairy cows were grazing. In order to achieve this, different scenarios were run based on four variables:

1. The location error of individual GPS devices.

2. Paddock shape (e.g., square and rectangle).

3. Paddock size (i.e., pasture allocation m^2 * herd size).

4. The number of GPS fixes (i.e., number tags/herd * device fix rate * hours in the paddock).

Table 5.1 outlines the main parameters used in the simulation to identify the grazed paddock.

A mean location error of 5.50 m was used as one location error variable for the simulation, representing the mean location error of the Agtech and Oyster2 devices tested in Chapter 3. In addition, a location error of 10 m was tested to represent less accurate devices. The location error of the individual devices affects the accuracy of paddock identification when cows are near the paddock boundary. Points recorded in this area may be recorded from the actual paddock being grazed or a neighbouring paddock or a race, hence the uncertainty (Figure 5.1). The size of the uncertainty zone is determined by the accuracy of each GPS device (Haultain, 2014).

Paddock shape varies between farms with long, narrow paddocks, common on dairy farms, having more fence length than a square paddock of the same area (Haultain, 2014). A greater fence to area ratio increases the probability of misidentifying the paddock based on a GPS location fix since, in narrow paddocks, the green region in Figure 5.1 is a greater proportion relative to the paddock area. Therefore, both square and rectangle paddocks were included in determining if paddock shape affects the ability to identify paddocks using GPS devices.

Table 5.1: Key variables used in a simulation exercise to determine the number of devices and fix rate required to identify grazed paddocks using GPS devices.

Variables	Options
Location error	5.50 m (Agtech/Oyster2 average) or 10 m
Fix rate	Hourly or two-hourly
Paddock shape	Square (1:1) or rectangle (2:1) in shape
Pasture allowance	50, 75, or 100 m^2/cow
Cow herd size	200, 300, or 400 cows
Number of devices per herd	1%, 2% or 4% of the total number

Various pasture allowances of 50, 75 and 100 m^2 per cow were tested to allow for the different systems used on the farm (e.g., low-intensity all pasture dairy systems versus high-intensity dairy systems where imported supplements are also used) and to factor in the different pasture feeding levels over the dairy season. The different pasture allowances combined with herd size formed the basis of the different paddock sizes tested in the simulation.

The number of GPS fixes per break was varied by altering the cow herd size and the fix rate of the devices independently. Typical herd sizes found on New Zealand dairy farms of 200, 300, and 400 cows were used as in large herd situations (>400 cows), it is common to split the total cow numbers into multiple herds. For example, a 600-cow farm may operate two herds of 300 cows, whereas an 800-cow farm often operates two or three herds. Furthermore, as the device cost represents a large capital outlay for larger herds, the number of devices per herd was tested at either 1%, 2%, or 4% of total herd size to identify any difference in paddock identification accuracy. Finally, both a one-hour fix rate and a two-hour fix rate were tested; this was the fix rate of the devices used in this study and a typical fix rate for commercially available devices. While the fix rate is an essential determinant of battery life, it also influences the ability to identify paddocks accurately, with more fixes providing greater certainty that the identified paddock is correct.

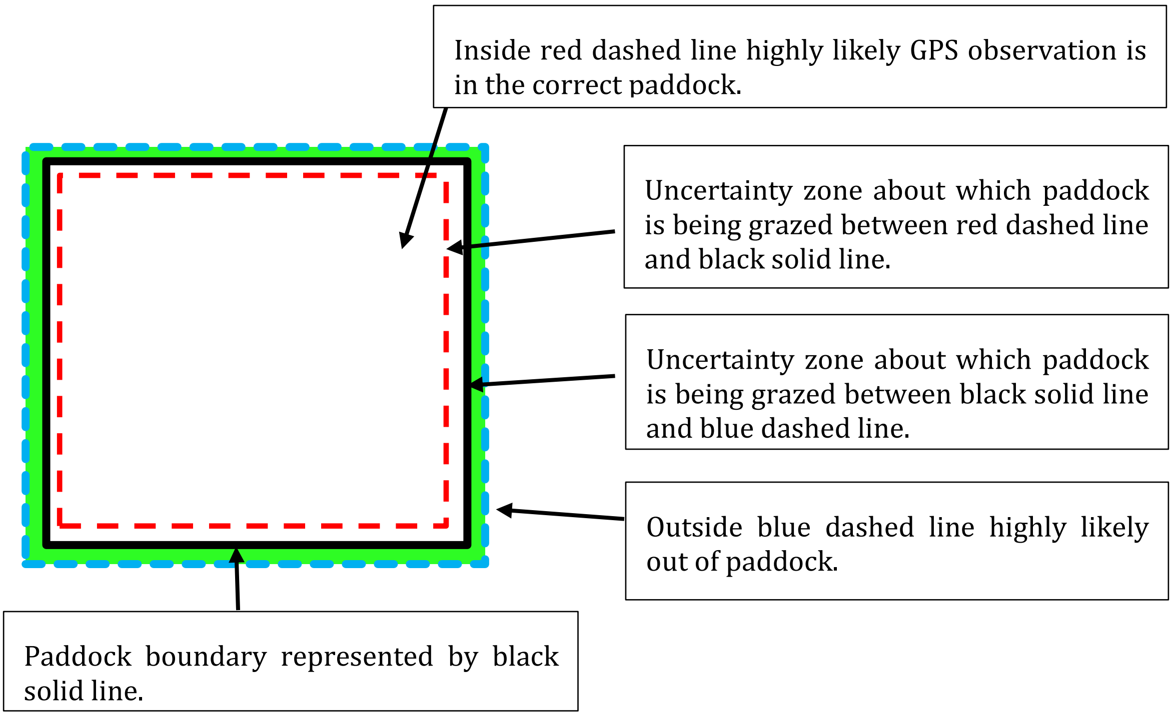

Figure 5.1: Diagram showing the different paddock zones available when using GPS devices. Uncertainty is created due to the location error of an individual device, which is the difference between the recorded and true GPS point. Adapted from Haultain (2014).

5.2.2 Fix threshold and calculation of area allocated

A second simulation experiment was carried out to determine whether it was possible to identify the area grazed using simulated GPS observations. In order to do this, 100 simulations were undertaken using RStudio (Version 1.4.1106) and R (Version 4.1.0 "Camp Pontanezen") (R Core Team, 2021), with several different parameters being adjusted, including the number of animals with devices, the fix rate of the devices and the device location error. This simulation was based on ten animals wearing a GPS device with a location error of 5.5 m, recording an observation once per hour. A simulated square paddock one hectare in size was then split into different proportions (0.25, 0.50, 0.75 and the whole paddock) to represent the different areas grazed. Subsequently, the paddock was divided into sixteen equal squares (approx 675 m^2 each), and the number of fixes in each square was then recorded.

Both simulations were based on a six-hour grazing break as this is a typical daybreak on many dairy farms measured from when the last cow arrives in the paddock after the morning milking until the first cow leaves the paddock in the afternoon. The milking season daybreak is usually the shortest period for livestock to be in a paddock during the year. The night break is of a longer duration (typically ~ 12 hours), though devices could be programmed to reduce the reporting frequency at night to save battery power if deemed necessary.

5.3 Results and discussion

5.3.1 Paddock size and shape and GPS device location error

Figure 5.2 and Figure 5.3 summarise the results of the first simulation experiment. They show the percentage of GPS observations correctly within the allocated paddock based on the four applied variables (i.e., location error, paddock shape and size, and the number of fixes).

