Measurement of spatial distribution of cattle dung under high and low stocking densities using remote sensing

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Abstract

Regenerative pasture management is increasingly being practiced in New Zealand and encompassing a range of principles which generally focus on using diverse plant species to maximise photosynthesis and strategically use grazing livestock, with an overall aim of improving soil health. An example of regenerative pasture management is undertaken on Mangarara Farm, a non-irrigated sheep and beef farm located in Elsthorpe in central Hawkes Bay. Mangarara farm focuses on having higher pre and post-grazing pasture biomass than more conventional practices and grazes these pastures at higher stocking density. In theory, this grazing practice leads to more pasture trampling into the ground and more even dung distribution than conventional grazing practices.

A new measurement method was developed in this study to test whether there is a change in the spatial distribution of cattle dung under regenerative management compared to conventional management. This method used a drone fitted with a red, green and blue (RGB) camera to identify and spatially map dung patches following grazing in a defined area (cells) on Mangarara farm. The research trial compared conventional and regenerative management using low and high stocking density. The control grazing (conventional) had a low stocking density of 6 Angus heifers moved every four days. In comparison, regenerative grazing had a high stocking density of 57 Angus heifers moved multiple times daily.

The novel drone method was validated against a systematic measurement approach to assess the accuracy of the drone in detecting dung patches, compared to the systematic manual marking of dung patches using a survey-grade Trimble GPS to manually mark every dung patch within the cell. The results showed that the drone detected for all cells a mean of 57% of the dung patches within the cells. Data analysis revealed that multiple key factors affected the drone accuracy, including trees, pasture height and the amount of bare soil and it is recommended that lower pasture height and less bare soil present will minimise variation in future measurements.

The same drone method was then used to compare the spatial distribution of dung under regenerative and conventional management. The results showed a significant difference between the median number of dung patches/ha for regenerative and conventional management. The analysis showed that the dung was not randomly distributed throughout the cell and that the regenerative management had slightly less clustering than the

conventional management, indicating that the dung was more evenly distributed through the cell under regenerative management.

The results from this study have shown that a drone fitted with an RGB camera successfully detected the spatial distribution of dung. However, some key limitations were identified, including wet soil conditions, bare soil and pasture height, which made it difficult to identify the dung due to a lack of colour contrast with the pasture and/or muddy soils. Dung with a higher liquid content was also difficult to delineate as one or several dung patches.

Despite these limitations, this novel drone fitted with an RGB camera method offers a cheaper alternative to the traditional labour-intensive method of measuring dung distribution via the grid method and provides scope to measure dung distribution under a range of topographies such as hill country. This new method provides an opportunity for more research on the distribution of dung under different grazing management conditions and offers the potential to improve our understanding of soil nutrient distribution and nutrient loss risk.

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Chapter 1

Introduction

1.0 Background

The primary sector is the most important economic sector in New Zealand (NZ) and makes up 81% of New Zealand's export products (2021 – 2022). The primary sector includes dairy, meat and fibre and forestry, and these sectors brought in $53 billion in export revenue in the 2021 to 2022 financial year (Ministry for Primary Industries, 2022). Between 2000 and 2015, dairy cattle numbers increased rapidly, with the number of dairy cows in NZ now greater than beef cow numbers (*StatsNZ,* 2021).

Along with the increases in total dairy and beef cow numbers, there has been increasing concern about the long-term sustainability of intensive dairy cattle systems. Concerns about water quality, greenhouse gas emissions (e.g., methane and nitrous oxide), soil compaction, and loss of biodiversity are all factors the industry is having to address to improve their future sustainability (Siegfried, 2020). One initiative focussed on improving the sustainability of pastoral-based grazing systems is Regenerative Agriculture (RA) and the adoption of regenerative management practices. Farmers see RA as offering some solutions to the environmental and societal challenges they face and an opportunity to supply a niche market that could gain export premiums (Grelet et al., 2021). Regenerative agriculture in NZ promotes different approaches to managing pastures and grazing animals and has gained some traction across the primary sector (Our Land and Water, 2021). Regenerative Agriculture has no specific definition, as it is an evolving concept grounded in key practices and principles (Merfield, 2019). Some examples of the practices promoted by the RA movement (Newton et al., 2020) are summarised here:

- Minimum or no tillage, as this reduces the breakdown and oxidation of soil organic, carbon which in turn leads to stable or increasing soil carbon in the soil, which can then lead to increased water and nutrient holding capacity.
- Encouraging water percolation into the soil through increased soil structure and infiltration rate. Improved soil structure, and water infiltration rate, reduces the risk of sediment and Phosphorus (P) loss in surface runoff.
- Promoting integration of livestock and mixed cropping operations.
- Minimising bare soil to protect the biological community in the topsoil and reduce sediment and nutrient loss in over-land flow.
- Fostering plant diversity.

A NZ wide survey involving 200 people, including scientists, farmers and growers, researchers, private consultants, industry levy bodies, banks, retailers, not-for-profit organisations, overseas researchers, educators, and rural professionals, was used to develop a set of key principles of RA relevant for NZ agriculture (Grelet et al., 2021). The survey highlighted the following principles:

- The farm is a living system;
- Make context-specific decisions-farm decisions depend on the context, and these can vary from time of year, place and person;
- Question everything-means the farmer is likely to be curious and ask lots of questions and willing to test different ideas;
- Learn together-work and connect with like minded people to share ideas with and learn;
- Failure is part of the journey-learn from failures as they provide the best learning opportunities;
- Open and flexible toolbox-be open to use new practices and to keep some practices to use when needed;
- Plan for what you want and start with what you have transition to regenerative management can take time, start with what you have and have a plan and clear goals of where you want to be;
- Maximise photosynthesis (year-round)-by keeping the green leaf on pasture to improve photosynthesis;
- Minimise disturbance-this is through using minimum till or direct drilling and minimising any pugging and compaction to the soil:
- Harness diversity-by diversifying the practices that is used on the farm, this can be completed by using different grazing management and diverse pasture;
- Manage livestock strategically-by managing stock adaptively to build biological function and soil fertility.

Grelet et al. (2021) concluded that practices that advance these principles would be considered part of a RA system. However, because there are no formal definitions, every farmer has tended to approach RA differently.

The case study farm is Mangarara farm, which is a 610 ha non irrigated hill country sheep and beef farm located in Elsthorpe in Central Hawkes Bay. Mangararan farm has 100 Angus breeding cows and 350 Angus heifers sold to butchers in Hawkes Bay and Auckland, and some Romney sheep (The farm, 2022). Mangarara farm is one example of a farmer exploring and operating their farm under RA principles, including focusing on maximising photosynthesis

(year-round), minimising disturbance, harnessing diversity and managing livestock strategically. The farm has adopted a grazing practice where cattle are grazed at a higher stocking density than conventional practices and are moved multiple times a day. Unlike more conventional grazing practices, grazing occurs at a higher pre-grazing pasture cover, and a higher residual pasture cover is left after grazing. The idea of using cattle grazing at a high stocking density is to improve the spatial distribution of dung and urine and to increase the trampling of pasture into the soil via animal treading. These practices are hypothesised to supply the soil microbiota with labile organic carbon via dung and plant matter, to enhance the capture and recycling of carbon and nutrients in the soil (The farm, 2022).

There has been little (Grelet et al., 2021) to no research on RA management practices in NZ and the implications this management may have on the broader farm system and environment. For example, no data are currently available under NZ conditions examining the influence of RA grazing practices on the distribution of excrement returned by the animal and the effects this may have on pasture growth, the nutrient cycle and risk of nutrient loss to receiving environments.

In particular, understanding the impact that a change in grazing practice from conventional to RA management may have on the distribution of dung return will improve our understanding of nutrient cycles within the paddock. Of interest is the impact of dung distribution on the phosphorus (P) cycle, as the return of P in dung represents the single most significant factor (animal transfer factor) determining annual P requirements (Cornforth & Sinclair, 1982). Improving the distribution of P returned in dung by the grazing animal and, at the same time, limiting the accumulation of dung at campsites where there are typically high concentrations of soil P, has the potential to reduce the amount of P fertiliser required to replace losses and could decrease the risk of P losses in overland flow from areas of the paddock with high P concentrations.

The current standard method for identifying dung patches and locating and mapping dung distribution within a paddock, is a systematic approach using a grid-based method (Yoshitoshi et al., 2015; Yoshitoshi et al., 2016; Morton & Baird, 1990). Within the paddock, dung patches are marked individually within each of the grids used to break the paddock into manageable mapping units. This is very time-consuming. Digital technologies, combined with drone mounted cameras, could offer a new method for identifying and mapping the spatial distribution of dung patches, enabling larger areas to be assessed in less time.

1.1 Research Objectives

This research has three specific objectives:

1. To test if a drone fitted with a Red-Green-Blue (RGB) camera can detect dung patches, and if that camera image can be used to map the spatial distribution of individual dung patches in a grazed pasture area.
2. Assess the accuracy of the drone fitted with a RGB camera method compared to a systematic GPS ground truth assessment.
3. Determine if the spatial distribution of dung changes under high stocking density compared to low stocking density.

Chapter 2

Literature review

2.0 Introduction

This literature review will explore:

- The effect the regenerative agriculture (RA) grazing practice of a high stocking density, may have on the spatial distribution of cattle dung patches.
- How the spatial distribution of dung patches may influence soil nutrient recycling and risks of nutrient loss.
- Current methods used to identify and measure the spatial distribution of dung patches in a pastoral system and the potential for new remote sensing methods to be used to measure dung distribution.

2.1 Dung distribution

The distribution of animal excrement is affected by multiple factors such as livestock type, stock number, behaviour and management, topography, access to shade and shelter and water and infrastructure (e.g., fences and location of water troughs). It has been shown by using traditional grid method, that 60% of dung and 55% of urine is returned unevenly and usually only cover 15 to 31% of grazed pasture in a paddock (Haynes & Williams, 1993). Animal excrement can also be transferred to non-productive farm areas such as laneways and yards. The distribution and area covered by dung tend to increase with an increase in stocking rate, as animals tend to camp across a larger area, which leads to a more even return of the dung to the grazed pasture (Haynes & Williams, 1993).

Rowarth et al., (1992) identified that approximately 60% of animal excrement was deposited on average, to 17% of the paddock area in NZ hill country using a traditional grid method. The research showed that for campsites, there was an increase in soil organic P as a result of dung deposition, compared to non-campsite areas Based on excrement P distribution and plant P uptake, it has also been shown that P transfer loss increases with an increase in slope, due to increased risk of P runoff (Rowarth et al., 1992).

Saggar et al., (1990), also showed that the distribution of sheep dung changed with slope class in NZ hill country, with 60% of dung returned to low slope (1-12 degrees), 30% of dung returned to medium slope (13-25 degrees) and only 10% of dung returned to high slope (>26

degrees) areas. Additionally, the study found that a large percentage of animal excrement was deposited in small areas, as low-slope areas comprised only one-third of the total study area. This behaviour by the animal drives the P transfer losses, moving P from a high slope to a low slope. Further, it was identified that pasture P concentration had a seasonal pattern, with maximum P concentrations occurring in late autumn (May to June) to late winter (August and September) (Saggar et al., 1990). Minimum concentration occurred in summer (December and January). The time of year will affect the P concentration found within the pasture, which will in turn, affect the P concentration found in dung and the amount transferred (Saggar et al., 1990).

Research has been conducted on the effect of stocking density on dung distribution in sheep and cattle. For sheep, research has shown that high stocking densities result in more dung patches being deposited (Thorrold et al., 1985; Morton & Baird, 1990), and the dung covers a larger area (Morton & Baird, 1990) and was more evenly distributed (Thorrold et al., 1985). When the stocking density was halved, the number of dung patches present was halved, and the distribution of the dung changed to more localised and smaller areas (Morton & Baird, 1990). Research at the University of Louisiana, USA, exploring the practice of management intensive grazing (MIG), which is intensive rotational grazing management (Allen et al., 2011), showed that there was more-uniform dung distribution under a high stocking density than under a low stocking density (DeRamus et al., 2015). These findings suggest that stocking density influences the distribution of dung, and that at lower stocking density, dung was more likely to cover a smaller percentage of the grazed area and be more likely to be found in campsites, which in turn increases the risk of P loss via overland flow.

Research in North Carolina looking at the spatial distribution of dung patches from 36 dairy cows in a 29ha block grazing over a period of eight months, found that 14% of dung was deposited in either the laneway, yard or dairy shed, with 86% of dung being deposited within the paddock (White et al., 2001). The study also showed that when the cattle were under heat stress in the warmer months, the dung distribution was greater within 30 m of water troughs compared to the colder months (White et al., 2001). This shows that weather conditions are another major factor influencing animal behaviour and dung distribution.

Research conducted in Japan at the National Agriculture and Food Research Organisation (NARO) with mixed-species sown pasture grazed by 20 Japanese Black cattle and five calves in a 0.85ha paddock, found that after four days of grazing, the spatial distribution of dung was not evenly distributed over the paddock (Yoshitoshi et al., 2015). The dung was distributed around the water trough and a stock camp at the top of the paddock, with few dung patches

located away from the stock camps. This shows that the dung distribution is not evenly distributed throughout the paddock and is affected by water trough placement. In this case, the stock camp was at the top of the paddock where the animals were resting (Yoshitoshi et al., 2015). An understanding of the distribution of dung can be used to advance the study of nutrient cycling within grazed paddocks.

2.2 Nutrient cycling in a grazed pasture

Understanding the nutrient cycle of a farm ecosystem is important to understand where nutrients are within the soil and how that affects pasture growth. An example of the nutrient cycle within a pasture system in Figure 2.1. The main losses from the system are leaching, overland flow, volatilisation and loss to animal product/pasture product or redistributed within the grazed area. Whereas the main nutrient gains are from fertiliser, animal transfer and plant organic nutrient transfer via brought in feed (Floate, 1970). Understanding the way nutrients are gained in the soil can help target management practices that could lower the risk of environmental loss, which in turn could lower the amount of nutrient that needs to be added to soil in the form of fertiliser to replace this loss. A decrease in the fertiliser requirement will in turn decrease the costs to the farm and potentially decrease the risk of nutrient loss.

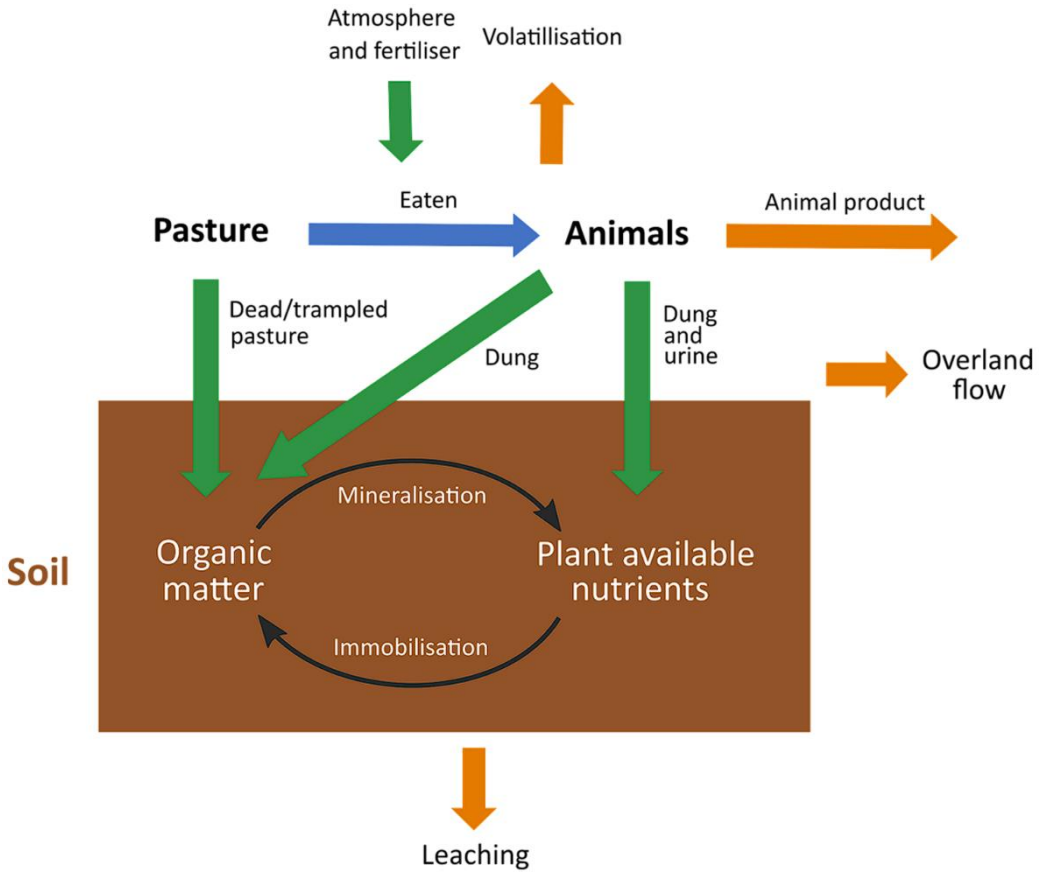


Figure 2.1: Generalised nutrient cycle of a grazed pasture (adapted from Floate, 1970).