When the location error of individual GPS devices is set to either 5.50 m or 10 m, the simulation results suggest that the paddock shape (square or rectangle) has only a minor effect on the percentage of GPS observations expected within a paddock. For example, if 1% of a 300-cow herd are fitted with GPS devices and allocated a pasture allowance of 50 m^2 /cow (1.50-hectare paddock), the simulation recorded an average of 92.9% and 92.4% of GPS observations in the paddock across 1,000 simulations for a square and rectangle paddock, respectively with a 5.5 m location error. Likewise, when the location error was increased to 10 m, there was little difference in the number of observations in the correct paddock for the same scenario based on paddock shape. In this situation, 87.7% of observations and 86.8% of observations for a square and rectangular paddock, respectively, were in the identified paddock. However, given the higher location error, the number of observations in the correct paddock was reduced. A similar pattern was observed for the other combinations tested.

While paddock shape appears to have almost no effect on the percentage of GPS observations expected in a paddock, the paddock size does have an effect based on the location error of the individual GPS devices. For instance, if a 200-cow herd are allocated a pasture allowance of 50 m^2 (1 hectare) and fitted with GPS devices that have a location error of 5.5 m, the simulation suggested that approximately 91.3% and 90.8% of total observations would be in the identified paddock for a square and rectangle paddock, respectively. As can be expected, if devices with a higher location error are used, the number of GPS observations in the true paddock can be expected to decrease. For example, suppose 1% of the above herd are fitted with devices with an average location error of 10 m and allocated a 1-hectare paddock. In that case, the simulation suggests that approximately 84.5% of observations and 83.5% of observations for a square and rectangular paddock should be in the true paddock, respectively.

If the pasture allowance for the same 200 cow herd described above is increased to 100 m^2 (2-hectare paddock), the percentage of observations expected to be in the correct paddock also increased to 93.8% and 93.6% for a square or rectangular paddock, respectively, when the location error is 5.50 m. Likewise, when the area for the herd described above is increased to 2 hectares, approximately 88.5% of observations are in the true paddock at a location error of 10 m compared with approximately 84% when allocated a 1-hectare paddock. For many New Zealand dairy farms, 2-hectares would be a standard paddock size

This simulation suggests that paddock shape influences how precisely GPS devices can identify the correct paddock, consistent with Haultain (2014). In that study, there was a slight difference in the identification of square and rectangle paddocks using GPS devices. Using a default setting of three-position fixes per device per paddock, they reported that at least one of the three position fixes was likely to be in the identified paddock 87% of the time for a 0.55-hectare square paddock. By contrast, at least one of the three fixes was likely to be in the correct paddock 83% of the time for a rectangle paddock of the same size.

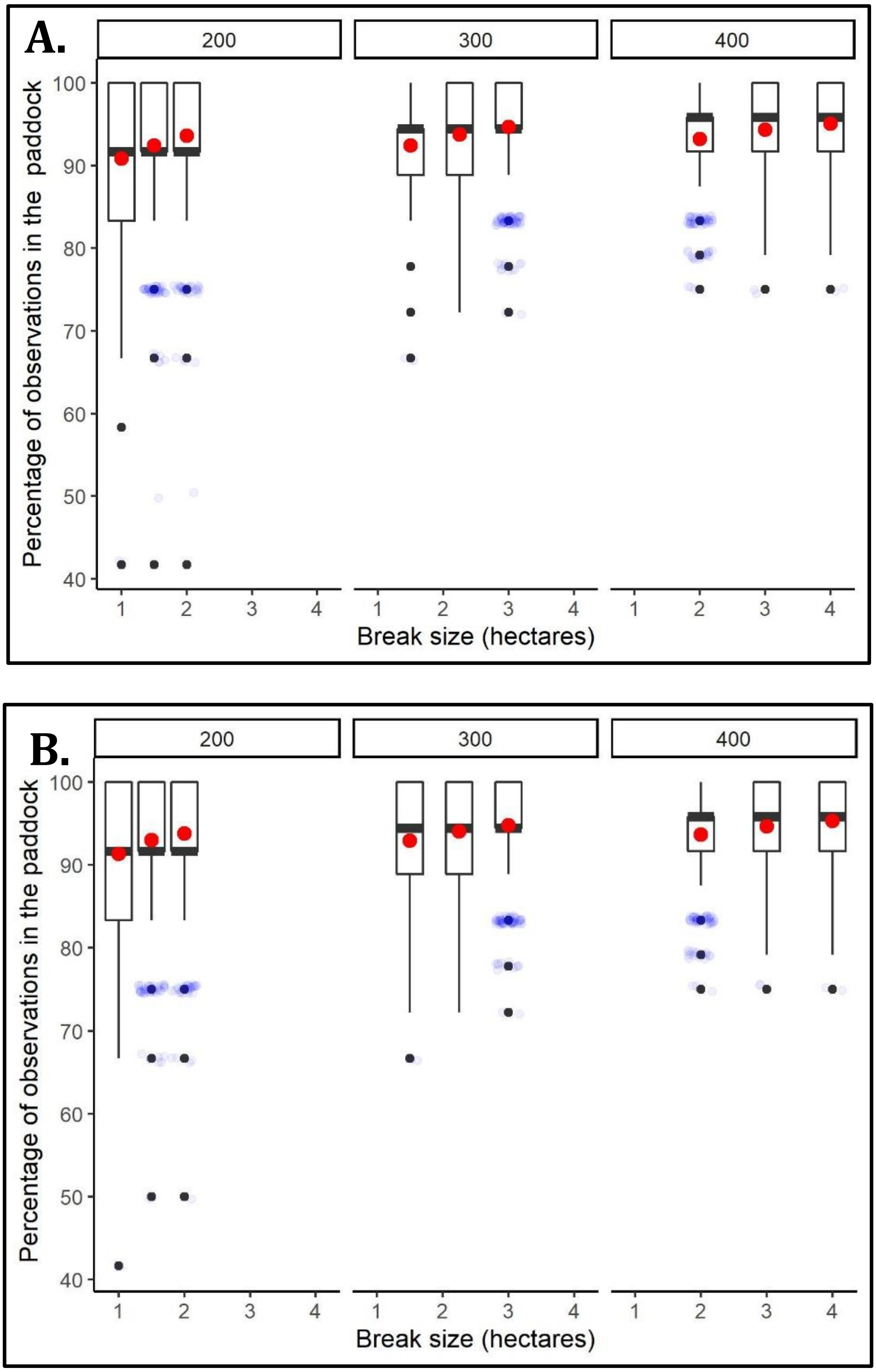

Figure 5.2: Percentage of GPS observations in the actual grazed paddock for a rectangular-shaped (A.) and square-shaped paddock (B.) after 1,000 simulations with 1% of the herd (200, 300, 400) tagged with GPS devices with a location error of 5.50 m and recording a GPS position once per hour for a six-hour pasture break. Break size based on a pasture allowance of 50, 75 or 100 m² per cow. The red circle shows the mean percentage, while the blue circles represent multiple points.