2.3 Changes in soil properties under dung and urine patches

Under grazed systems, cattle urine is a major source of N in the pasture system (Williams & Haynes, 1994). Cattle urine can also positively affect pasture production, with increases in pasture production up to 2,000 kgDM/ha in response to the N component of the urine (Saunders, 1982). However, some negative impacts related to the high N and K concentrations in the urine can include scorching of the pasture, increased risk of N loss from the root zone and animal health issues of milk fever and grass tetany, if the high N and K pasture is grazed (Williams & Haynes, 1994). For example, a urine patch could receive the equivalent N application of 400 to 1200 kg N/ha (Selbie et al., 2014). This can lead to a large N surplus in the soil, increasing the risk of N leaching and atmospheric losses via nitrous oxide (Ledgard et al., 2009).

Dung contains organic forms of nitrogen (N), sulphur (S), phosphorus (P) and potassium (K) (Williams & Haynes, 1994). Under a dung patch in a grazed pasture soil, there is an increase in soil biological activity (e.g., increasing soil enzymes and earthworm abundance), in response to the increase in organic matter associated with the animal excreta (Bacher et al., 2018). This increase in soil biology can lead to an increase in the mineralisation of organic forms of nutrient in the dung, making them more available for plant uptake. There is also the potential for an improvement in the soil structure, with previous research reporting an increase in soil porosity and a decrease in bulk density under a dung patch, due to increased organic matter and soil biological activity (Williams & Haynes, 1994).

Cattle dung can increase pasture production due to its impact on soil nutrient status (Williams & Haynes, 1995). The majority (95%) of P in animal excretes is found in the dung (not urine), with approximately 70% of ingested P returned to the pasture in dung (Haynes & Williams, 1993). The P present in dung includes both inorganic P, which is plant-available, and organic P, which needs to be mineralised to be plant-available (Barrow, 1987). The herbage P concentration and digestibility of the pasture affect the inorganic and organic P ratio in dung. Up to 75% of the total P in the dung patch could be present in an inorganic P form and be readily plant available (Barrow, 1987). The Olsen P test is a soil test that estimates the amount of plant available P in the soil pool, which is used to indicate the soil fertility status (Sims, 2000). The Olsen P status under a dung patch or around campsites where a large number of dung patches are deposited, has been reported to increase up to 2-fold (Aarons et al., 2004b). Under these dung patches, a 2-fold increase in the labile inorganic P within the soil has also been measured (Aarons et al., 2004a).

Greater soil organic C (SOC) and microbial biomass have been measured under dung patches and these were associated with greater microbial enzyme activity (Williams & Haynes, 1995). Soil organic carbon is important for enhancing the soil's physical, chemical, and biological processes and properties within the soil. Associated with an increase in SOC, is an increase in soil aggregate stability, which helps with water retention capacity, water infiltration, plant-available water and decreased risk of soil erosion (Blanco-Canqui et al., 2013). The other benefit of increasing SOC is the potential positive net carbon dioxide sequestration from the atmosphere into the soil. This would help reduce the amount of carbon dioxide in the earth's atmosphere, helping reduce global warming (Fornara et al., 2011). Dung patches, on average, take 115 days to fully degrade and mineralise all the nutrients in to plant available forms (Castle & MacDaid, 1972; Vibart et al., 2021). One negative aspect of dung patches is that the pasture immediately under the dung patch can die due to lack of light, and over time, new tillers from plants on the edges of the dung patch fill the gap (Williams & Haynes, 1995). In general, dung positively affects soil nutrient status and soil biology by increasing the SOC, improving water retention and plant growth.

Under the RA grazing practice of higher stocking density compared to conventional practices, animal excrement may be more evenly spread around the paddock. This could lead to more plant litter being trampled into the soil surface, more even nutrient distribution throughout the paddock and therefore better capture of the P, and N returned in dung and urine by the microbial community and earthworms. This might subsequently increase the rate at which dung patches break down (due to greater microbial biomass), and the amount of nutrients recycled within the soil. Under RA grazing management, with the higher pasture covers protecting the soil surface, there may also be higher water infiltration into the soil, which could lower the risk of overland flow and material from dung patches being lost in surface water runoff from the paddock.

In contrast, there is a greater risk of pugging occurring under higher stocking density as there is a larger number of animals within a small area (Schmalz et al., 2013). Increased pugging of the soil leads to higher soil compaction and can lead to a lower soil water infiltration rate (Houlbrooke et al., 2011). Higher stocking density has also been shown to increase soil compaction even if pugging is not present (Beukes et al., 2013). Increased soil compaction and pugging has led to a greater amount of overland flow, leading to a higher risk of sediment loss and dung patch material being lost from the paddock (Houlbrooke et al., 2011).

2.4 Environmental impact

Animal excreta can contribute to poor water quality in NZ, through direct deposition into waterways or through overland flow and leaching. A disproportionate amount of nutrients in water comes from the direct loss of nutrients (N and P) from urine and dung patches from grazing animals (DairyNZ, 2023). Cattle dung is a major source of pathogens and P and represents a major source of this nutrient lost via overland runoff into waterways (Haynes & Williams, 1993; McDowell et al., 2006). However, pollution also comes from urban, farming and forestry, which has led to 95 to 99% of the freshwaters in NZ exceeding the water quality guidelines (Ministry for the Environment., 2020). An increase of N and P concentration in surface waterways can lead to eutrophication, which causes waterways to be unsuitable for drinking, industry, recreation, or fishing (Carpenter et al., 1998) and can lead to algal growth which strip the oxygen from the water and can influence native fish habitat (Fried et al., 2003). Therefore, it is critical to decrease the amount of N and P that is lost to the waterways, if improvements to NZ's water quality are to be made.

The RA management practices of using higher stocking density and leaving higher residual pasture covers than under conventional management should lead to more beneficial outcomes for soil, including less bare ground and greater plant litter return. These outcomes can lead to an increase in the capture of soil nutrients and soil organic carbon, increased infiltration of water, improved water-holding capacity and increases in soil microbial species within the soil (Teague, & Barnes, 2017). A greater rate of water infiltration into the soil will lead a lower risk of nutrient loss from dung via overland flow.

If dung is evenly distributed across a paddock, this will decrease the animal transfer factor, leading to a lowering of the amount of P that needs to be applied via fertiliser. This would also lead to a reduction in the risk of P loss from the source, which in turn creates a tighter P cycle. It has also been shown that the distribution of dung patches influences earthworm spatial distribution (Bacher et al., 2018). If dung is evenly distributed, earthworms are more likely to be evenly distributed over a larger area of the paddock, leading to a faster decomposition of the dung patches and more effective nutrient recycling to the plant. These previous findings suggest that more evenly distributed dung patches could lead to lower loss of P via overland flow and less animal transfer, leading to better utlisation of P by the plant and a tighter nutrient cycle.

2.5 Quantifying dung distribution

Understanding the distribution of dung within a grazed pasture is important as it is the key factor driving the soil P requirement within the paddock (Cornforth & Sinclair 1982). This is because a large proportion of P is consumed and excreted by the grazing animal each year (Haynes & Williams, 1993). The animal generally redeposits this dung in stock camps, which tend to make up only a small proportion of the paddock (15 to 31%) (Haynes & Williams, 1993). This means that a large part of the paddock receives little to no dung. As a result, the soil P concentration in stock camp areas becomes enriched with P, resulting in higher pasture growth. If the dung was distributed more evenly over the paddock, this could increase the P that is available to the plants and could decrease the need for P fertiliser inputs. Factors influencing animal grazing behaviour and dung deposition by default, are therefore key drivers in determining annual soil P requirements. Another benefit of understanding the dung distribution is that this information could be used to design a variable-rate fertiliser plan. For example, fertiliser applications could be reduced or cease in and around stock camp areas and then applications could be increased in other areas of the paddock known to receive low inputs of dung.

2.5 Techniques for identifying and mapping of dung distribution.

Previous research measuring the spatial distribution of dung patches has utilised visual and manual grid-based approaches (Yoshitoshi et al., 2015; Yoshitoshi et al., 2016; Morton & Baird, 1990). The research completed by Yoshitoshi et al., (2016) examined a paddock which was split into cells of ~ 10m x 10m. Each cell was ground truthed to identify if dung was present or absent (Yoshitoshi et al., 2016). The spatial distribution of dung was visualised relative to features in the paddock, including stock camps and areas adjacent to water troughs (Yoshitoshi et al., 2016). Another study used a visual method, where 1 ha of grazed pasture was split into five blocks of 0.19 ha each in Greymouth, NZ (Morton & Baird 1990). Each block was divided into 60, 2 x 2 m quadrats, with the number of dung patches present in each square identified using the grid method to determine the spatial distribution and volume of dung across each block. It showed that the number of dung patches present in the blocks increased with increasing stocking density (Morton & Baird, 1990). Although the grid pattern method can accurately measure the spatial distribution of dung within the paddock, this method is very time-consuming and limits the ability to monitor dung distribution over time or across difficult terrain such as NZ hill country.

Imagery from drone mounted cameras have been used recently to locate dung patches by identifying elevated growth of pasture and or visual identification of individual patches (Dennis

et al., 2013. Shine, 2019). The method of locating patches by identifying plant colour was used by Dennis et al. (2013), by flying a drone fitted with a RGB camera at an altitude of 30 m, 14 days after grazing by 100 dairy cows over a 24-hour period. The images captured by the drone camera were then placed in ImageJ (ImageJ, 2023), and they used the process of Hue Saturation and Brightness (HSB) to identify the dung patches. The HSB process converts the image pixels to black and grey pixel colours. The darker the image pixel, the darker the pixel will be, which allows the darker pasture colour from the dung patches to be identified. The study calculated the area of dung covering the measured area and the number of dung patches. One of the images was validated by walking the area measured and marking areas of pasture growth and pasture colour that looked like it was associated with a dung patch (Dennis et al., 2013). The image analysis could clearly and accurately identify animal excrement patches in the grazed pasture and these data were used calculate the number and size of the patches. However, it wasn't possible to discriminate between dung and urine patches (Dennis et al., 2013).

The other method of visually identifying the spatial distribution of dung patches from images taken from a drone includes the method that Shine (2019) reported. In a 25ha meadow located in Nebraska, USA, under set stocking or intensive rotation grazing, a drone fitted with a multispectral camera was flown at 70 m altitude, with an image overlap of 75%. The drone was flown at different times to find the best day to locate dung patches under the different grazing management. The daily images were uploaded into ArcGIS Pro (Esri, 2023a) and linked with global position system (GPS) coordinates using the PIX4d programme (Shine, 2019). The spatial distribution of dung was identified using a density-based clustering tool (DBSCAN) in ArcGIS pro, which identifies clusters of dung patches within the images. The dung patches were ground truthed by walking small areas of the paddock and marking dung patches using a Trimble GPS. Results showed that the drone could identify on average, 82.6% of the dung patches actually present over a range of days. However, the time and number of days after dung patches were deposited, affected the accuracy of dung patch detection under different grazing management. Under intensive rotational grazing, the window of opportunity to locate dung patches was during the first couple of days following grazing, this is due to the grass standing back up after grazing and obscuring the dung. Under more conventional set stock grazing management, the best window was 7 to 10 days after grazing started. As the dung started to dry out and decompose, detection became more difficult. The study showed that after 14 days of grazing, 47% of the dung patches were detected. After 15 days, this number dropped to 17%. The authors concluded that images of fresh dung in the days following deposition, provide the best chance of locating dung patches using drone mounted camera (Shine, 2019).

Despite the limited number of publications on methods for locating dung patches with imagery from a drone, the published research imagery taken by drones suggests that this could be a viable method for locating dung patches. Past publications (Shine, 2019; Dennis et al., 2013) have used multispectral cameras to locate dung patches by way of detecting fresh dung patches directly and by detecting dung patches via detection of increased pasture growth, however detection via pasture growth is unable to distinguish dung from urine patches. Other options for detecting dung using drones could include the use of a Red-Green-Blue (RGB) camera to detect fresh dung patches directly from the image. Very few studies have used drone mounted RGB cameras to detect dung patches in NZ to date, yet a systematic comparison of a drone vs grid method would provide a useful tool for exploring the influence of grazing practices on dung return. For example, under RA management of higher stocking density, short grazing duration and leaving higher pasture residuals, a drone fitted with an RGB camera may be unable to pick up all patches as some of the dung may get trampled into the soil or dung patches may be difficult to identify because of the higher residual pasture covers associated with RA grazing practices.

2.6 Drone use for locating urine patches

Drones fitted with an RGB camera have been previously used to locate urine patches under intensive grazing and dairy systems (Jolly et al., 2019; Maire et al., 2018; O'Neil et al., 2020; Mehra et al., 2020). There are two examples of drones fitted with an RGB camera to detect artificial urine applications in dairy-grazed pastures. The first study, Jolly et al., (2019), was conducted in Palmerston North and Ruakura, NZ, using a drone fitted with an RGB camera and flown at an altitude of 40m, 14 days after urine was applied. The camera recorded images with a 75% overlap and then joined these images together. The images were then put through ImageJ and Hue Saturation and Brightness (HSB) processes to locate urine patches (Jolly et al., 2019). The second study, O'Neil et al., (2020) was undertaken in southeast Ireland, where a drone fitted with an RGB camera was flown at an altitude of 40m, 9 and 20 days after urine was applied. Images were also processed in ImageJ using the HSB process to locate urine patches (O'Neil et al., 2020). Another example of drone use was when artificial urine was artificially applied to pasture in Australia (Mehra et al., 2020). The drone fitted with an RGB camera was flown at an altitude of 35m, and images processed as described in the first example of drone use were also able to locate urine patches (Mehra et al., 2020). The examples show the camera could accurately locate all of the artificial applied urine patches and separate urine patches from pasture growth in a dairy pasture.

Other examples of drone used to detect cattle urine patches in intensively grazed pastures have occurred in Japan (Maire et al., 2018), where a drone fitted with an RGB camera was flown at an altitude of 35m several months after grazing. Images had at least an 80% overlap and were joined and processed in ImageJ using HSB. The camera was able to identify of urine patches. However, the paper did not calculate the drone accuracy against a ground truth method (Maire et al., 2018). These studies demonstrate that imagery can be used to locate urine patches under intensive conventional grazing management, suggesting there is opportunity to modify these methods to locate dung under RA grazing management which involves longer pastures following grazing at a higher stocking density. The ability of the method to identify dung patches in longer pastures could be a potential limitation of the technique.

2.7 Spatial and temporal aspects

The Dennis et al., (2013) study located dung patches based on pasture colour, whereas the Shine (2019) study used spatial analysis to measure the distribution of dung patches. However, neither study applied a formal validation process to compare the drone detection to a standardised method of dung identification and spatial distribution. For dung detection to be successfully used in the field, both spatial and temporal aspects need to be assessed.

2.7.1 Temporal aspects

One way to validate the temporal accuracy of the drone mounted camera to identify dung patches is through the use of Sensitivity and Specificity measures. Sensitivity measures the drone's ability to identify the true positives and not categorize the positives as false negatives. The definition of Specificity is the drone's ability to identify the true negatives and not categorize these as false positives (Trevethan, 2017). The Sensitivity and Specificity method are commonly used in the medical field (Wichainun et al., 2013; Loong, 2003) and agriculture (Brooks et al., 2021). However, currently there are no published data, applying this method to assess the accuracy of a drone mounted camera to identify dung patches. The False positive fraction (FPF), which is 1-specificity (probability that a true negative will test positive = False Positive divided negative) will be examined in the current thesis.

The Sensitivity and Specificity measures are used to create Receiver Operating Characteristic (ROC) curves which are a graphical way to show the connection between Sensitivity and Specificity (Ekelund, 2011). The ROC curve is used to identify the optimal point where the best trade-off between Sensitivity and Specificity within the test is optimum (Rossi, 2018). At the optimal point, the false positive rate is the lowest, and the true positive is the highest. The

area under the curve (AUC) can be used to measure the test's discriminative ability and allow for a comparison between two different predictors (Ekelund, 2011; Zehner et al., 2019). If the AUC is over 50%, the ROC results are better than chance, and the higher the number, the better is the result (Ekelund, 2011).

2.7.2 Spatial analysis

Dennis et al., (2013) did not do any spatial analysis to assess the accuracy of dung patch detection, whereas Shine (2019) used the tool density-based clustering tool (DBSCAN) in ArcGIS pro to show the spatial scale of cluster and density. Another tool that can be used to show the cluster of dung is Local Moran's I which is a statistical analysis method which identifies statistically significant hot spots, cold spots and spatial outliers. The results of the Z-score and the p-values are measured, which identifies if we should reject or accept the null hypothesis (Cheniti et al., 2021). To visually display the distribution of dung, the kernel density map in ArcGIS pro can be used to calculate the density of a point feature within an area (Esri, 2023b). Kernel density has been used previously to show the spatial distribution of animal excrement (Yoshitoshi et al., 2015; Yoshitoshi et al., 2016).

2.8 Conclusion

Distribution of dung can be used to assess the uniformity of animal excrement and to compare spatial distribution differences between regenerative and conventional management. A more even distribution is likely to lead to more even distribution of earthworms and more effective recycling of nutrient between the plant, dung, and soil, which could lower the need for nutrient inputs.

Despite the growing interest in RA management, there is little or no research on the effects of RA grazing management on the distribution of dung, urine and earthworms, the implications this may have on soil nutrient concentrations and the nutrient cycle, and therefore nutrient loss risk, compared to conventional management practices. One of the recommendations from the RA white paper was that more research on the impact of RA on freshwater was needed (Grelet et al., 2021) as urine and dung from dairy and beef cattle have the potential to impact the quality of freshwater. Understanding the distribution of dung deposits under RA grazing management can help identify the risk of nutrient loss and these risks could be related to overall risk to freshwater.

The current standard grid-based method of measuring dung distribution in grazed pastures is labour intensive and impractical in hill country terrain. Although not well studied, this review

has highlighted the potential of remote sensing to identify and map the spatial distribution of dung patches under grazing systems using drone mounted cameras, but these new methods need to be tested under a wide range of grazing practices in NZ. This review has also highlighted the need to validate these methods by assessing Sensitivity and Specificity, an area of research which has not been thoroughly addressed previously.

Chapter 3

Validation of a drone fitted with an RGB camera to identify and locate dung patches

3.0 Introduction

Drones fitted with an RGB camera have been successfully used to locate urine patches under intensive beef and dairy cattle grazing systems (Jolly et al., 2019; O'Neil et al., 2020). To date, two publications have described the use of drones fitted with cameras to locate dung patches (Dennis et al., 2013; Shine, 2019). Dennis et al., (2013) used a drone fitted with an RGB camera to fly a paddock 14 days after grazing to distinguish the difference in colours between pasture growth in areas of excrement and areas with no excrement. However, drone images could not distinguish if the colour change/pasture growth was caused by dung or a urine patch. Shine (2019), using a drone fitted with a multispectral camera, was able to locate dung patches in the pasture and identify dung patches at an overall accuracy of 82.6%. However, it was noted that accuracy declined with increasing time post grazing. These two studies show that drones fitted with a camera offer a method for identifying dung patches in a grazed pasture. Neither study tested the uses of a drone and RGB camera-based approach immediately after a grazing event. Such an approach would be useful in locating dung patches under different grazing regimes, including grazing practices advocated in regenerative agriculture (RA). To be useful, any approach would need to be validated against the current systematic approach, which involves a systematic ground truth to locate and identify each dung patch and geo-referenced using a survey-grade Trimble GPS tool. This chapter aimed to test if a drone mounted with an RGB camera could be used to identify and locate dung patches under RA and conventional grazing treatments over several grazing events. The study also aimed to validate the accuracy of this method using manual ground truthing of dung patches and measures of Sensitivity and false positive rate.

3.1 Method

3.1.1 Trial site

To evaluate the ability of a drone fitted with an RGB camera to locate and identify dung patches in grazing cells under two different grazing treatments, regenerative grazing (RA management) and control (Conventional management). A trial site located on Mangarara farm, which is 610 hectare none irrigated hill country sheep and beef farm located in Elsthorpe

central Hawkes Bay. Mangarara farm have 100 Angus breeding cows, 350 Angus heifers sold to butchers in Hawkes Bay and Auckland, and some Romney sheep (The farm, 2022).

The research study at Mangarara farm was sampled in November 2022. The cells sampled were located in a 9-ha paddock, with size of cells located in table 3.1. The paddock had rolling hill topography, with the majority of the paddock being low slope (0-12 degrees), with small areas of medium slope (13-24 degrees) (Figure 3.1). Two dominant pasture types were present, with ryegrass dominant at the paddock's south end and fescue dominant at the paddock's north end. The Pallic soils found in the paddock include the Oaklea loam (Oaklea_9a.1 ~50%), Airedale silt (Airedale_1a.1 ~25%), and Hastings loam (Hastings_28b.1 ~25%) (Manaaki Whenua Landcare Research, 2023). All soils have moderate to high vulnerability to water logging, with the anion storage capacity (ASC) in the topsoil low (23%) to moderate (38%) (Manaaki Whenua Landcare Research, 2023). This soil information has been sourced from Smap (Manaaki Whenua Landcare Research. 2023) which is presented at a scale of 1:50 000. This coarse scale information can lead to inaccuracies when interpreted at a farm scale. The coarse scale can lead to not all 3 soils being present in the trial paddock. The paddock has been divided into 15 laneways, each with 3 to 4 cells depending on the length of the laneway and a total of 67 cells (Figure 3.2). Rainfall during the study was measured using weather stations located at both the north and south ends of the study site. The weather stations were Watchdog 2000 series with a rain sensor measuring rain accumulation.

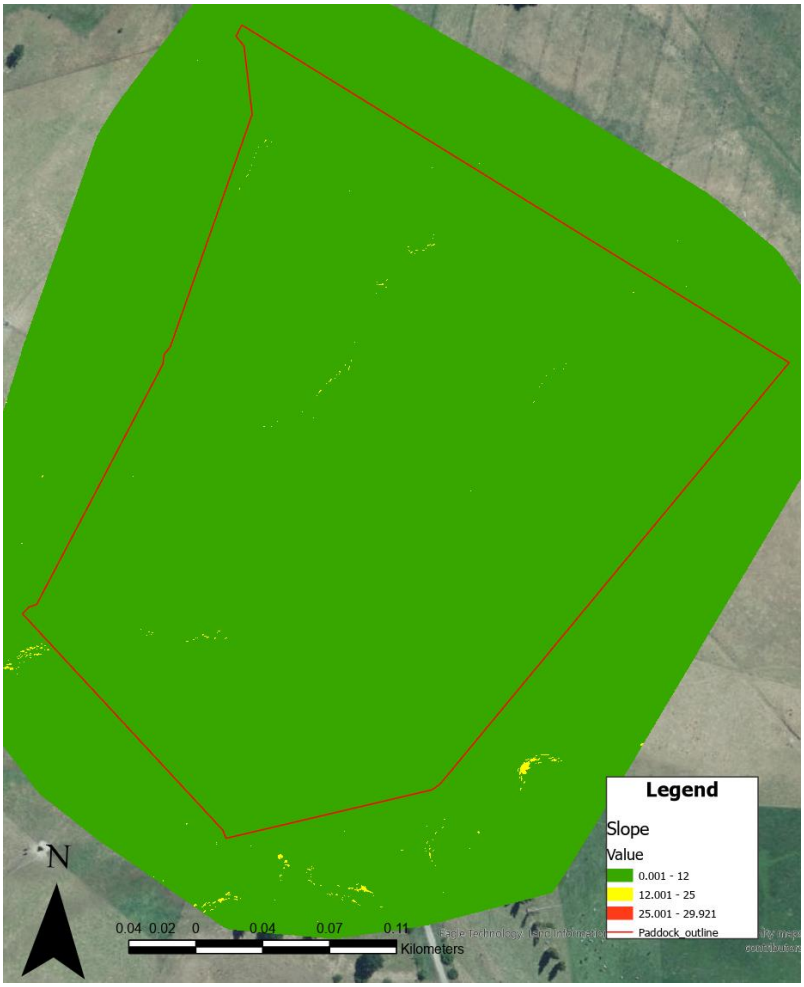


Figure 3.1: Slope map of the study area on Mangarara farm.

3.1.2 Grazing treatments

For the control grazing treatment, two sets of six cells were located at the paddock's north and south end and were grazed by six Angus heifers, with each group moved every three to four days to create a low stocking density. In contrast, the regenerative treatment was grazed with 57 Angus heifers to create a high stocking density, and these animals were moved two or three times a day depending on pasture availability and weather conditions. These treatments created a 9-fold difference in the stocking density, with the mean stocking density for the control treatment being 17,000 kg live weight/ha and the regenerative being 162,450 kg live weight/ha. Stocking density for each cell was calculated as the number of animals grazing, the cell multiplied by the mean animal weight (kg), divided by the area (ha) of the cell. Eight of the 12 cells were grazed using regenerative grazing management, and the control grazing treatment was applied to four cells to test the methods being examined in this study.

The difference in dominant pasture types within the paddock was a legacy of the study paddock originally being two different paddocks, with one of these paddocks dominated by fescue species located at the north end of the paddock. In contrast, ryegrass species dominated the paddock at the south end of the study site. Botanical composition was measured for each of these pasture areas in November. The fescue pasture contained (% on a dry matter basis) 48.1% fescue, 26.4% ryegrass, 12.5% white clover, 7.3% other grasses, 2.9% cocksfoot and 2.7% other species. The ryegrass pasture contained (% on a dry matter basis) 67.0% ryegrass, 16.5% white clover, 10.2% other grasses, 3.4% fescue, 1.8% other species and 1.1% cocksfoot.

Figure 3.2: Map of the 67 cells of the grazing study and two grazing treatments on Mangarara farm

3.1.3 Drone mounted camera method

The drone used in the current study was a DJI Mavic 3 drone fitted with an RGB camera. The camera specifications are: 20MP camera, f/2.8-f/11 adjustable aperture, with vision detection autofocus technology (VDAF) (DJI, 2023). The camera was used to take images at an altitude of 30m of all 12 cells (eight regenerative cells and four control cells) within three days of heifers grazing the cells. Twelve cells were selected for the systematic and drone measurements due to time restrictions of the site being 3 hours drive away and measurements required as close to grazing as possible. The 12 cells that were selected provided a range of conditions for validation. The drone's altitude over the paddock was determined from previous research using drones to locate urine patches, where the drone was flown at 40m and 35m (Maire et al., 2018; Jolly et al., 2019). At this height, the drone was above the trees bordering some of the cells in the current study, which was deemed to be appropriate for this study. The drone was used to perform photogrammetry of each cell, which involves taking multiple images with at least 75% overlap and combining the images using a program called Pix4dreact into one large image (*Pix4D,* 2023). The images of the cells are then placed into ArcGIS Pro (Esri, 2023a), with the dung patches manually identified and marked within the image taken by the drone.

Factors that could have affected the collection data were the presence of trees along the edge of the cells, waterways within the cell and the two different dominant pasture species within the paddock. The 12 cells, therefore, provided a range of conditions that could influence the efficacy of the drone-mounted camera in locating the spatial distribution of dung patches. This variance was included as a factor in validating the accuracy of the drone/camera method.

3.1.4 Description of treatments and measurements

Table 3.1 provides details of the grazing treatment, dominant pasture type, amount of rainfall that fell when the animals were grazing the cell and the number of Angus heifers grazing each cell. Stocking density is calculated as the mean animal weight per ha within each cell, with regenerative treatments having a stocking density nine times higher than the control treatment. Grazing duration was calculated as the number of hours the animal spent grazing the cell. The regenerative treatment cattle spent a mean of 13.8 hours grazing each cell, with a range of 6.5 to 24.5 hours. Whereas the control treatment cattle spent a mean of more than four days (102 hours) grazing each cell. The drone images were taken within two days of the cessation of each grazing event and within six days from the start of grazing (Table 3.1).

Table 3.1: Description of the cells used for validation of the drone method.

Cell	Date of grazing and time put in	Date and time of taking drone images	Date and time for systematic approach	Grazing treatment	Cell size (ha)	Pasture type	Rainfall (mm)	Animal number	Stocking Density (kg LW/ha)	Grazing duration (hours)
1	14/11/22 1:00 pm	16/11/22 Morning	16/11/22 Morning	Regenerative	0.13	Fescue	0.0	57	145478	6.5
2	14/11/22 7:30 pm	16/11/22 Morning	16/11/22 Morning	Regenerative	0.12	Fescue	0.0	57	165203	14.0
3	15/11/22 9:30 am	16/11/22 Morning	16/11/22 Morning	Regenerative	0.12	Fescue	0.0	57	158488	10.0
4	15/11/227:30 pm	16/11/22 Morning	16/11/22 Morning	Regenerative	0.12	Fescue	0.0	57	162450	14.0
5	16/11/22 9:30 am	17/11/22 Morning	17/11/22 Morning	Regenerative	0.10	Fescue	0.0	57	193010	24.5
36	28/11/22 3:00 pm	30/11/12 Morning	30/11/12 Morning	Regenerative	0.12	Ryegrass	0.0	57	159787	17.0
37	29/11/22 8:00 am	30/11/12 Morning	30/11/12 Morning	Regenerative	0.11	Ryegrass	0.0	57	183906	10.0
38	29/11/22 6:00 pm	30/11/12 Morning	30/11/12 Morning	Regenerative	0.10	Ryegrass	0.5	57	198918	14.0
41	25/11/22 7:00pm	30/11/12 Morning	30/11/12 Morning	Control	0.12	Ryegrass	4.5	6	17244	110.0
46	25/11/12 7:00pm	30/11/12 Morning	30/11/12 Morning	Control	0.12	Ryegrass	4.0	6	17100	110.0
51	30/11/22 9:00 am	6/11/22 Morning	6/11/22 Morning	Control	0.12	Fescue	0.9	6	17244	95.0
56	30/11/22 9:00am	6/11/22 Morning	6/11/22 Morning	Control	0.12	Ryegrass	0.6	6	16959	95.0

3.1.5 Outcome variables

Outcome variables were either spatially defined or temporal. For the temporal approach, the method involving a drone fitted with an RGB camera to identify dung patches was validated against a systematic ground truth approach. The systematic approach to measure dung patches on the ground involved walking each of the 12 cells to identify each dung patch using a survey-grade Trimble GPS tool to provide a geo-reference point for each dung patch. This systematic approach was completed immediately after the drone images were taken. The systematically marked dung patches were then imported into ArcGIS Pro.

The systematically marked dung patches were compared with the drone-marked dung patches to assess the accuracy of the imagery taken by the drone camera to identify dung patches. The following categories were created as part of the analysis.

1. Where systematic and drone camera dung patches aligned, this was marked as positive, which means the drone picked up dung patches correctly.
2. Where drone-marked dung patches that did not align with the systematic-marked dung patches, they were marked as false negative.
3. Where the drone camera identified dung patches which did not align with the systematic-marked dung patches, these were marked as false positive.

The number of positive, false negative and false positive dung patches was used to assess the accuracy of the drone method to locate dung patches.

3.1.6 Statistical analysis

Statistical analysis of the data was completed for all cells and then stratified by either control or regenerative grazing treatments. The analysis was conducted on the dung patch count/ha, assessed by the 1. systematic approach, 2. drone-mounted camera method and 3. drone and systematic-matched dung patches. The false positive and false negative results were presented per ha. The dung patch matches and the false negative results were also presented as percentages. For each of these analyses, a bulk mean was calculated for all cells, and then a stratified mean was calculated for each treatment.

3.1.6.1 Temporal validation

In order to validate this new method of identifying dung patches, a demonstration of the suitability of the method and the accuracy of the results was necessary. This ensures that the method is fit for purpose. Sensitivity (Se) and false positive rate (FPR) describe the accuracy of a test when compared to an accepted/traditional measure.

To the author's knowledge, this analysis, which is commonly used in medical research, has not been used by the agricultural research sector nor in the analysis of the detection of dung patches before. The definition of Se is to test the probability of correctly identifying the true positives and not categorising positives as false negatives. The definition of FPR is to test the probability of correctly identifying the true negatives and not categorising them as false positives. Se and Sp are used to assess the accuracy of the test by only identifying true positives and negatives (Trevethan, 2017). Se and Sp are calculated from the number of positives, negatives, false positives and false negatives. The false positive rate (FPR (1-Specificity)) is used to identify the number of false positives present, as the lower the false positive rate, the higher the number of false positives. The higher the percentage of Se, the lower the number of false negatives identified as positives. For the Se and FPR, 95% confidence interval are calculated.