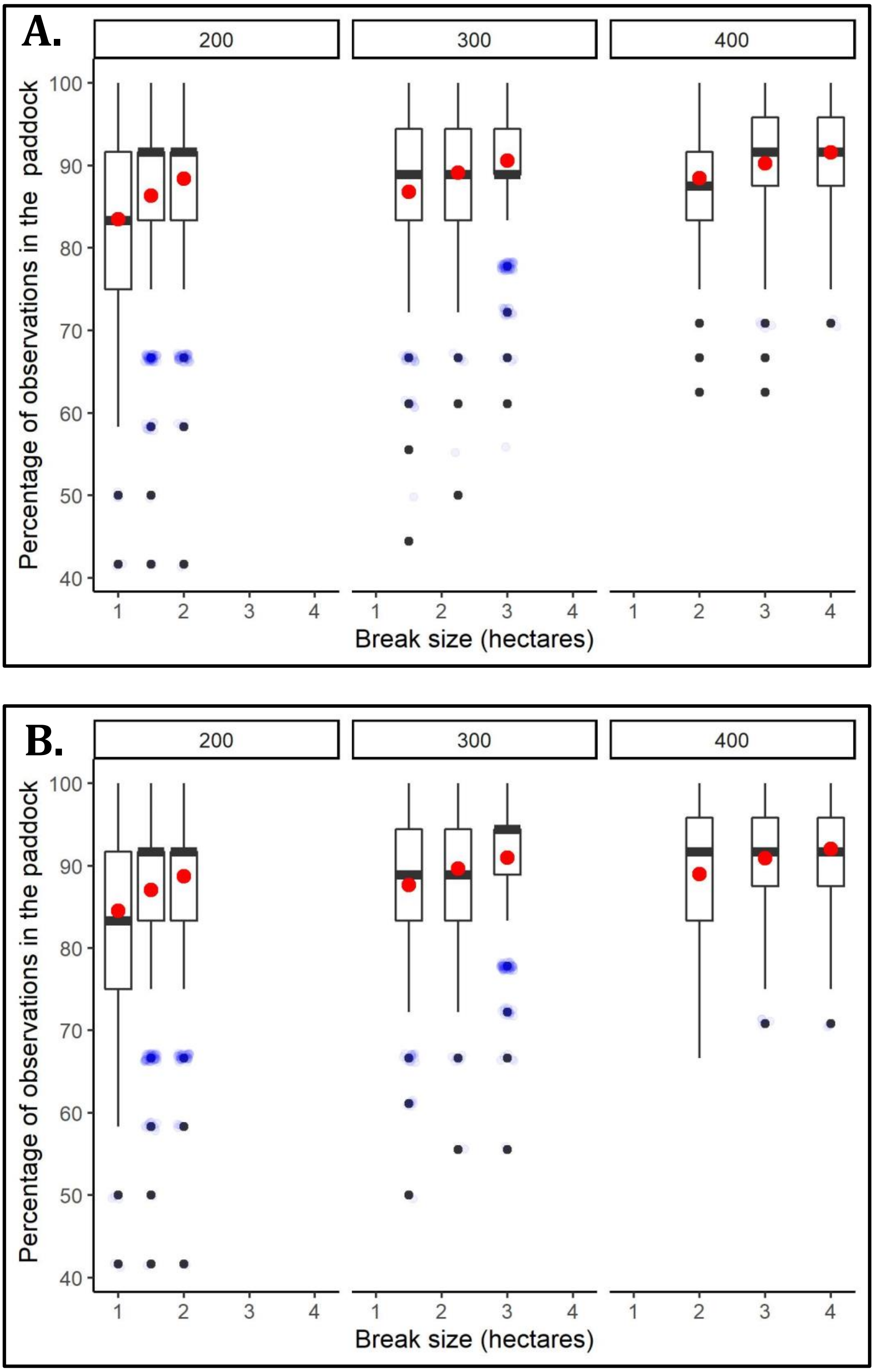

Figure 5.3: Percentage of GPS observations in the actual grazed paddock for a rectangular-shaped (A.), and square-shaped paddock (B.) after 1,000 simulations with 1% of the herd (200, 300, 400) tagged with GPS devices with a location error of 10 m and recording a GPS position once per hour for a six-hour pasture break. Break size based on a pasture allowance of 50, 75 or 100 m² per cow. The red circle shows the mean percentage, while the blue circles represent multiple points.

5.3.2 Number of devices per herd and fix rate

This simulation showed that increasing the number of devices per herd from 1% to 2% leads to only a slight increase in the number of GPS observations expected in the true paddock. Likewise, when the number of devices was further increased to 4% of the herd fitted with GPS devices, the increase was even more modest for the percentage of GPS observations in the true paddock. This result was consistent with all scenarios tested. For example, for a 400-cow herd allocated 50 m^2/cow of pasture in a square paddock (2 hectares), the likelihood of the GPS points being in the true paddock was approximately 94% in both scenarios, an increase of approximately 1-1.5% when only 1% of the herd was fitted with devices. A similar pattern was observed when the paddock shape was changed from square to rectangle. In this scenario, the probability that the GPS points are in the true paddock is again around 94%. Similarly, if a herd of 200 cows grazes the same area of 2 hectares, a similar trend was observed when the number of GPS devices was increased. Figure 5.4 presents the simulation results for the percentage of GPS observations in the true paddock when 4% of the herd is fitted with GPS devices for square and rectangle paddocks

The percentage of GPS observations in the true paddock in all tested scenarios was similar for both a one-hour fix and a two-hourly fix rate. For example, when a 300-cow herd are grazing a 3-hectare paddock, and 1% are fitted with GPS devices, the percentage of GPS observations in the true paddock for, either square or rectangular, was approximately 94.5% at either an hourly or two hourly fix rate. This was based on a total of 18 fixes during the six-hour grazing period at an hourly interval (i.e., 300 cows * 1% devices * 6 hours grazing = 18 fixes total) compared with a total of 9 fixes at a two-hourly fix rate. Likewise, if 1% of a 400-cow herd in a 2-hectare paddock are fitted with GPS devices, the simulation suggested that approximately 93% of observations would be in the true paddock at either an hourly or two-hourly fix rate. Therefore, as the fix rate dictates the battery life of the GPS units, a two-hour fix rate could help maximise the battery life of the devices. This is also supported by Haultain (2014), who suggested that three or more GPS fixes are needed per paddock to identify it using GPS devices correctly.

However, while the results of this study show that tagging 1% of a farmer's herd with GPS devices such as ear tags can identify the paddock grazed with similar results to either 2% or 4% of the herd that has devices, other factors also need to be considered. Firstly, it is common for cows to be drafted out on a dairy farm for various reasons, including mating and animal health. Secondly, on large farms, the milking herd may spend up to a third of the day either at the milking shed or walking to and from it, thus reducing the time spent in the allocated grazing area. Thirdly, there is also the possibility that a GPS collar or ear tag may fall off or the batteries go flat. Therefore, if only 1% of the herd are tagged with GPS devices in small herds of less than 300 cows in certain circumstances like those described above, there may be only one or two GPS devices remaining per herd at a given time. In these situations, the likelihood of identifying the paddock is likely to be decreased if only 1% of the herd is fitted with GPS devices. Consequently, as suggested by both Haultain (2014) and McGranahan *et al.* (2018), a minimum of three animals per herd should be fitted with GPS devices if the aim is to identify the grazed paddock.