A Receiver Operating Characteristic (ROC) curve was used to relate Se and FPR (Ekelund, 2011), with the optimal point determined as the optimal point, where the best trade-off between Se and FPR is achieved (Rossi, 2018). R Studio was used for the temporal analyses, including the EpiR package (Stevenson & Reynard, 2023) and the ROCit package (Rickert, 2019). The code for Se and Sp and ROC curves is presented in Appendix 1.1 and 1.2, respectively. The area under the curve (AUC) over 50% indicates a test that is better at identifying dung patches than chance.

3.1.6.2 Spatial validation

Kernel density mapping was used to validate the detection of dung patches between the systematic and drone-marked methods. This approach was used to identify variations in detection between drone-marked and systematic-marked dung over a paddock/cell/space.
Kernal density mapping is a GIS tool that calculates the density of a feature class within an area (Esri, 2023b). The kernel density uses the dung patch point feature and creates a map showing the distribution over space. As the colour darkens, a higher number of dung patches in the area is indicated. For each dung detection method, the kernel density tool with the point feature was used to compare the dung patches density distribution map within each cell. The resulting two kernel density maps were then visually assessed with a comparison between the variability and location of the systematic-marked and drone-marked dung patches conducted.

3.2 Results

3.2.1 Comparison of dung patch detection between methods

The total number of dung patches identified by the systematic approach for all 12 cells in November 2022 had a mean of 2727/ha (SD 1103) (Table 3.2). The total number of dung patches identified by the drone method for all 12 cells in November 2022 had a mean of 1805/ha (SD 1090). The mean number of false negatives and false positives was 1125/ha (SD 342) and 202/ha (SD 243), respectively. The mean accuracy of systematic and drone-mounted camera-measured dung patch matches is 57% (SD 15). The percentage of false negatives was 43% (SD 15). The mean number of dung patches identified by the drone between regenerative cells compared with control cells was 2116 (SD 1223) and 1183 (SD 305), respectively.

Table 3.2: Dung patches per hectare identified by the drone mounted camera method compared to the systematic approach and their associated false negative, false positive and matches for each of the 12 cells studied.

Cell	Systematic (dung/ha)	Drone (dung/ha)	False negative/ha	False positive/ha	Drone Systematic match/ha	Drone Systematic accuracy (%)	False negative (%)
Regenerative cells							
1	1104	1560	194	649	911	82	18
2	1983	856	1186	59	797	40	60
3	2089	1293	943	146	1146	55	45
4	2242	1083	1192	33	1050	47	53
5	4257	3871	1158	772	3099	73	27
36	3385	1975	1451	41	1934	57	43
37	3245	2245	1151	151	2094	65	35
38	5092	4041	1184	133	3908	77	23
Mean	**2925**	**2116**	**1058**	**248**	**1867**	**62**	**38**
Standard deviation	**1318**	**1223**	**375**	**291**	**1133**	**15**	**15**
Control cells							
41	1882	857	1134	109	748	40	60
46	2450	1542	975	67	1475	60	40
51	2387	1017	1529	160	857	36	65
56	2612	1314	1405	107	1207	46	54
Mean	**2333**	**1183**	**1261**	**111**	**1072**	**46**	**55**
Standard deviation	**315**	**305**	**252**	**38**	**333**	**11**	**11**
Mean overall	**2727**	**1805**	**1125**	**202**	**1602**	**57**	**44**
Standard deviation	**1103**	**1090**	**342**	**243**	**1000**	**15**	**15**

3.2.2 Sensitivity and false positive rate assesment

The mean sensitivity for all cells was 57% (95% CI 58% to 59%; SD 15) (Table 3.3). When stratified to regenerative and control treatments, the sensitivity mean was 62% (95% CI of 64% to 64%; SD 14) and of 11% (95% CI 45% to 47%; SD 11), respectively. When looking at the false positive rate, the overall mean was 89% (95% CI of 88% to 89%; SD 11). When the false positive rate was stratified to regenerative and control treatments, was 88% (95% CI 88% to 89%; SD 14), and 90% (95% CI 90% to 91%; SD 50) respectively.

Cell 51 (Control cell, Table 3.3) measured the lowest sensitivity of 36% and measured one of the lowest false positive rates of 84%. Cell 1 had the highest sensitivity of 82%, indicating a low number of false negatives. Cell 1 had the lowest false positive rate of 58%, indicating many false positives within the cell.

Table 3.3: Assessment of the accuracy of the drone mounted camera methd compared to the systematic dung patch measurement using the sensitivity and the false positive rate.

Cell	Sensitivity % (95% CI)	False positive rate % (95% CI)
Regenerative treatment		
1	82 (80 to 85)	58 (56 to 61)
2	40 (38 to 42)	93 (91 to 95)
3	55 (53 to 57)	89 (87 to 90)
4	47 (45 to 49)	97 (96 to 98)
5	73 (71 to 74)	80 (79 to 81)
36	57 (55 to 59)	98 (97 to 99)
37	65 (63 to 66)	93 (92 to 94)
38	77 (76 to 78)	97 (96 to 97)
Mean	**62 (0.63 to 0.64)**	**88 (88 to 89)**
Standard deviation	**15**	**14**
Control treatment		
41	40 (38 to 42)	87 (85 to 89)
46	60 (58 to 62)	96 (95 to 97)
51	36 (34 to 38)	84 (82 to 86)
56	46 (44 to 48)	92 (90 to 97)
Mean control	**46 (45 to 47)**	**90 (90 to 91)**
Standard deviation	**11**	**5**
Combined treatments		
Mean	**57 (58 to 59)**	**89 (88 to 89)**
Standard deviation	**15**	**11**

3.2.3 Receiver operative characteristic (ROC) curve

The AUC value is 64.5% (Figure 3.3). Based on the ROC, drone identification of dung patches can be optimised at a false positive rate of 62% with a sensitivity of 87%.

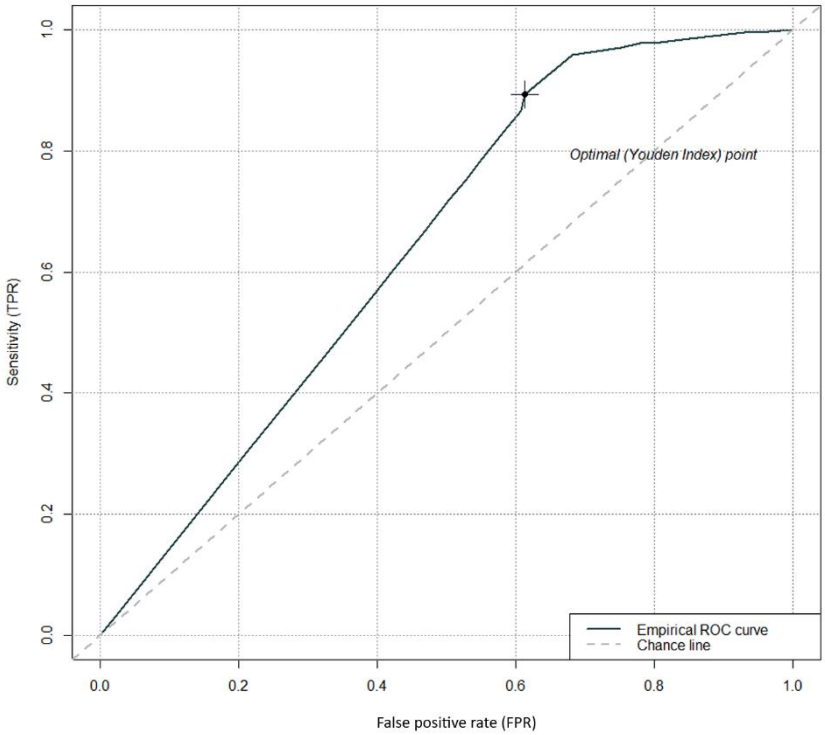


Figure 3.3: The receiver operative characteristic (ROC) curve derived from the dung patch data collected using the drone mounted camera and systematic methods for the 12 cells examined in the validation study. The ROC curve was compared to the 1:1 line (chance line) to determine the optimal point. The ROC curve shows false positve rate (FPR) and the sensitivity (true positive rate, TPR).

The AUC value is 61% (Figure 3.4). Based on the ROC, drone identification of dung patches can be optimised at a false positive rate of 60% with a sensitivity of 80%.

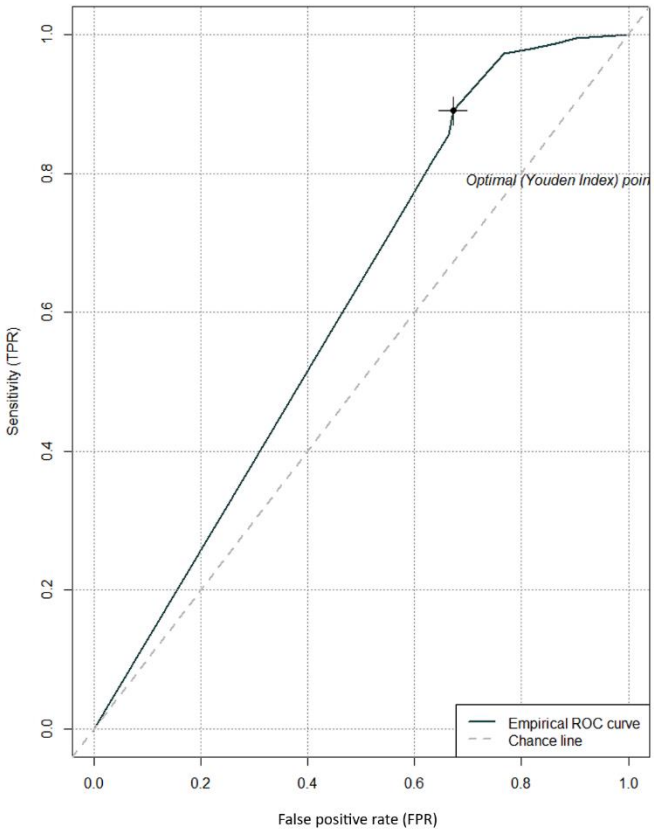


Figure 3.4: The receiver operative characteristic (ROC) curve derived from the dung patch data collected using the drone mounted camera and systematic methods for the 8 regenerative cells only examined in the validation study. The ROC curve was compared to the 1:1 line (chance line) to determine the optimal point. The ROC curve shows the false positve rate (FPR) and the sensitivity (true positive rate, TPR).

The AUC value is 72% (Figure 3.5). Based on the ROC, drone identification of dung patches can be optimised at a false positive rate of 40% with a sensitivity of 90%.

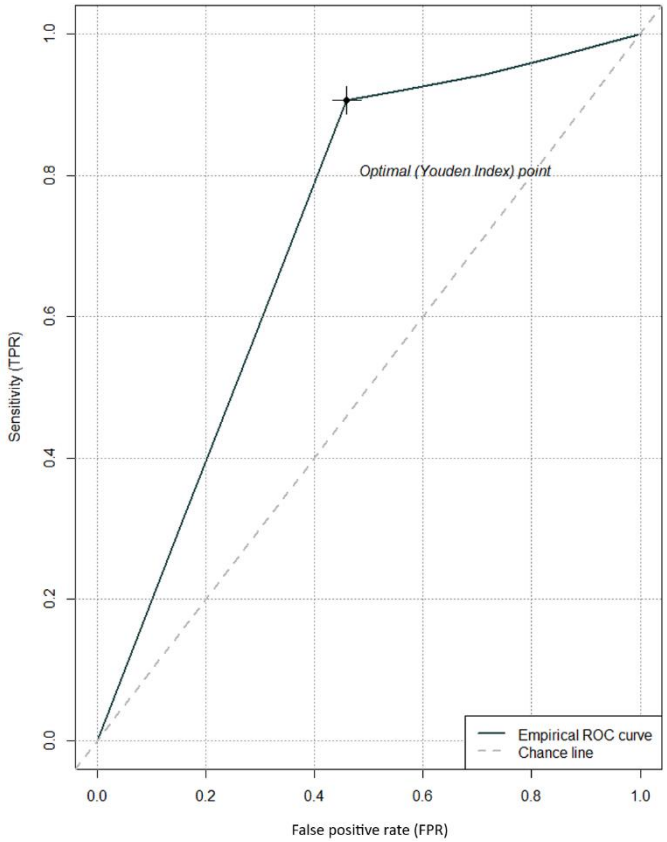
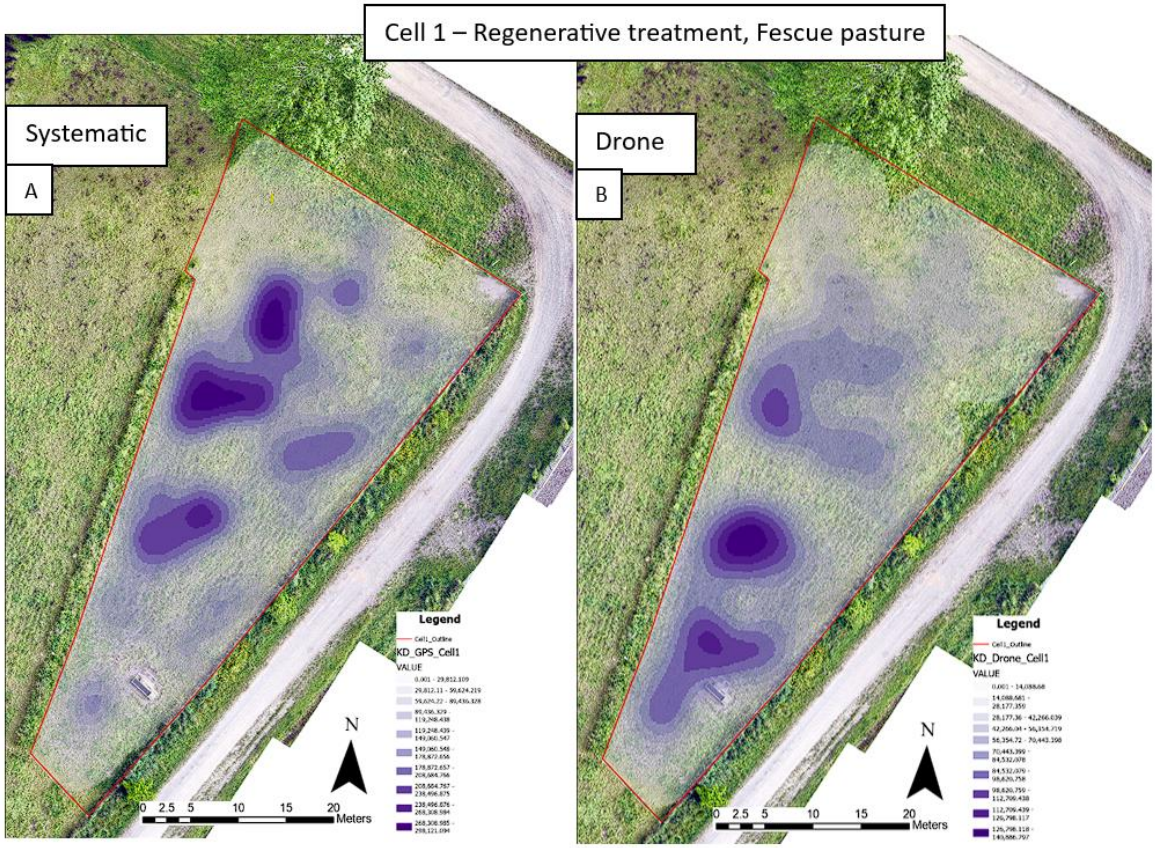
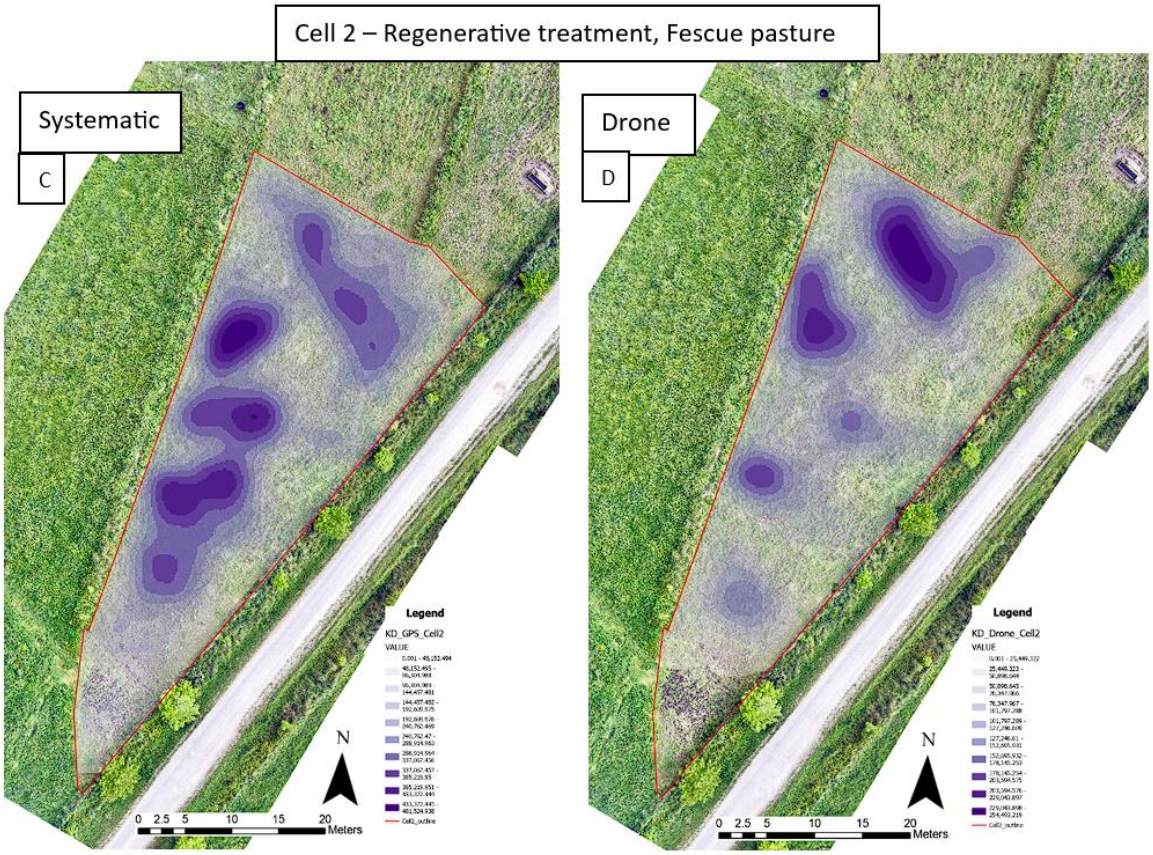


Figure 3.5: The receiver operative characteristic (ROC) curve derived from the dung patch data collected using the drone mounted camera and systematic methods for the 4 control cells only examined in the validation study. The ROC curve was compared to the 1:1 line (chance line) to determine the optimal point. The ROC curve shows the false positve rate (FPR) and the sensitivity (true positive rate, TPR).