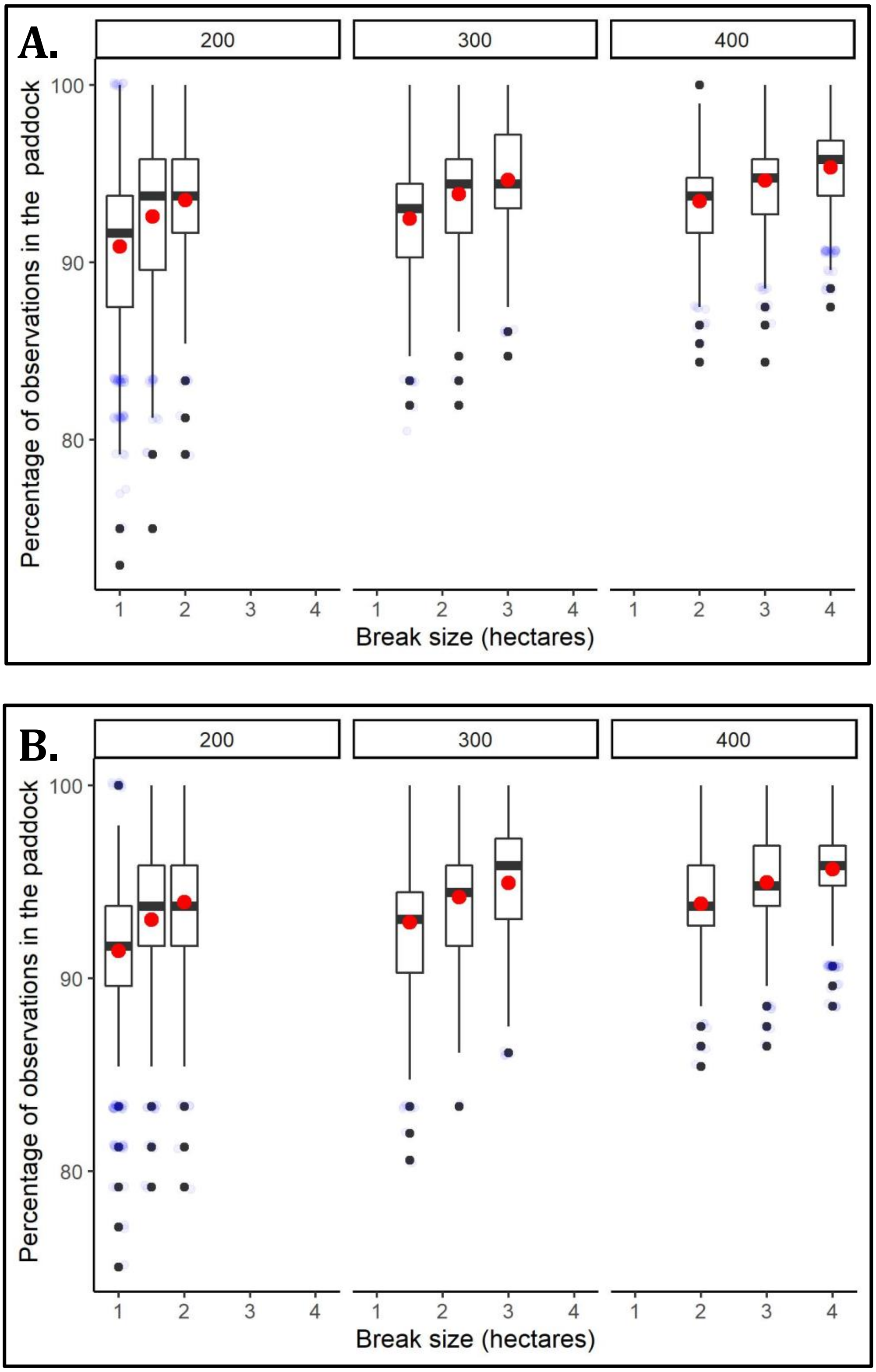

Figure 5.4: Percentage of GPS observations in the actual paddock grazed for a rectangle-shaped paddock (A), and square-shaped paddock (B.) after 1000 simulations with 4% of the herd (200, 300, 400) tagged with GPS devices with a location error of 5.50 m and recording a GPS position once per hour for a six-hour pasture break. Break size based on a pasture allowance of 50, 75 or 100 m² per cow. The red circle shows the mean percentage, while the blue circles represent multiple points.

5.3.3 Simulation limitations: The number of devices and fix rate

Given that this simulation model is based on a six-hour pasture break, there are several important points to highlight. First, the simulation analysis assumes that the cows are only offered one paddock per break, not parts of multiple paddocks. Secondly, cows may go to a feed pad or crop break on many farms either directly after the morning milking or before the afternoon milking, which has not been considered. Also, cows may be separated into a small treatment mob (e.g., for mastitis or lameness) or drafted for artificial insemination. Finally, milking times may, on occasion, also be altered due to electrical supply issues, labour availability or for on-farm reasons such as reduced milk production or a desire to maintain cow condition (i.e., once daily, twice daily or 16 hourly milking frequency). Instead, the simulation assumes that the herd remains in the allocated paddock throughout the six hours. Where grazing time is changed, this will have implications for the number of devices per herd and the required fix rate to ensure that the grazed area can be identified with some confidence using GPS devices, as previously discussed.

5.3.4 Simulation results: Number of devices and fix rate compared to on-farm study.

When compared with the results of the on-farm study (Chapter 4), it appears that the simulation has overestimated the percentage of GPS observations likely to be in the correct paddock. For example, when approximately 2.8% of the trial herd was fitted with GPS devices with a MLE of 5.4 m (Agtech), 55.7% of total observations were recorded in the allocated paddock. Likewise, when 0.5% of the trial herd was fitted with digitanimal collars, 63.3% of total observations were recorded in the allocated paddock. One likely reason for the lower number of observations in the allocated paddock in the on-farm study is that the on-farm data included the time spent at the cowshed and the time spent on the farm races travelling to and from the cowshed or paddock. However, the simulation excluded these non-paddock times. Another likely reason for the fewer GPS observations in the correct paddock in the on-farm study is that the devices failed to send fixes at the manufacturer’s specified rates.

5.3.5 Estimation of grazing area using the number of GPS observations

Chapter 4 examined whether the grazed area could be estimated using a convex hull approach. This chapter uses a different approach to estimate the area grazed based on the number of fixes in each square when a paddock is divided into sixteen equal-sized squares. We assume that we already know the paddock grazed and have the paddock boundaries. Consequently, we can filter out any observations that happen to be outside the paddock being grazed.

Figure 5.5 and Figure 5.6 visually present an example of this approach when allocated either a quarter, half, three quarters or the whole of a one-hectare square paddock, respectively, when the threshold for identification as 'grazed' (i.e., the minimum number of fixes per square) is set to two. These figures show that this approach provides a good indication of the area grazed when the threshold is set to a minimum of two fixes per square. The figures show Scott Farm in the background for scale. Although being a research farm, it has smaller herds and paddock sizes than commercial farms.

However, as shown in Figure 5.5, the main challenge with this approach is deciding on the appropriate fix threshold. In this example, when allocated a quarter of a paddock, one square outside the allocated area recorded a minimum of two fixes. This could occur when an animal grazes near the fence line or devices with a high location error are used in on-farm practice. Likewise, the simulation shown in Figure 5.6 recorded a minimum of two fixes in fifteen of the sixteen squares when allocated the whole paddock, with the remaining square recording less than two. Again, this situation could occur in on-farm practice and could be due to the area not being favoured by grazing livestock. Alternatively, no fixes may have been recorded in that area due to the fix rate of the individual device.

To better understand the ideal fix threshold when using this approach, receiver operating characteristic (ROC) curves were plotted based on the proportion of the paddock allocated and the results of 100 simulations for each scenario. Figure 5.7 and Figure 5.8 show the ROC curves when allocated either a quarter, half, three quarters or the whole of a one-hectare square paddock, respectively. ROC curves are designed to graphically illustrate the trade-off between sensitivity (true positives) and specificity (false positives)(Fan *et al.*, 2006). True positives occur when the instance is positive and classified as positive. For the examples shown in Figure 5.5 and Figure 5.6, this occurs when the individual squares are in the allocated break, the green dashed line. Likewise, if the instance is negative but classified as positive, this is known as a false positive (Fawcett, 2006). The best cut-off value will provide both a high sensitivity and a high specificity. This value can be found in the upper left corner of the ROC curve (Fan *et al.*, 2006).

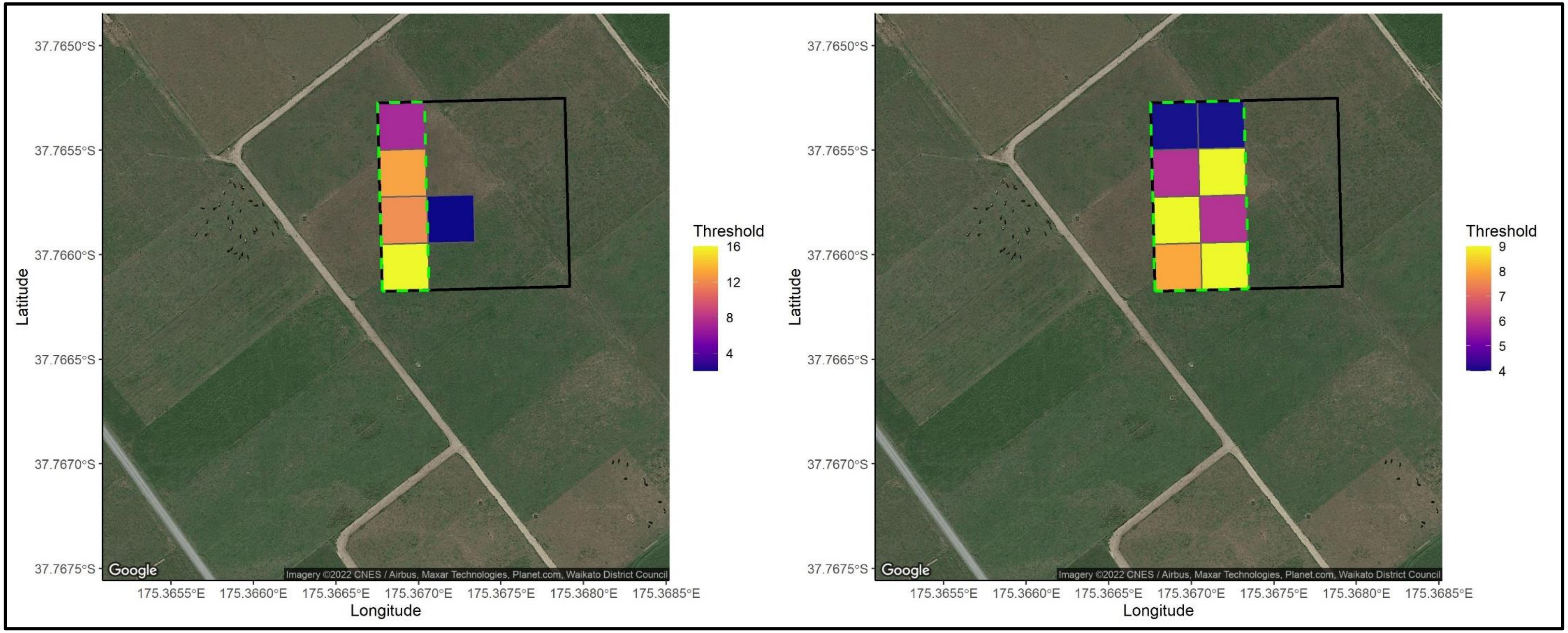

Figure 5.5: Number of fixes in each square when the fix threshold is a minimum of two when allocated either a quarter or half a paddock. The green dashed outline shows the grazing break, with the black outline showing the paddock boundary.

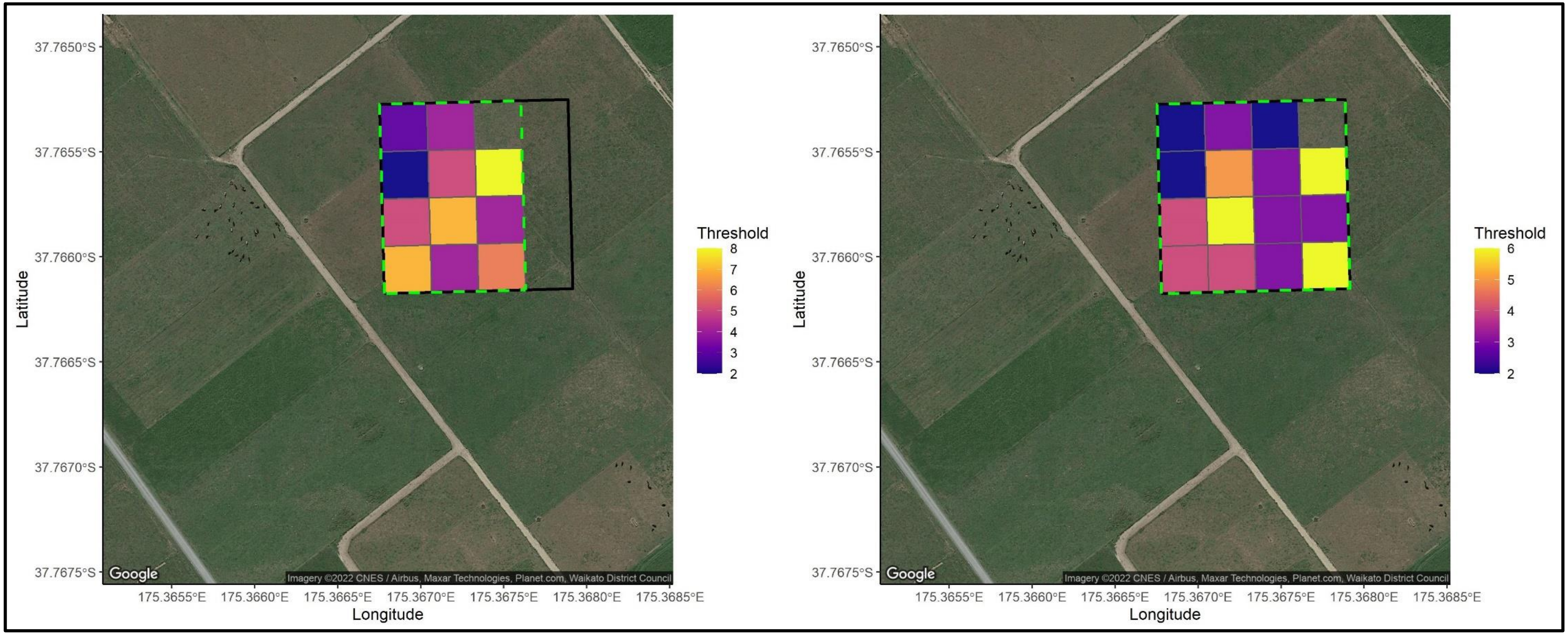

Figure 5.6: Number of fixes in each square when the fix threshold is a minimum of two when allocated three quarters or the whole paddock. The green dashed outline shows the grazing break, while the black outline shows the paddock boundary.