3.2.4 Dung patch kernel density map

The kernel density map shows examples of a good match of the dung distribution between the systematic approach and drone-mounted camera method, which are cells 46 and 56 (Figure 3.6). Examples of a good match between the spatial distribution of dung measured with the systematic approach and the drone-mounted camera method are cells 1 and 36. Examples of a difference in the dung distribution between the systematic approach and the drone-mounted camera method are cells 2 and 38 (Figure 3.6).


Cell 1 – Regenerative treatment, Fescue pasture
Systematic
A
Drone
B
Legend
KD_GPS_Cell1
KD_Drone_Cell1
VALUE
N
0 2.5 5 10 15 20
Meters


Cell 2 – Regenerative treatment, Fescue pasture
Systematic
C
Drone
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Legend
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KD_Drone_Cell2
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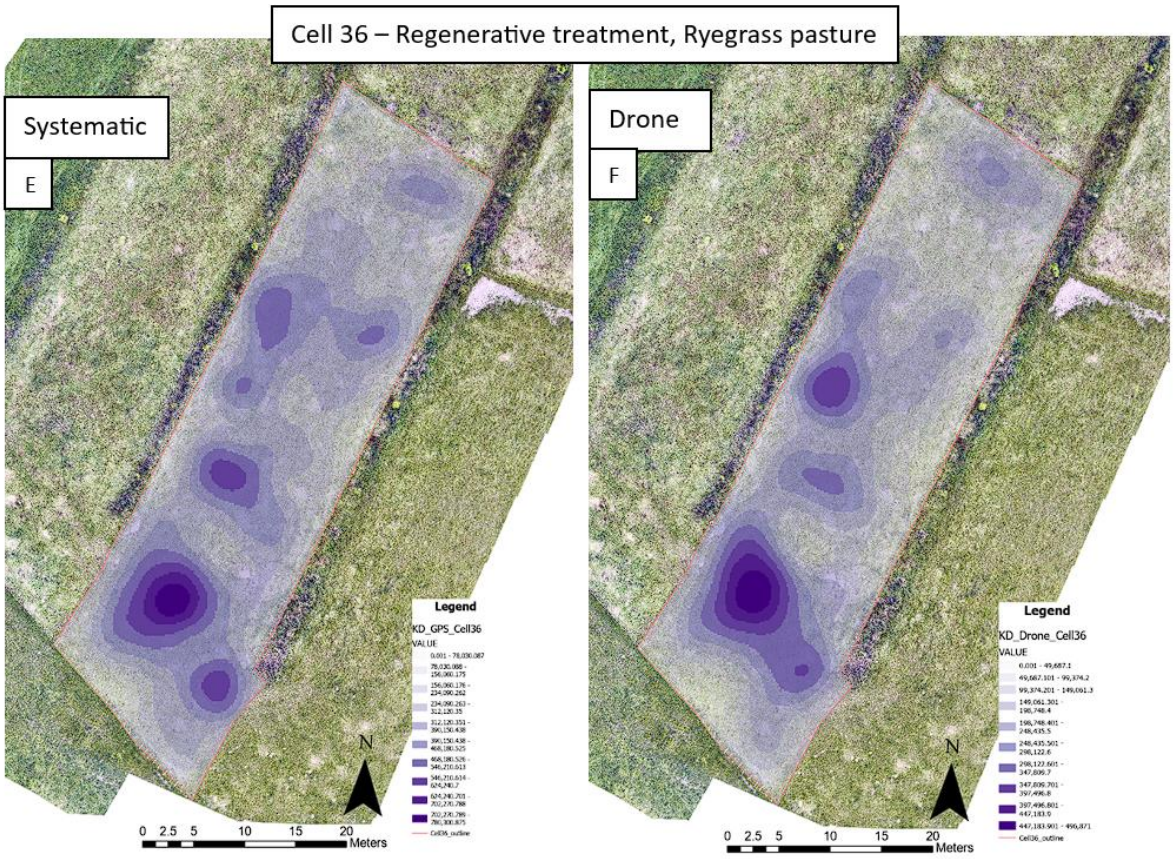
Cell 36 – Regenerative treatment, Ryegrass pasture
Systematic
E
Drone
F
Legend
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VALUE
Legend
KD_Drone_Cell36
VALUE
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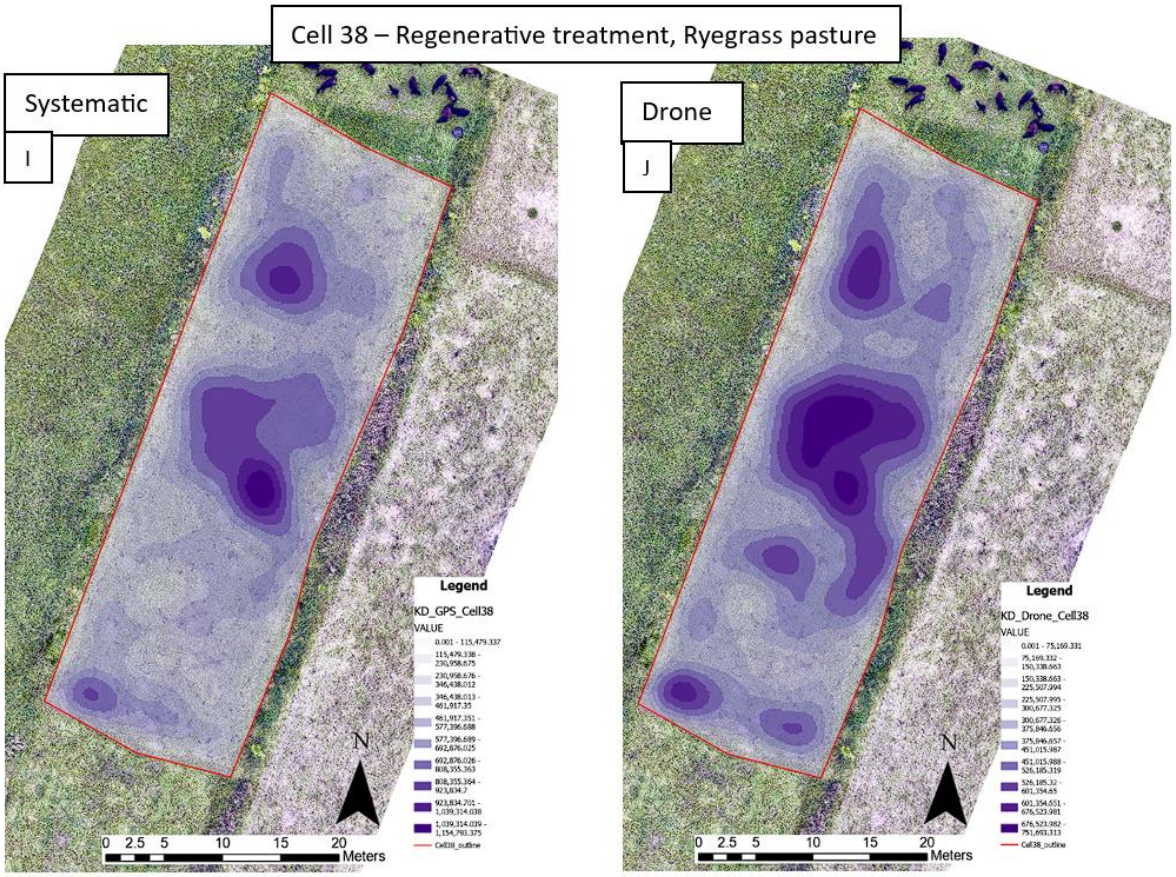
Meters


Cell 38 – Regenerative treatment, Ryegrass pasture
Systematic
I
Drone
J
Legend
KD_GPS_Cell38
VALUE
Legend
KD_Drone_Cell38
VALUE
N
0 2.5 5 10 15 20
Meters

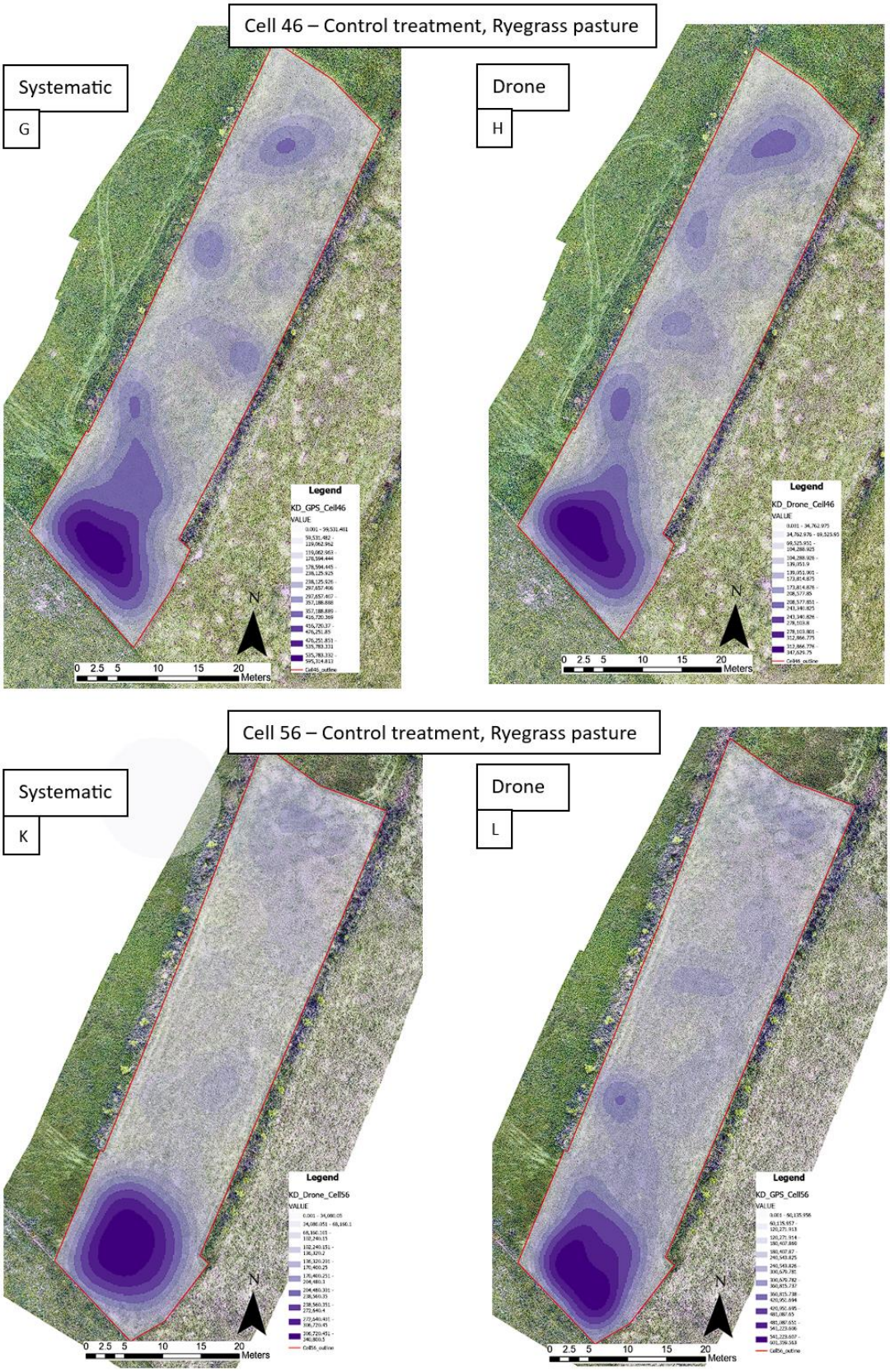


Figure 3.6: Examples of dung patch kernel density maps for the dung patches for the dung patches identified by the systematic method (Figure 3.6 A, C, E, G, I and K) and the dung patches identified by the drone mounted camera method (Figure 3.6 B, D, F, H, J and L).

3.3 Discussion

This study aimed to examine the ability of remote sensing using a drone mounted with an RGB camera to identify cattle dung patches under RA and conventional grazing treatments. The result showed that images taken from an altitude of 30m could identify dung patches under various on-farm pasture management conditions. Additionally, dung patches could be correctly identified (mean accuracy of 57%) in images taken by a drone on pasture grazed under high and low stocking density, grazing for different durations, under two pasture types with variable standing biomasses, and with varying amounts of bare soil and shade from trees.

The drone method developed in this study could identify nearly two-thirds of dung patches identified using the current labour-intensive systematic approach present in the twelve cells used in the validation of this new method (Table 3.2). Shine (2019) used a multispectral camera 14 days after grazing and reported that 47% of dung patches were detected. While the methods of detection, using a camera mounted on a drone, were similar between the two studies, the type of camera used and the time between dung deposition and image collection were different. However, in the current study, the drone method consistently identified fewer dung patches compared to the numbers identified when each cell was walked, and dung patches identified by eye. The underestimate was approximately 300 dung patches/ha, but importantly, the drone images were more likely to fail to identify dung patches that were present on pasture (false negatives) than identify dung patches that were not present (false positives) and hence reduce the accuracy of the method. Further work to increase the number of dung patches/ha identified under various pasture management and grazing conditions by remote sensing using the drone, would further enhance the accuracy of the method.

In the current chapter, in addition to standard statistical methods, Se and FPR were used to assess the accuracy of the drone-mounted camera method. This novel approach is commonly used to evaluate and validate new diagnostic tests in the medical and veterinary industries (Wichainun et al., 2013; Loong, 2003; Brooks et al., 2021). Se, a measure of the ability of the drone method to identify the true positives and not categorise the positives as false negatives and the FPR, a measure of the drone's ability to identify the true negatives and not categorise these as false positives (Trevethan, 2017). Cells with low sensitivity are due to the number of false negatives compared to the number of systematic dung patches. When the sensitivity is higher, false negatives are lower than the systematically marked dung patches. The false positive rate shows how good the drone is at identifying dung patches without identifying false positives. An example of this is cell one, which has a false positive rate of 58%, caused by the

number of false positives of 649 and the drone dung patches of 1560. This means that 58% of drone dung patches are true positives, and 42% are false positives. Cell 36 has a false positive rate of 98% due to the number of false positives of 41 and the drone dung patches of 1975. This means that 98% of the drone dung patches are true positive, and 2% are false positive. The sensitivity and false positive rate were used to generate an ROC curve to determine whether the optimum diagnostic accuracy of the drone detection method. Overall, the optimum point had a false positive rate of 60% and a sensitivity of 90%. This indicates that the drone-based method is better than chance and importantly the method can differentiate with a high accuracy of locating a dung patch deposited by the animal in a grazed pasture from other components of the grazed pasture (e.g., soil surface, pasture plants trampled by the animal, surface water, etc.). No previous studies to our knowledge have attempted to assess the accuracy of remote sensing for identifying dung patches, including identifying the optimum diagnostic accuracy of the drone detection method.

In contrast to the multispectral camera research by Shine (2019) and Dennis et al., (2013), the current research used the same RGB camera on a drone to locate dung patches as did Dennis et al., (2013). However, the current research method showed that dung patches could be located fresh (within six days for control and within two days for regenerative), rather than taking images 14 days later and distinguishing between urine and dung patches. A multispectral camera takes images over multiple spectral bands, which can lead to more information from the images than is achieved with a standard RGB camera (He et al., 2021). The multispectral camera provides more options to pick up dung patches and can distinguish between dung and pasture. It covers more of the light spectrum bands, so it can distinguish based on colour differences, which will help locate dung patches in bare soil. However, multispectral cameras are very expensive compared to RGB cameras and were not available for the current research project. One area of future research is the use of multispectral cameras to locate and spatial identify cattle dung patches. Despite using a cheaper camera, the results show that an RGB camera can effectively identify dung patches. However, we found that the RGB camera used in the current study could not pick up all of the dung patches, but this research picked up, on average, over half of the dung patches and was effective at mapping the distribution of dung. Despite some loss of accuracy, RGB cameras are currently a more cost-effective option and require a smaller drone to operate.

When the cells were stratified by the regenerative and control treatments for analysis, the mean drone accuracy was 62% and 46% for the regenerative and control treatments, respectively. The Se and FPR stratified under regenerative or control treatments showed that the regenerative treatment Se was higher than the control treatment. The control treatment

had a higher FPR than the regenerative treatment. This shows that under the regenerative treatment, the drone-mounted camera method is better at locating true positives without categorising them as false negatives. Under the control treatment, the drone-mounted camera method was better at locating true negatives without categorising them as false positives. This could be due to a higher drone accuracy measured on the regenerative cells compared to control cells. When the Se and FPR were stratified for the two treatments and used for the ROC curve, it showed there was a difference between the two treatments. The regenerative treatment ROC curve (Figure 3.4) showed that the AUC was 61%, which is better than chance. However, the control treatment ROC curve (Figure 3.5) showed that the AUC was 72%, which is better than chance. This indicated that the control treatment had a better chance of identifying dung patches with an acceptable level of FPR and Se compared with the regenerative treatment. The difference could be due to the controlled grazing event extending for three days, which meant the drone could not be flown until five days after the start of grazing, by which time, the dung started to dry and decompose. Our experience and that reported in the literature (Shine, 2019), was that the drone camera was less able to identify dung patches. This is further highlighted when looking at the regenerative cells, where the number of dung patches was higher than under the control cells, which may be due to the larger number of animals (57) in each cell. It also shows that the regenerative cells have a higher mean accuracy than all of the cells, which could be due to a higher number of dung patches present and the dung being fresher, as the drone was flown closer to the time when the dung was deposited.

In the current chapter, the second step of validation was spatially explicit. Mapping techniques were used to enable a visual comparison of the two detection methods. Dung was not evenly distributed across a paddock, which is similar to previous studies (Morton & Baird, 1990; Thorrold et al., 1985; DeRamus et al., 2015). Additionally, the spatial comparison shows that even if the drone is not picking up all the dung patches, it is able to depict the distribution of dung within the cells. The drone-mounted camera method shows the distribution of dung within the cell. An example of the two kernel density maps not being a good match is shown in cell 2 (Figure 3.6 C and B). This is because cell two had one of the lowest accuracies (40%), which led to the dung distribution maps being different under the systematic compared with the drone method. An example of a good match between the two-kernel density maps is cell 56 (Figure 3.6 K and L). The cell has one of the lowest drone accuracies (46%), but the dung patches are located at one end of the paddock, which leads to both methods showing the same distribution of dung. While further work is required to improve the identification of dung patches under different grazing conditions, this visual distribution map could be used to target

fertiliser applications or identify areas in the paddock that may have a high risk of nutrient loss, which will allow farmers to put steps in place to lower the risk in these high-risk areas.

The kernel density maps show that both measurement methods effectively represent the distribution of dung in the paddock, despite there being slight differences between them (Figure 3.6). This result shows that even if the drone is not picking up all the dung patches, it is able to depict the distribution of dung within the cells. These kernel density map results led to the use of the drone method to measure the distribution of dung under regenerative and control grazing treatments (Chapter 4).

The research in this chapter found that several factors affect the accuracy of drone imaging in picking up dung patches. The key factors affecting the accuracy were trees, pasture height, bare soil and grazing duration. The height of the pasture affected the accuracy of the drone. When the pasture height was long, this reduced the drone's ability to locate dung patches. This was due to the pasture shading and obscuring dung patches, which led to the dung patches not being measured by the drone. If the pasture height is lower, the pasture is less likely to shade the dung, which could lead to higher drone accuracy. More research is needed to understand pasture height's impact on drone image accuracy. Another factor affecting accuracy was the amount of bare soil within the cell. The drone accuracy declines if more bare soil is present under wet conditions. This is due to the chances of the dung being trampled into the soil, which makes it harder for the drone to see the dung contrast with the soil, which leads to dung patches being missed and lower accuracy.

Another factor affecting accuracy is the presence of trees along the paddock's edge, as these interfere with the detection of dung by the drone camera. The tree branches overhang the cell, which causes shading over the cell as the drone cannot capture images through the branches and leaves. The drone could not fly under the branches as it would be too close to the ground. An example of this effect is seen in cell 41 (Figure 3.7), in which the trees cover 161.71 m2 (14%) of the cell. Under the tree, the drone could not locate dung patches, as shown in the low drone accuracy in this cell of 40%.

Figure 3.7: Cell 41 example of trees over hanging the cell and reducing the accuracy of drone detection of dung patches.

Another key factor influencing drone accuracy is the grazing duration, which is how long the cattle graze the cell. If the cattle are grazing the cell for a long period of time, the accuracy of the drone method can be affected as dung patches start to decompose, and dung can get shaded by regrowing pasture. The results show that drone accuracy was lower on the control cells, with a mean of 46% compared to the regenerative cell of 62%. As the drone was flown six days after grazing started, the dung could have been trampled into the soil or may have dried out and/or been shaded by the grass, leading to the drone not being able to pick up the dung patches lowering the accuracy. If cells that had a low accuracy of <50% were removed from the analysis, the mean accuracy increased to 67%. This emphasizes the need to understand the factors that compromise the drone method's accuracy in order to improve the method's performance.

When comparing the drone method to a systematic approach to locating dung, the results show that the drone does not pick up all of the dung present, while the systematic approach does. The drone shows the same dung distribution as the systematic approach, with little difference between the two distributions of dung in space. The main difference between the

drone method and the systematic approach is the time it takes to pick up the dung patches. Within this research, the systematic approach took around 1 hour to mark dung patches within cells, with the cells ranging in size from 0.1ha to 0.13ha (Table 3.1). The drone method for the same cell took 5 minutes to fly the cell and 30 minutes to process and manually mark the dung patches. This shows that the drone took half the time to mark dung patches. However, when focusing on a larger area, the time difference will become greater as the drone can fly the whole 9ha paddock in 15mins, whereas walking and marking the whole paddock would take over a day and possibly up to a week to mark all the dung patches present in the 9ha paddock. This shows that the drone method is a much quicker way to mark dung patches and map the distribution of dung within a paddock. Remote sensing of dung would allow more research to be conducted over a larger area and opens the opportunity to measure dung in harder-to-reach places such as hill country where the drone can safely fly over steep hills when it is difficult to walk and mark dung patches in this terrain.

3.4 Conclusion

This research shows that a drone fitted with an RGB camera can identify (on average 57% of dung patches) and locate cattle dung and the spatial distribution of the dung under low and high stocking density and RA management and pastures. The Se and FPR results show that each cell has a range of Se and FPR results. Some cells have higher Se and FPR than other cells. Which means some cells have a lower number of false positives and negatives.

The results from the ROC curve show that the drone method is better than chance and that control cells had a higher AUC than regenerative cells. This means that the drone had a higher chance of picking up dung patches correctly with a lower number of false negatives and false positives in the control cells. Multiple factors affect the accuracy of the drone in picking up dung patches within the paddock, mainly the height of the pasture, amount of bare soil and trees present. More research is clearly needed on the use of drone mounted cameras to understand under what conditions drone accuracy can be further improved.

The result from the dung patch kernel density map shows that even with the drone method, some cells show a slight difference in the distribution of cattle dung compared to the systematic approach. This shows that even when the drone accuracy is low, it can be used to show the distribution of cattle dung under regenerative and control grazing treatments. These findings gave us confidence to use the drone method in Chapter Four to compare the distribution of cattle dung under regenerative and control grazing treatments.

Chapter 4

Dung distribution comparison between regenerative and control management

4.1 Introduction

Since one of the key principles of regenerative agricultural (RA) management is focused on increased stocking densities and increasing the distribution of excrement deposition, understanding the impact this practice has on dung distribution is critical. Animal excrement poses an important risk factor to freshwater as the distribution and intensity of excrement deposition can influence nutrient loss from farm paddocks to waterways (McDowell et al., 2009; Smith & Monaghan, 2003) and also influence soil nutrient availability and cycling within a paddock.

The effects of stocking density on the distribution of dung have received some attention, with research identifying higher stocking densities associated with, dung being more evenly spread over the paddock (Morton & Baird, 1990; Thorrold et al., 1985; DeRamus et al., 2015). Further, dung was less likely to be deposited in campsites compared to grazing at a lower stocking density (Morton & Baird, 1990; Thorrold et al., 1985; DeRamus et al., 2015). These findings indicate that dung distribution could be more evenly spread over the paddock under higher stocking densities, more commonly associated with RA management, potentially creating more even soil nutrient distribution and lowering the risk of nutrient loss. However, higher stocking densities might increase the risk of soil damage during periods when soils are wet, through pugging of the soil, which increase the risk of sediment loss via overland flow. Another consideration with stocking density is soil water infiltration, as higher stocking densities have been found to increase soil water infiltration, through the increase in organic matter (Teague & Barnes, 2017). The increased soil water infiltration could theoretically decrease the volume of overland flow and decrease the amount of nutrients lost via this pathway.

To date, there has been no research on the effect of RA grazing management on cattle dung distribution in NZ. Therefore, the current study aimed to measure the number and distribution of dung deposits under RA and conventional grazing management treatments and to compare the effect of pasture type on dung deposits, using a drone fitted with an RGB camera. The study also aimed to compare the spatial distribution of dung between grazing treatments. This research uses the drone-based method developed and validated in Chapter 3, as this method

has been shown to successfully locate dung patches in a grazed pasture, with an average accuracy of 57%, which provides a good assessment of dung distribution following grazing.

4.2 Method

4.2.1 Trial site and study design

The trial site on Mangarara Farm was described in Chapter 3. Briefly, the trial site was split into 67 cells, with 12 control and 55 regenerative cells (Figure 4.1). For the conventional grazing henceforth termed the control grazing treatment, two sets of six cells were located at the paddock's north and south ends of the trial site and grazed by six Angus heifers, with each cell moved every three to four days. The regenerative treatment was grazed with 57 Angus heifers and moved once, twice or thrice daily depending on pasture availability and weather conditions. The aim was to create a 9-fold difference in the livestock stocking density between the two treatments.

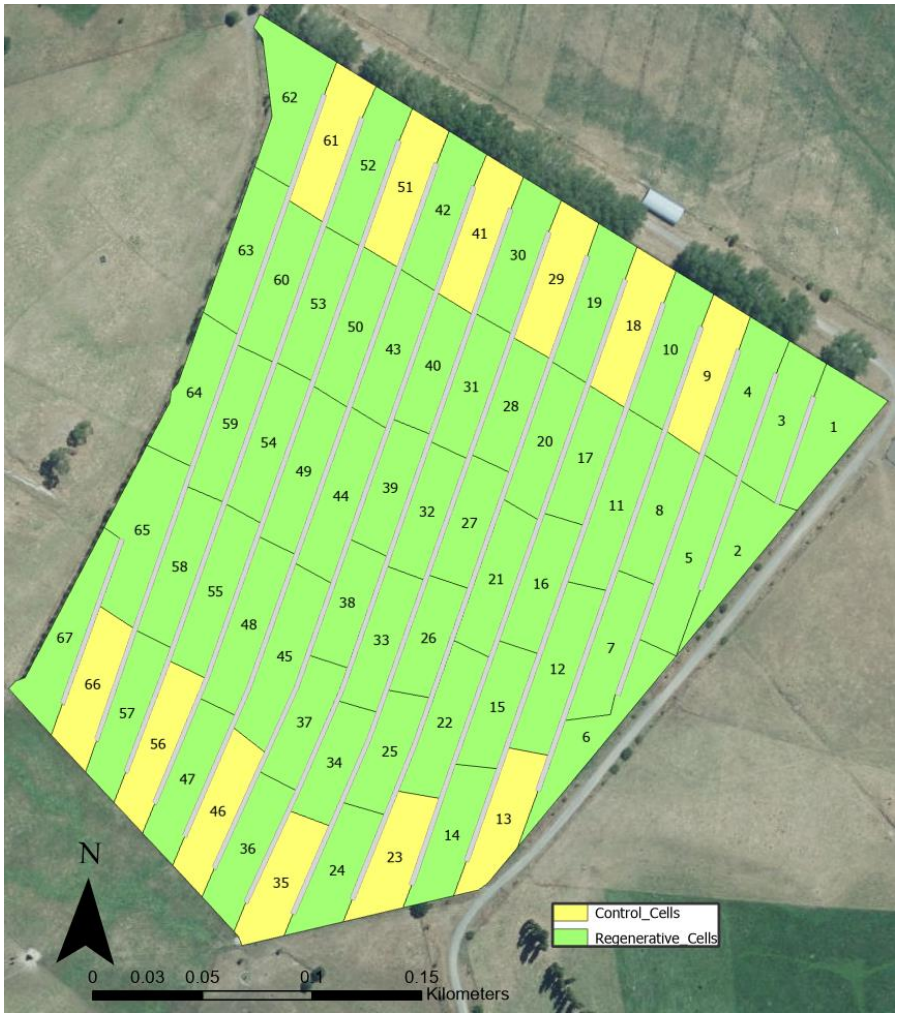


Figure 4.1: Map of the grazing site on Mangarara farm

4.2.2 Description of grazing events

Four grazing events were compared, starting on 20/12/2022 and finishing on 3/01/2023. The amount of rainfall, number of cattle, stocking density and time cattle grazed each cell are recorded in Table 4.1. The grazing events overlap with the last day of one grazing being the start of the next grazing event, as the cattle were moved during the middle of the day.

4.2.2.1 Grazing one

In grazing 1, the regenerative cells stocking density ranged from 169,194 to 217,842 kg live weight (LW)/ha, with a mean of 184,540 kg live weight/ha (Table 4.1). Stocking density for each cell was calculated as the number of cattle grazing the cell, multiplied by the average cattle weight (kg) and divided by the area (ha) of the cell (Scarnecchia, 1985). The control cells stocking density ranged from 19,462 to 19,627 kg LW/ha, with a mean of 19,545 kg LW/ha. The time regenerative cattle spent in the cells ranged from 5 hr to 19.5 hr, with a mean of 11 hr. Whereas the control cells spent 85 hr within each cell.

4.2.2.2 Grazing two

In grazing 2, the regenerative cell stocking density ranged from 153,860 to 207,566 kg LW/ha, with a mean of 182,484 kg LW/ha (Table 4.1). The control cell stocking density ranged from 18,677 to 19,462 kg LW/ha, with a mean of 19,070 kg LW/ha. The time regenerative cattle spent in the cells ranged from 6 hr to 18.5 hr, with a mean of 12 hr spent in the cell, whereas the control treatment cattle spent 74 hr grazing the cell.

4.2.2.3 Grazing three

In grazing 3, the regenerative cell stocking density ranged from 173,244 to 220,020 kg LW/ha, the mean being 196,594 kg LW/ha (Table 4.1). The control cell stocking density ranged from 18,984 to 19,300 kg LW/ha, the mean being 19,142 kg LW/ha. The time regenerative cattle spent in the cell ranged from 3 hr to 17 hr, with a mean of 10 hr. The control animals spent 79 hr grazing the cell.