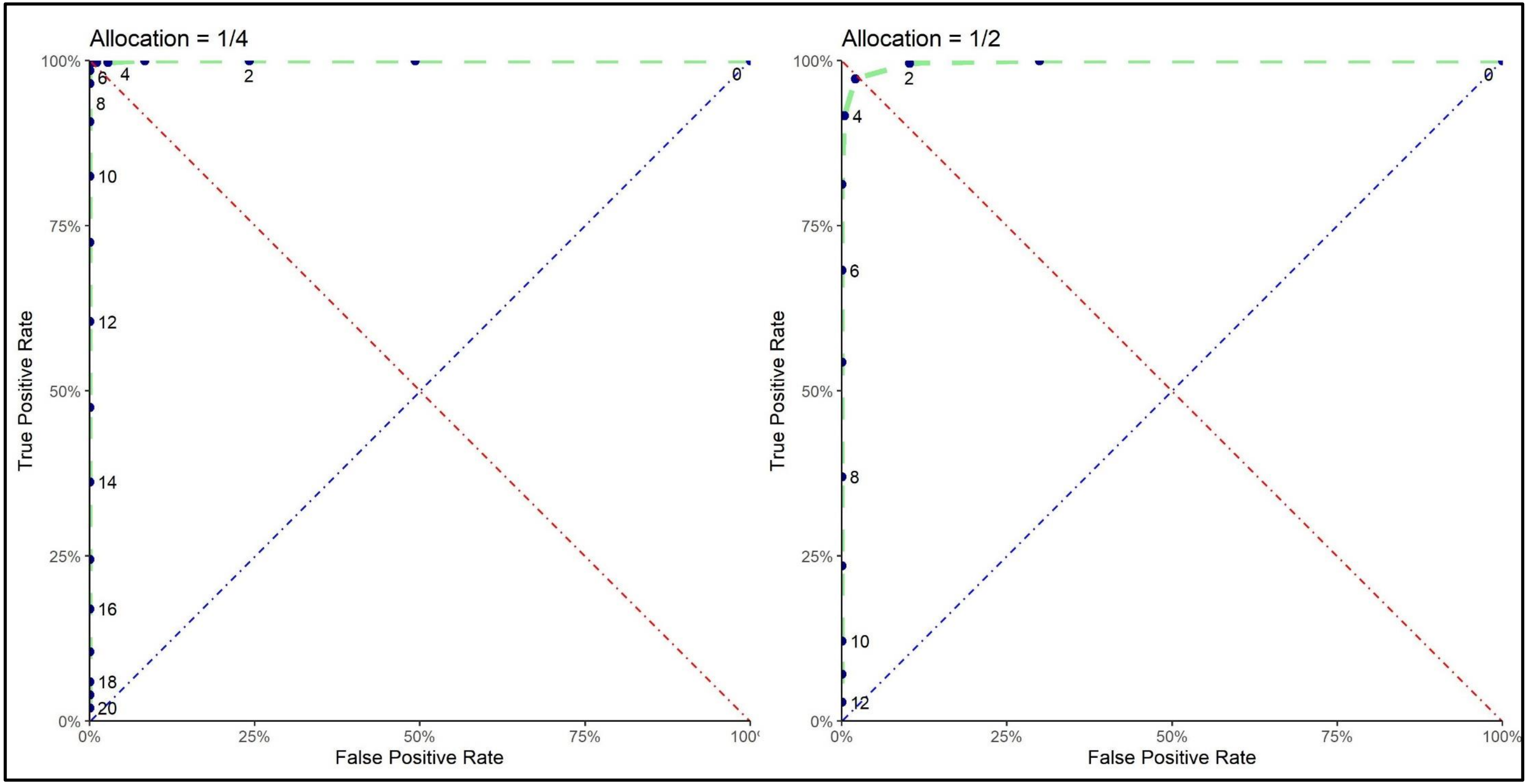

Figure 5.7: ROC curve when allocated either a quarter or half a paddock for 100 simulations. Fix threshold shown by numbers 0-20.

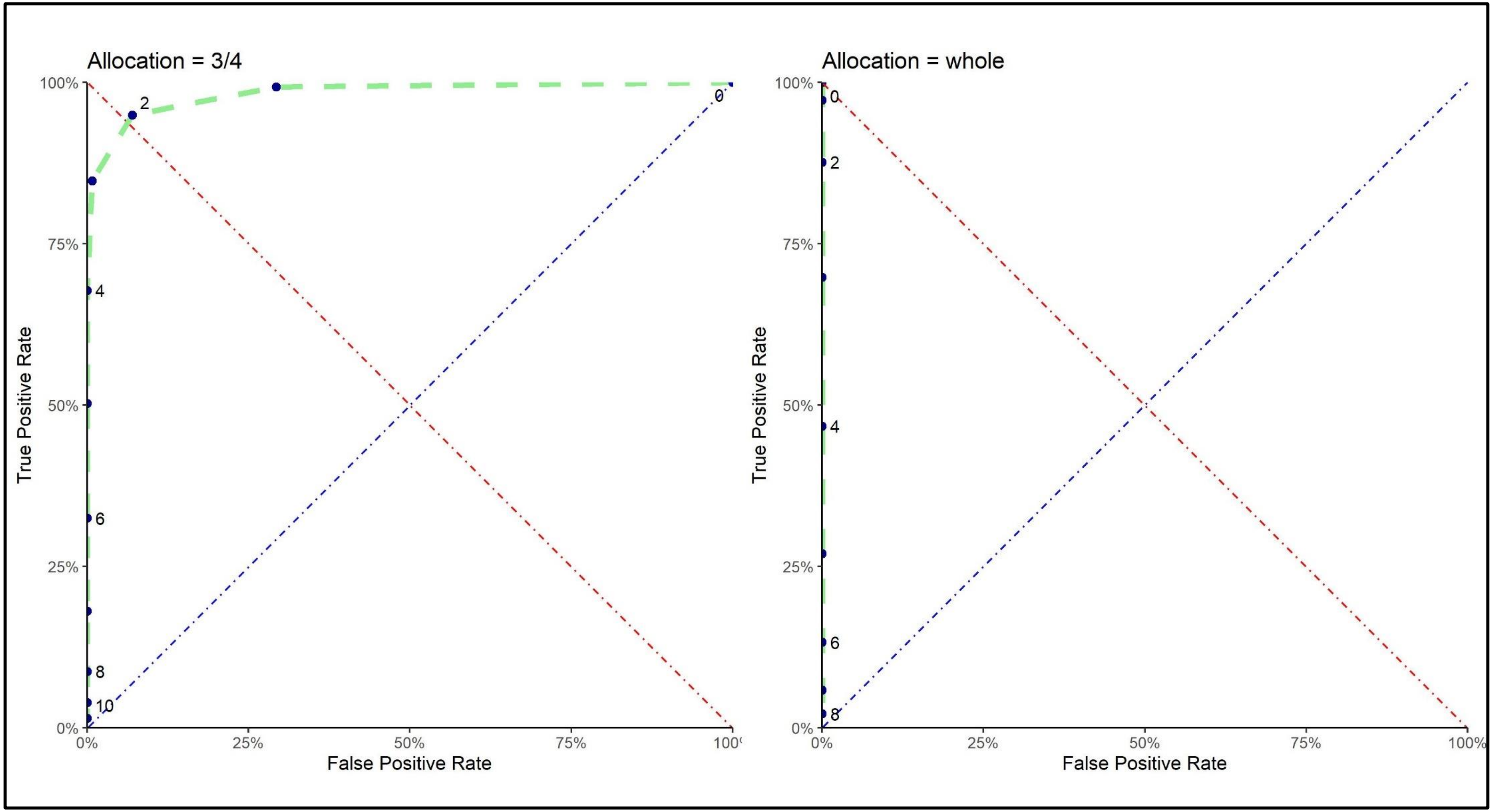

Figure 5.8: ROC curve when allocated either three quarters or the whole paddock. Fix threshold shown by numbers 0-10.

When allocated a quarter of the paddock, the ROC curve suggests that the fix threshold to maximise the true positive rate and minimise the false positive rate is five. In comparison, if allocated half a paddock, the fix threshold at which the true positive rate is maximised and the false positive rate is minimised is three. It was impossible to get false positives in this simulation experiment when allocated the whole paddock. As discussed earlier, any points outside the paddock boundary were filtered out, hence the green vertical line shown in Figure 5.8. Therefore, as shown by the results of this simulation, if attempting to use this method to estimate the allocated area, the trend is that as the area allocated decreases, a higher fix threshold is needed to identify the allocated area.

As proportion is unknown ahead of time, if we choose one threshold for any possible proportion allocated, some proportions will be under or overestimated. Ideally, based on the data distribution, choosing an appropriate threshold that reduces under or overestimation might be possible. For example, if the median number of fixes per square (excluding zeroes) was ~10, it is likely to be a small allocation, so the threshold could be 4. On the other hand, if the median number of fixes per square (excluding zeroes) was 4, it is likely to be a larger allocation; hence, a fix threshold of 2 might be more appropriate.

While this technique shows promise in calculating the area allocated, other factors also need to be considered. For example, further work could include accounting for different paddock shapes and sizes and break proportions or fences that on-farm might not line up with the squares. However, this was outside the scope of this thesis. Additionally, when break fencing paddocks, some farmers do not use back fences once the area has been grazed. Therefore, using this method with no back fence is likely to overestimate the area allocated on a given day. Finally, if using this method to estimate the area allocated, a key determinant is likely to be the fix rate of the individual devices, with a higher fix rate likely beneficial, as shown by the results of both experimental simulations (i.e., paddock identification and area allocated). For example, to identify the paddock, 18 fixes were recorded in 6 hours (i.e., 300 cows * 1% devices * 6 hours grazing = 18 fixes total). In contrast, to calculate the area allocated, 60 fixes in a 6-hour grazing period were used (10 animals * hourly fix rate * 6 hours grazing).

5.4 Conclusion

An objective of this study was to identify the number of devices required to identify which paddock is currently being grazed or was recently grazed. Based on the simulation results, it is sufficient that 1% of the herd is fitted with GPS devices (i.e., one device per 100 cows) if the aim is to identify the paddock grazed. However, a minimum of three cows per herd should be fitted with GPS devices to identify the grazed paddock. This gives a buffer if cows fitted with GPS devices are removed (e.g., drafted out or die), the devices stop working or fall off. The fix rate can be either hourly or two-hourly, as shown by the simulation results, where there was little difference in the percentage of observations observed in the paddock between either fix rate.

An alternative approach was trialled to estimate the area allocated using a grid method to divide the paddock grazed into sixteen squares. While this method shows promise, further work is needed to identify the ideal threshold for different paddock sizes and shapes. In both situations, more fixes will provide greater certainty that the identified paddock is correct and provide a more reliable estimate of the allocated area. Therefore, if the GPS device's battery capacity allows a one-hour fix rate or higher (e.g., every 30 minutes) should be used, thus providing more fixes and greater certainty of the paddock grazed and the area allocated.

Chapter 6

Conclusions

6.1 Introduction

The overall objective of this study was to assess the accuracy and precision of GPS location devices suitable for use on livestock and determine if they could be used to automate the recording of paddocks grazed and the area allocated on New Zealand dairy farms. A further aim was to identify the number of GPS devices required per herd and the fix rate needed to achieve the above objective. Chapters 1 and 2 reviewed the project's background and previous work in the area. Chapters 3 and 4 presented the results of static testing of the GPS devices and an on-farm study conducted on a 400-cow dairy farm in Canterbury, New Zealand. Chapter 5 then presented the results of a simulation exercise to determine the number of devices and the fix rate required to automate the recording of grazed paddocks and determine the area allocated.

This final chapter summarises the key findings of this study as presented in Chapters 3-5. In addition, the limitations of this research are discussed, and recommendations for future research are identified.

6.2 Device static testing

A difference in GPS device type accuracy and precision was observed under static conditions at Scott Farm, Newstead, New Zealand. The MLE (i.e., device accuracy, the standard deviation of the distance between the true and estimated reported location) was similar for the Oyster2 collars and Agtech solar-powered ear tags at 5.7 m and 5.4 m, respectively and consistent with earlier studies (Agouridis *et al.*, 2004; Morris & Conner, 2017). In contrast, the MLE of the mOOvement solar-powered ear tags was more than five times greater (34.2 m) than that of any of the previously mentioned devices.

Like location error, the Circle Error Probable (CEP, device precision), which measures how tightly the logged positions from one GPS device are clustered together, was similar for the Oyster2 and Agtech devices at the 95% level at 11.9 m and 13.9 m, respectively. However, as might be expected given the location error of the mOOvement devices, the 95% CEP for these devices was considerably higher at 77.6 m. Consequently, when it is essential to estimate an animal's location (e.g., identifying the grazing area), the mOOvement devices (with default settings) tested in this study are unlikely to provide this with sufficient confidence.

6.3 Automatic paddock identification and area allocated

The results of this study suggested that it is likely feasible to use GPS devices to provide automated recording of grazing events. In a preliminary data analysis of paddocks grazed over four days (eight grazing breaks), the digitanimal cow collars recorded an average of 62.3% of observations in the correct paddock (range 50-73.1%) compared with 32.9% in adjacent paddocks or farm races (range 23.5-50%). This was slightly higher compared with the Agtech devices at 52.5% of observations in the allocated paddock (range 34.9-71.6%) and 45.2% of observations for the mOOvement devices (range 32.4-57.1%). The difference in paddock identification accuracy between device types is consistent with the difference in the accuracy of the individual devices, as explained above. The different fix rates of the individual device types may also contribute to this result. The digitanimal and Agtech devices recorded an animal's location approximately once per hour compared with the mOOvement devices, which recorded approximately once every two hours.

A convex hull approach was used to estimate the grazing area allocated. This approach underestimated the allocated area most of the time, as expected since an overestimate is only possible when the paddock itself is not convex. The calculated grazing area ranged from 57.6% to 112.3% of the actual area for the Agtech devices and from 30.7% to 123.3% of the actual area for the mOOvement devices. For the digitanimal devices, the estimated area ranged from 25.5% to 64.8% of the actual area. More GPS observations are required to estimate the area allocated more accurately.

This suggests that a higher fix rate is beneficial if the objective is to record grazing events automatically or estimate the area allocated (e.g., every thirty minutes). Furthermore, the additional observations would confirm that the identified paddock and area allocated are correct. Overall, this preliminary investigation suggested that fix rate and device accuracy are two crucial factors when attempting to automate the recording of the grazed paddock and estimate the area grazed using GPS devices.

6.4 Number of GPS devices per herd

The simulation results showed that increasing the number of devices per herd from 1% to 2% or 4% of the total herd number resulted in only small increases in the percentage of observations in the correct paddock. Hence, when considering the cost of the individual devices, the slight increase in observations in the correct paddock is likely not worth the cost of additional devices. Likewise, the percentage of observations in the correct paddock was similar for either an hourly or two hourly fix rate. However, additional observations provide more certainty that the identified paddock is correct. Therefore, when also considering the results of the on-farm study (Chapter 4), it is suggested that farmers use GPS devices with a one hour or more frequent fix rate and fit a minimum of three devices per herd if the aim is to record grazing events automatically.

An alternative approach to the method described in Chapter 4 to estimate the allocated grazing area was tested by dividing the paddock grazed into sixteen equal-sized squares. This method shows promise in determining the allocated area. However, a key determinant of this method's success is the fix threshold selected (i.e., the number of fixes per square). This preliminary approach shows that, in general, as the area allocated decreases, a higher fix threshold is required to estimate the area allocated accurately. Given that the proportion is not known ahead of time, an algorithm needs to be developed to adjust the threshold relative to the distribution of fixes.

6.5 Research implications on-farm

As discussed in previous chapters, there are several benefits of recording paddock grazings on-farm. The primary one is the identification of poorer performing paddocks on-farm. For example, with default management regularly going into the paddock with the highest pasture cover, the number of grazings per year is expected to be high; therefore, there is likely to be a high amount of feed grown (depending on post grazing residuals) and vice versa for poorer performing paddocks. Once identified, the problem can be investigated and addressed, including reseeding, or spreading additional fertiliser to increase drymatter production and the number of grazings per year. If paddock grazings can be automatically recorded using GPS devices, it will be easier to identify the low performing paddocks, as only some farmers manually record paddock grazings regularly.

Paddock grazing information could also be used as a data feed to other programmes which rely on this information, such as feed budgeting software like Minda Land and Feed and Pasture Coach. In addition, it may be possible to incorporate the paddock grazing information collected by the GPS devices with other on-farm management and data collection systems in the future. In this case, it may be possible to calculate the pasture harvested per paddock, and area allocation or provide estimates (or validate other estimates) of pasture growth rates. This information would help with feed budgeting decisions such as how much pasture to feed or the use of nitrogen fertilisers and supplements.

6.6 Research limitations

Any experiment or study has some limitations due to factors such as the research design, the methodology used, or unforeseen circumstances (Ross & Bibler Zaidi, 2019). For example, in this study, Covid-19 impacted the ability to visit the experimental site. Likewise, this research is subject to several limitations, including the availability of on-farm data for the GPS devices, the number of devices tested, and paddock shape. Thus, before extending the conclusions of this study beyond the conditions under which it was conducted, these limitations must be considered.