4.2.2.4 Grazing 4

In grazing four, the regenerative cell stocking density ranged from 180,344 to 22,4510 kg LW/ha, with a mean of 204,632 kg LW/ha (Table 4.1). The control cell stocking density ranged from 19,300 to 19,462 kg LW/ha, and the mean was 19,381 kg live weight/ha. The time the regenerative cattle spent in the cell ranged from 5 hr to 15 hr, and the mean time spent grazing the cell was 9 hr. The control cattle spent a mean of 92 hr grazing the cells.

Table 4.1: Grazing treatment, rainfall, number of cattle, stocking density and time cattle grazed each cell for grazings 1-4.

Cell	Treatment	Pasture	Rain (mm)	Cattle number	Stocking density (kg liveweight/ha)	Time in cell (hour)	Cell size (ha)
Grazing 1 (20/12/2022 to 24/12/2022)							
1	Regenerative	Fescue	0.4	57	164,194	5.0	0.13
2	Regenerative	Fescue	7.2	57	186,458	13.0	0.12
3	Regenerative	Fescue	1.1	57	178,878	19.5	0.12
4	Regenerative	Fescue	0.2	57	183,350	5.5	0.12
5	Regenerative	Fescue	0.7	57	217,842	7.0	0.10
6	Regenerative	Ryegrass	0.0	57	169,246	15.0	0.13
7	Regenerative	Ryegrass Fescue	2.7	57	183,350	7.5	0.12
8	Regenerative	Fescue	23.0	57	193,000	14.5	0.11
9	Control	Fescue	35.3	6	19,462	85.0	0.12
13	Control	Ryegrass	31.8	6	19,627	85.0	0.12
Grazing 2 (24/12/2022 to 27/12/2022)							
10	Regenerative	Fescue	0.0	57	181,835	11.0	0,12
11	Regenerative	Fescue	0.0	57	153,860	14.5	0.14
12	Regenerative	Ryegrass	0.7	57	153,860	12.5	0.14
14	Regenerative	Ryegrass	0.0	57	181,835	11.0	0.12
15	Regenerative	Ryegrass	0.0	57	207,566	6.0	0.11
16	Regenerative	Fescue	0.0	57	194,708	18.5	0.11
17	Regenerative	Fescue	0.0	57	203,722	7.5	0.11
18	Control	Fescue	0.7	6	18,677	74.0	0.12
23	Control	Ryegrass	0.5	6	19,462	74.0	0.12
Grazing 3 (27/12/2022 to 30/12/2022)							
19	Regenerative	Fescue	0.0	57	181,835	17.0	0.12
20	Regenerative	Fescue	0.0	57	188,051	11.5	0.12
21	Regenerative	Fescue	0.0	57	188,051	12.0	0.12
22	Regenerative	Ryegrass	0.0	57	173,244	12.0	0.13
24	Regenerative	Ryegrass	0.0	57	183,350	3.0	0.12
25	Regenerative	Ryegrass	0.0	57	209,543	6.0	0.11
26	Regenerative	Ryegrass	0.0	57	220,020	14.0	0.10
27	Regenerative	Fescue	0.0	57	209,543	5.5	0.11
28	Regenerative	Fescue	0.0	57	215,706	8.0	0.10
29	Control	Fescue	0.0	6	18,984	79.0	0.12
35	Control	Ryegrass	0.5	6	19,300	79.0	0.12
Grazing 4 (30/12/2022 to 3/01/2023)							
30	Regenerative	Fescue	0.7	57	183,350	11.0	0.12
31	Regenerative	Fescue	0.0	57	203,722	10.0	0.12
32	Regenerative	Fescue	0.0	57	211,558	15.0	0.10
33	Regenerative	Ryegrass	0.0	57	196,446	7.0	0.11
34	Regenerative	Ryegrass	0.6	57	215,706	5.0	0.10
36	Regenerative	Ryegrass	1.7	57	180,344	12.0	0.12
37	Regenerative	Ryegrass	1.3	57	207,566	7.0	0.11
38	Regenerative	Ryegrass	0.2	57	224,510	5.0	0.10
39	Regenerative	Fescue	0.8	57	211,558	12.0	0.10
40	Regenerative	Fescue	1.0	57	211,558	8.0	0.10
41	Control	Fescue	5.6	6	19,462	92.0	0.12
46	Control	Ryegrass	5.1	6	19,300	92.0	0.12

4.2.3 Drone mounted camera method

A DJI Mavic 3 drone fitted with an RGB camera (20MP camera, f/2.8-f/11 adjustable aperture and vision detection autofocus technology (VDAF) (DJI, 2023) was used in the current study. The drone was flown at an altitude of 30m to avoid trees located along the boundary of one end of the trial site. The drone was flown within two days of cattle grazing a cell, and a photogrammetry technique was used, which involved capturing multiple photos of the cell with at least 75% overlap of each image. The images were imported into the app of Pix4dreact version 1.4.2, which joined all images into one. This process was repeated every two to three days for three weeks to capture the images of all the regenerative and control grazing cells following grazing. The Pix4d images were then uploaded into ArcGIS Pro version 2.9.0. The date the grazing and drone images were taken are presented in Appendix 2.1.

4.2.4 Dung location

The dung patches were digitally identified by visual observation using ArcGIS Pro. The colour bands were inverted from band one (blue instead of red) to band three (red instead of blue) to assist with identification and create a contrast between dung patches and the surrounding pasture and bare soil. Following identification, the number of dung patches were divided by the area of the cell (ha) to calculate the number of dung patches/ha. An automated method of locating dung patches was explored as a potential method in the current research, however it was discovered that high proportions of bare ground, as present in the current study, interfered with the accurate locating of dung patches.

4.3.1 Statistical analysis

The outcome variable was dung patches/ha. The exposure variables of interest were treatment (control or regenerative) by grazing number, pasture type by grazing number, grazing number (1 to 4) (and rainfall and time in cell). The median, interquartile range (IQR) and range, or mean and standard deviation (SD) were calculated for the dung patches/ha, as appropriate. Figures were presented as box and whiskers plots. Significance difference was determined using the P-value from the Wilcox test. Significant associations between the effect of grazing treatment and pasture type on dung patches/ha were examined using a Kruskal-Wallis non-parametric test. Local Moran's I tests were used to assess the spatial distribution of dung within all cells, within cells for each grazing and between control cells. All temporal statistical analyses were conducted in R version 4.1.2 (Appendix 2.2). All spatial statistical analyses were conducted in ArcGIS Pro. Calculation for dung patches per hour, is the total number of dung patches per ha divided by the time cattle were in the cell. The amount of

dung/ha/hr was multiplied by 24hr and then divided by the number of animals in the cell to calculate the amount of dung/animal/day.

4.4 Results

4.4.1 Effect of grazing treatment on the number of dung patches/ha

When stratified for each treatment, the overall mean was 1,391 dung patches/ha, the regenerative mean was 1,610 dung patches/ha and the control treatment was 1,173 dung patches/ha. There was no significant difference (P=0.078) in dung patches/ha between the treatments, but there was a significant difference (P=0.045) in dung patches/ha between grazing one and four

4.4.1.1 Grazing one

In grazing one, the median number of dung patches/ha in the regenerative cells was 1,204 (IQR 912 to 1,607) dung patches/ha (Figure. 4.2). In the control cells the median was 1,036 (IQR 754 to 1,319; maximum 3,098) dung patches/ha. There was no significant difference (p=0.6604) in dung patches/ha between treatments for grazing one.

4.4.1.2 Grazing two

In grazing two, the median for the regenerative cells was 1,454 (IQR 936 to 2,060) dung patches/ha (Figure. 4.2). The median for the control cells was 1,122 (IQR 940 to 1,305) dung patches/ha, but there was no significant difference (P=0.889) between the treatments.

4.4.1.3 Grazing three

In grazing three, the regenerative cell median was 1,314 (IQR 901 to 1,855) dung patches/ha (Figure 4.3). The median in the control cells was 973 (IQR 856 to 1,090) dung patches per ha. There was no significant difference (P=0.2182) between the treatments.

4.4.1.4 Grazing four

In grazing four, the median for the regenerative cells was 2,118 (IQR 1,754 to 2,458) dung patches/ha (Figure 4.3). The median in the control cells was 1,560 (IQR 1,393 to 1,726) dung patches/ha. There was no significant difference (P=0.2727) between the treatments.

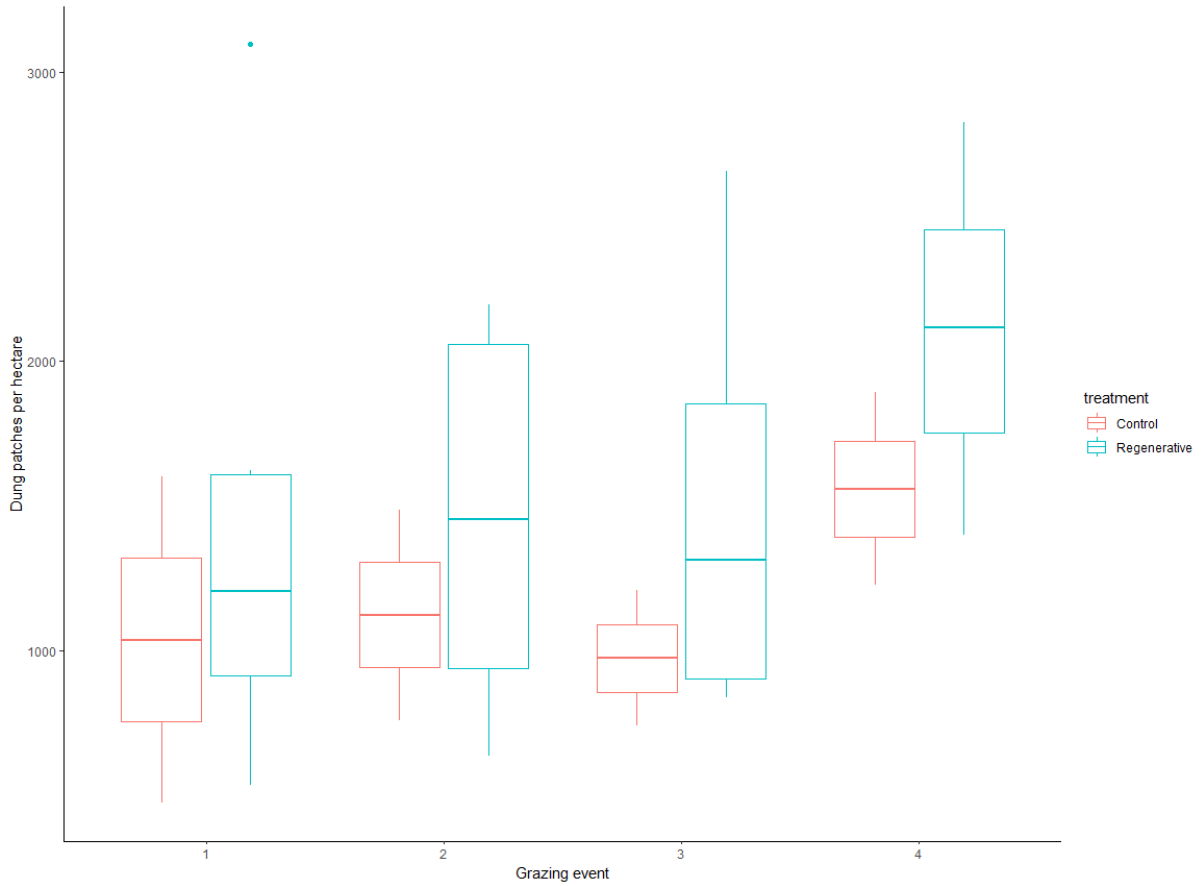


Figure 4.2: Box and whisker plots comparing the number of dung patches/ha following each grazing treatments for the four grazing events, showing the median, upper and lower quartile for each treatment and grazing.

4.4.2 Effect of pasture type on the number of dung patches/ha

The overall mean of dung patches/ha for cells dominated by fescue pasture was 1169, whereas the mean for ryegrass was 1,676 dung patches/ha. The mean number of dung patches/ha for the regenerative cells with fescue was 1,539 (IQR 993 to 2,019) and the regenerative cells with ryegrass was 1,805 (IQR 1,693 to 2,198). The control cells with fescue pasture measured a mean of 798 dung patches/ha (IQR 671 to 875) and the control cells with ryegrass was 1,547 (IQR 1,417 to 1,674) dung patches/ha.

There was an overall pasture type effect (P=0.04847). Between grazings there was a significant difference in the number of dung patches/ha in fescue cells (P=0.04) and no significant difference between the number of dung patches/ha in ryegrass cells (P=0.49). The pairwise comparisons of treatment and grazing on fescue pasture is presented in Table 4.2. There was a significant difference between the number of dung patches/ha for regenerative cells (grazing 4) and all control cells (P=0.02). There was also a significant difference in the

number of dung patches between regenerative cells in grazing 3 and grazing 4 (P=0.02), when the pasture type was fescue.

4.4.2.1 Regenerative cells-Grazing one.

The median number of dung patches/ha in the regenerative cells for grazing one was 1,119 (IQR 830 to 1,446) and 1,623 for fescue and ryegrass, respectively (Figure. 4.3).

4.4.2.2 Regenerative cells-Grazing two.

The median number of dung patches/ha on the regenerative cells for grazing two on fescue pasture was 1,328 (IQR 1,061 to 1,608) dung patches/ha (Figure 4.3). The median for the regenerative cells on ryegrass was 2,049 (IQR 1360 to 2124) dung patches per ha (Figure 4.3).

4.4.2.3 Regenerative cells-Grazing three.

The median number of dung patches/ha on the fescue pasture for the regenerative cells for grazing three was 1,231 (IQR 901 to 1,314) dung patches/ha. The median for the regenerative cells for grazing 3 on ryegrass was 1832 (IQR 1,490 to 2,143) dung patches per ha (Figure 4.3).

4.4.2.4 Regenerative cells-Grazing four

The median number of dung patches/ha for the regenerative cells for grazing four on the fescue pasture was 2,528 (IQR 2,019 to 2,731) dung patches/ha. The median number of dung patches/ha for the regenerative cells for grazing four on the ryegrass pasture was 1,794 (IQR 1,741 to 2,217) dung patches/ha (Figure 4.3).

4.4.2.5 Control cells

The control (all control cells combined) cells had a median of 748 (IQR 671 to 875) and 1,554 dung patches/ha (IQR 1417 to 1674) on fescue and ryegrass pasture, respectively (Figure 4.3).

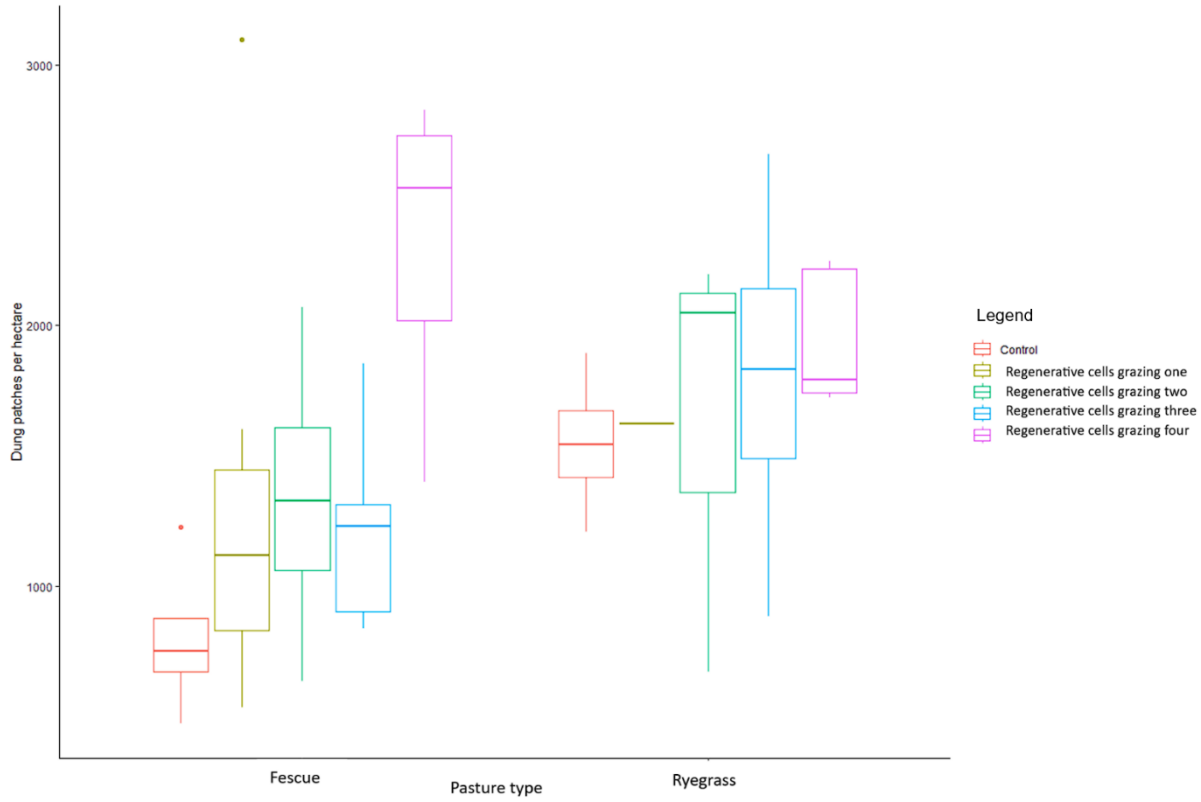


Figure 4.3: Box and whisker plots comparing the number of dung patches/ha measured for each treatment and each grazing, as influence by pasture type of either fescue or ryegrass. Showing the median, upper and lower quartile for each treatment and grazing.