One of the primary limiting factors was the availability of on-farm data for the digitanimal cow collars and Agtech ear tags. As the Irrigation Insight programme concluded midway through this research project, data was only available for a short period for the digitanimal cow collars. In addition, on-farm data was limited for the Agtech devices due to the downtime of a base station that could not be repaired or replaced during the experimental period. This was primarily due to the Covid-19 pandemic, which limited the availability of replacement parts (e.g., solar panels) and the opportunity to install these parts due to the New Zealand government's restrictions on work and travel.

The faulty base station was not immediately identified because there was no integrated approach to check to ensure that the tag data were stored correctly. Instead, the data was uploaded from the individual base station to the cloud and later imported into RStudio for data analysis. Consequently, a better troubleshooting system and communication process should be established to prevent this in future experiments, for example, a daily check of the devices via the tag manufacturers web portal or scheduled exception reporting. Due to the limited on-farm data for the Agtech devices, it is, therefore, harder to draw firm conclusions on whether they can be used to record paddock grazing events over the entire year. Consequently, it would be beneficial to repeat the on-farm study to collect more data, which would allow for more general conclusions to be drawn.

Another limitation relates to the number of GPS devices of each type available for this research. As shown by the static testing results presented in Chapter 3, although all the devices within a type were manufactured in the same way, there were individual differences in how they operated. However, due to several constraints, including budget and the availability of individual devices for this study, this meant that for the static test component, only two Oyster2 devices were tested. Likewise, only two digitanimal cow collars were tested in the on-farm study as they were part of an existing trial (Irrigation Insight). Ideally, a higher number of devices would be used to account for the variability between devices within a device type, providing a greater representation of their accuracy when recording paddock grazing events.

A third limitation relates to paddock shape. Most paddocks were either square or rectangular on the trial property, which is typical of farms in the Canterbury region of New Zealand. However, the predominant paddock shape may not necessarily be square or rectangular on dairy farms in other regions of New Zealand, particularly where the contour is not flat or where the property may have been converted from another use such as forestry to dairy. In this case, more work may be needed to validate the approach.

6.7 Future research

Currently, many farmers manually record grazing events, either on paper or electronically, as no automated process exists. Therefore, this thesis has focused on how GPS devices might be used to automate the recording of grazing events on-farm by combining the information collected by the GPS devices and a digital farm map. Although this study has shown that GPS devices could be used to automate the recording of grazing events, further work is required before it could become common practise on-farm.

The Agtech and mOOvement devices used in the current study both required an on-farm base station to transfer the data to the cloud. Future work could repeat the experiments discussed in Chapters 3 and 4 using direct-to-satellite GPS ear tag options such as the Ceres Tag and GSatRancher (CSIRO, 2020; Frost, 2020; Global Satellite Engineering, 2022). If these tests show that the devices are accurate to within 5-10 m of the actual location, they could be an excellent option for automatically recording grazing events on-farm. The main advantage of these devices is that the data is sent directly to the satellite and the cloud. Consequently, less maintenance and human intervention would be required.

Further work could examine the feasibility of integrating the GPS device data with other monitoring systems used on-farm, such as Levno and Halo (Milk Vat Monitoring Systems) and satellite pasture measurement, e.g., SPACE. For example, to provide estimates of daily feed intake, the pasture harvested per paddock and an estimate of current pasture growth rates. This could allow farmers to utilise their pastures more effectively or adjust feeding levels if required, potentially improving farm productivity and profitability. Furthermore, if a performance history of individual paddocks could be established, it would help guide other farm decisions such as regrassing and fertiliser use.

Another trial could examine the accuracy of the tested GPS devices when used on farm equipment such as effluent applicators and irrigators. With the increasing environmental regulations being placed on today's farmers and many regional councils requiring proof of placement for effluent and irrigation use, GPS devices could be used to supply proof of placement and avoid repeat irrigator applications to the same area. Additionally, using GPS devices on effluent applicators and irrigators could identify where spreading could be improved by preventing under or over-application of effluent or water to a particular area.

It would be beneficial to repeat the on-farm component of this study (Chapter 4). Firstly, due to a power supply issue to the Agtech base station (and other reasons described in Section 6.6 Research limitations), data was only available for a short period (concurrent with the other devices) despite the ear tags remaining attached to the animals for approximately ten months. Hence, repeating the experiment over an extended period would provide better data to assess the accuracy of the individual devices' ability to identify the grazed paddock. Secondly, it would be worthwhile to repeat the on-farm component of this study on a farm (or farms) with irregularly shaped paddocks (i.e., not square, or rectangular) to establish the importance of paddock shape on paddock identification accuracy.

At certain times of the year, cows will frequently move between mobs. For example, in the spring (or autumn for autumn calving herds), calving cows may spend two weeks in the springer mob and one week in the colostrum mob before joining the main milking herd. Therefore, to ensure at least three GPS devices per herd so the paddocks grazed can be recorded automatically, they would need to be easily transferable between animals. However, ear tags are not easily transferable. Consequently, it would be advantageous to investigate if the GPS ear tags studied could be fitted to cow collars and if this affects their performance. If they can be fitted to cow collars without affecting their performance, it may ensure that the minimum device numbers are met per mob. Thus, the paddock grazings for these mobs, which constantly change during the calving period, can be recorded since cow collars are easily fitted and removed. However, there will be a trade-off between the time spent moving collars between animals versus the value of the collected data.

Finally, it would be worthwhile to investigate further the ability of GPS devices to automatically calculate the area allocated per grazing break. Knowing the area allocated and not just the paddock grazed is potentially quite valuable given that this determines rotation length, a critical factor in feed budgeting decisions.

These additional studies would provide vital information to support farmers' future adoption of this technology, particularly as the number of GPS options available for livestock use increases and the cost decreases. The ability of GPS devices to be used for multiple purposes on-farm and for their data to be integrated with other on-farm systems could also lead to greater adoption of this technology than would occur if they are solely used for recording grazing events. For example, integrating satellite and pasture growth models could allow for more improved decision making and improved pasture harvest.

6.8 Conclusions

This preliminary study using the current generation of GPS devices has shown that it is appropriate for 1% of herd size (minimum of three devices per herd) to be fitted with GPS devices if the overall aim is to identify the paddock grazed. More devices are likely required to determine the area allocated ~3%. With the regular recording of grazing events, improvements in pasture management and a better understanding of pasture performance are likely, potentially leading to increased farm profitability. However, before this technology may be adopted on-farm for this purpose, an extended study is required to provide better data to assess the accuracy and precision of the individual devices and gain a greater understanding of the effect of paddock shape on accurately estimating the area allocated. Furthermore, other potential on-farm complications not considered in this study include the use of crops, on/off grazing, and the effects of multiple herds during the winter and early spring periods (e.g., dry cows, springers, colostrums, and milkers). Nonetheless, with a greater focus on maximising pasture utilisation on dairy farms today and the increasing range (e.g., direct to satellite options) and decreasing cost of GPS devices, there is likely to be greater interest in this technology in the future.

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Appendix 1

Direct costs per hectare	**Cost including GST per hectare ($)**
Glyphosate 4 L/ha plus penetrant (0.2 L/ha)	75
Light disc then drill	150
Trojan perennial ryegrass 22 kg/ha, *Kotare* 2 kg/ha, *Weka* 2 kg/ha (Superstrike treated)	420
Slug bait	80
Cambridge roll	55
Establishment fertiliser, including spreading (200 kg/ha DAP)	235
Broadleaf herbicide	90
Total cost	**1,105**

Adapted from P. Hames, personal communication, June 4, 2021.