Table 4.2: Pair wise comparison between the regenerative cells for each grazing event (1-4) and all the control cells on fescue pasture.

Pasture type		**Regenerative grazing one**	**Regenerative grazing two**	**Regenerative grazing three**	**Regenerative grazing four**
Fescue	**Regenerative grazing two**	0.788	-	-	-
Fescue	**Regenerative grazing three**	0.876	0.905	-	-
Fescue	**Regenerative grazing four**	0.073	0.111	0.016	-
Fescue	**Control**	0.315	0.343	0.063	0.016
Ryegrass	**Regenerative grazing two**	1.000	-	-	-
Ryegrass	**Regenerative grazing three**	0.800	0.905	-	-
Ryegrass	**Regenerative grazing four**	0.330	0.790	0.730	-
Ryegrass	**Control**	0.800	0.630	0.490	0.110

4.4.3 Comparison of time spent on cell compared to dung patches/ha/hr

The mean number of dung patches/ha/hr in the regenerative cells (grazing 1) was 128 (SD 40), 123 (SD 55) for grazing 2, 176 (SD 87) for grazing 3 and 251 (SD 74) for grazing 4. (Table 4.5). The control treatment (all controls for each grazing pooled together) showed the mean dung patches/ha/hr was 14 (SD 6). There was a 9 to 18-fold difference in the number of dung patches/ha/hr between the regenerative and control cells. The number of dung patches/ha/hr increased with each grazing. The dung patches/animal/day there was no difference between regenerative and control treatment.

Table 4.3: Drone measured dung patches/ha/hr and per day calculated for each regenerative cell and the control cells combined from the number of dung patches measured in each cell after grazing.

Regenerative grazing one			Regenerative grazing two			Regenerative grazing three			Regenerative grazing four			Control cells		
Cell	**Dung /ha/hr**	**Dung/ animal/ day**	**Cell**	**Dung /ha/hr**	**Dung/ animal/ day**	**Cell**	**Dung /ha/hr**	**Dung/ animal/ day**	**Cell**	**Dung /ha/hr**	**Dung/ animal/ day**	**Cell**	**Dung /ha/hr**	**Dung/ animal/ day**
1	199	11	10	58	3	19	53	3	30	127	6	9	6	3
2	123	6	11	83	5	20	161	7	31	253	12	13	19	9
3	159	8	12	164	10	21	103	5	32	182	8	18	10	5
4	97	5	14	200	10	22	141	8	33	249	12	19	9	10
5	160	7	15	112	5	24	294	15	34	359	15	23	20	5
6	108	6	16	112	5	25	329	15	36	187	10	35	15	7
7	89	5	17	194	9	26	190	8	37	317	14	41	13	6
8	89	4				27	152	7	38	345	14	46	21	10
						28	164	7	39	236	10			
									40	252	11			

4.4.4 Spatial distribution and clustering of dung patches result.

4.4.4.1 Local Moran's I results for all cells

Figure 4.4 shows the spatial distribution and clustering of dung patches throughout the four grazing events in all 42 cells of the trial site. Dung was not randomly spaced within cells, instead it was clustered over space and time. In grazing one and into grazing two, there was a significantly lower spatial autocorrelation of dung patches compared to the mean, indicating a lower number of dung patches per cell when compared to neighbouring cells (low-low cluster). In the middle of the study period, there was no significant spatial autocorrelation or clustering. At the end of the study period there was a high spatial autocorrelation, with more dung patches per cell than the mean (high-high cluster). There were no outliers in the dataset.

Figure 4.4: Local Moran's I for all cells. The black cell outline indicates the control cells marked with a C. The red cell outline indicates the cells grazed under regenerative practices, black cells control grazing. Each dot represents a dung patch, and the colour of the dots represent a different degree of clustering from not significant to high-high cluster.

4.4.4.2 Grazing one

In grazing one the first two and a half cells (cells 1, 2 and 3) were low-low, indicating a significantly lower risk of clustered dung patches compared to the mean. In the middle cells (cells 3, 4, 5, 6 and 7) there were no significant clusters. The last four and a half cells (cells 7, 8 ,9 and 13) are high–high clusters, indicating a high risk of dung patches. The control cell dung patches are high-high. This showed that the dung was not evenly distributed throughout the cells, with the number and distribution of dung patches increasing over time.

4.4.4.3 Grazing two

In grazing two, the first three cells (cells 10, 11 and 12) were low-low, indicating a significantly lower risk of clustered dung patches compared to the mean. In the middle cells (cells 14, 15 and 16) there were no significant clusters. The last three and a half cells (cells 16, 17, 18 and 23) are high–high clusters, indicating a high risk of dung patches. The control cell dung patches are high-high. This showed that the dung was not evenly distributed throughout the cells, with the number and distribution of dung patches increasing over time.

4.4.4.4 Grazing three

In grazing three, the first three and a half cells (cells 19, 20, 21 and 22) were low-low, indicating a significantly lower risk of clustered dung patches compared to the mean. In the middle cells (22, 24, 25 and 26) there were no significant clusters. The last four and a half cells (cells 26, 27, 28, 29 and 30) are high–high clusters, indicating a high risk of dung patches. The control cell dung patches are high-high. This showed that the dung was not evenly distributed throughout the cells, with the number and distribution of dung patches increasing over time.

4.4.4.5 Grazing four

In grazing one, the first four cells (cells 30. 31, 32 and 33) were low-low, indicating a significantly lower risk of clustered dung patches compared to the mean. In the middle cells (cells 34, 36, 37 and 38) there were no significant clusters. The last four cells (cells 39, 40, 41 and 46) are high–high clusters, indicating a high risk of dung patches. The control cell dung patches are high-high. This showed that the dung was not evenly distributed throughout the cells, with the number and distribution of dung patches increasing over time.

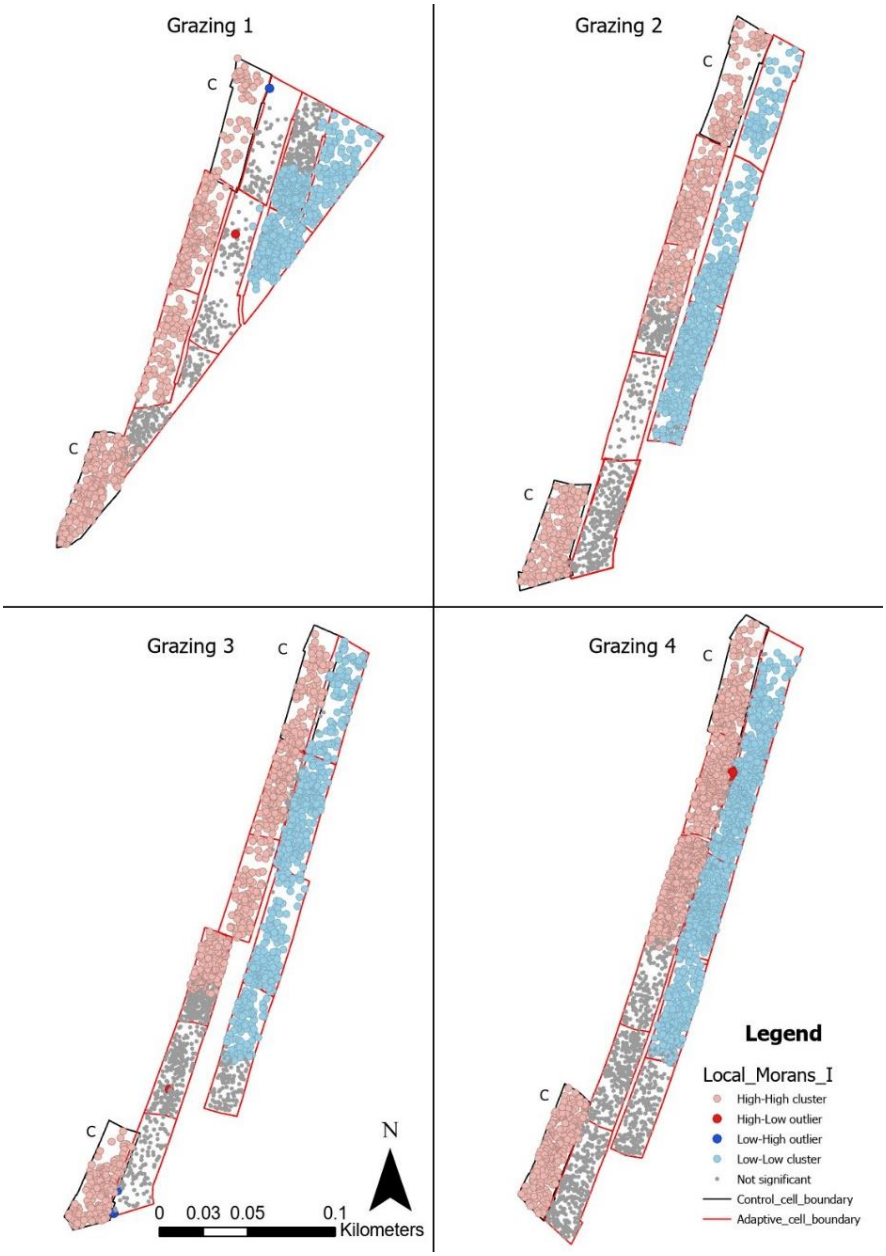


Figure 4.5: Local Moran's I test for the four grazing events. Regenerative cells are shown with a red outline and control cells have a black outline and are marked with a C next to each control cell.

4.4.4.6 Grazing event summary

The number of high-high, low-low and non-significant clusters for each grazing event is presented in Figure 4.6. All the control cells were high-high, with spatially clustered dung patches higher than the mean.

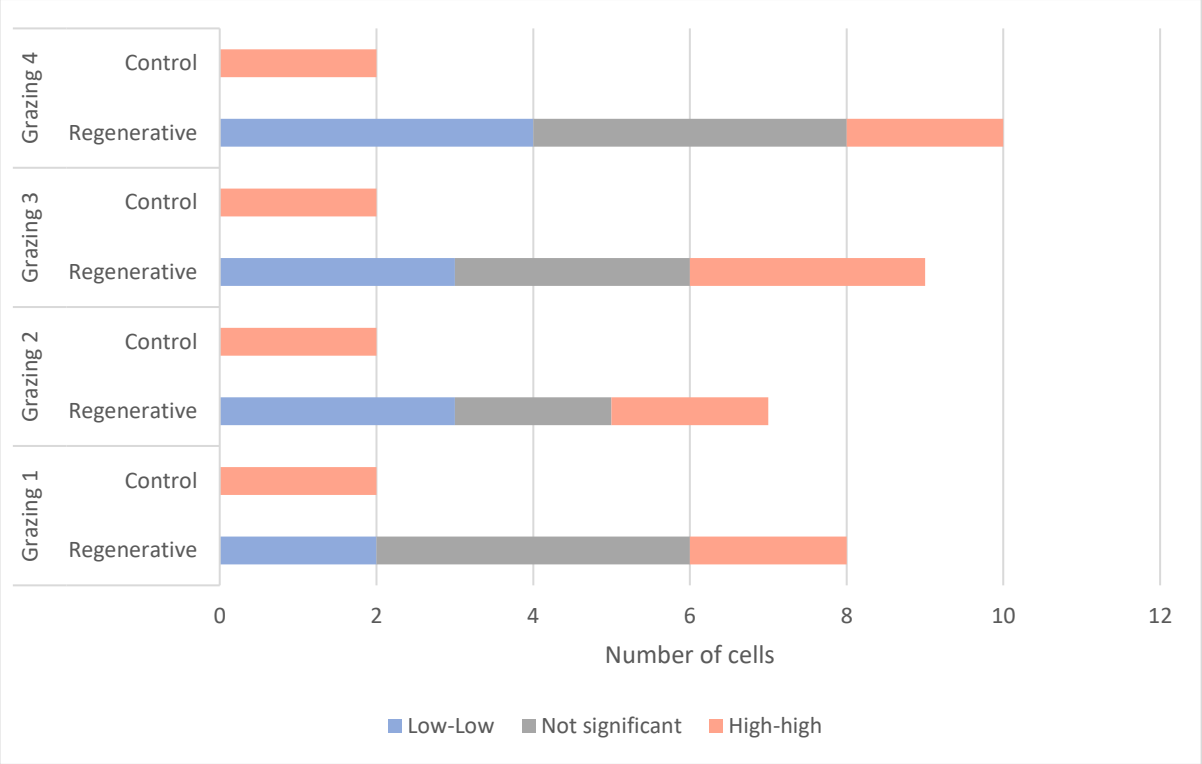


Figure 4.6: The local Moran's I result on clustering of dung patches/ha for each grazing event to show the difference between the control and regenerative grazing treatments.

4.5 Discussion

The objective of this chapter is to determine if the spatial distribution of the dung changes under high stocking density compared to low stocking density. To the authors knowledge, there are no previous studies that have looked at the number and distribution of cattle dung between regenerative and conventional grazing practices. Development of this knowledge is important as it can improve our understanding of soil nutrient distribution and cycling and the potential impact that regenerative management may have on nutrient loss risk. It is possible that a higher stocking density could lead to more even distribution of cattle dung, which could lower the risk of nutrient loss to the environment from overland flow.

The overall number of dung patches/ha in the cells under a regenerative grazing practice was higher than in cells under control grazing, as well as for all four grazing events (Figure 4.2). While the difference was not statistically significant, the trend observed in the current study is similar to previous research findings in this area. Past research identified a significant higher number of dung patches/ha under a higher stocking density using a grid method (Morton & Baird, 1990; Thorrold et al., 1985; DeRamus et al., 2015). Of the comparable studies, only one used Angus heifers, but the stocking rate changed to maintain pasture height, and cattle were moved more slowly than the current study. There are several reasons why significant

differences were not identified in the current study. Firstly, the lack of sensitivity of the drone method to identify dung patches may have been a reason, as past research used a grid method which has a higher sensitivity. Secondly, in the current study, the stocking rate (stock units/ha) stayed the same while the stocking density changed. Whereas in past research, the stocking rate changed by increasing the number of stock grazing over the same area and time in order to create a higher stocking rate and in turn a higher stocking density (Morton & Baird, 1990; Thorrold et al., 1985; DeRamus et al., 2015). This suggests that if the stocking rate stays the same even when changing the stocking density, there is likely to be no difference in the number of dung patches/ha. Thirdly, two of the past research studies studied sheep rather than cattle, which could lead to a different result (Morton & Baird, 1990; Thorrold et al., 1985). Whereas one of the studies used Angus heifers, similar to the current study (DeRamus et al., 2015).

The lack of difference between the regenerative and control treatments in the current study could also be caused by some cells having a lower-than-expected number of dung patches/ha compared to other cells in the grazing treatments. In grazing four, no cells had a lower than-expected number of dung patches/ha compared to other cells within the grazing event (Appendix 2.3). Multiple factors affecting the drone mounted camera method's ability to identify dung patches have previously been identified in Chapter 3. Some examples include grazing one, where cell one measured 993 dung patches/ha, which is lower than other cells, as cattle only spent 5 hours within the cell, which is lower than the other cells within the grazing event. In grazing two, cell 15 measured 670 dung patches/ha and cattle spent 6 hr within the cell, which is lower than other cells within the grazing. In grazing three, cell 19 measured 901 dung patches/ha, which is lower than other cells due to the amount of bare soil present in the cell leading to issues with identification of dung patches.

The findings in Chapter 3 suggest that bare soil interference could influence the amount of dung patches measured within the cell. Another cell that was lower than expected, was cell 24, which measured 838 dung patches/ha due to the cows spending 3 hr within the cell, which is lower than the other cells. As shown in past research, the time the cattle spend in an area affects the number of dung patches present. The longer, animals spend in an area, the more dung patches are deposited (Oudshoorn et al., 2008).

This study found that pasture type influenced the number of dung patches/ha for the regenerative cells for each grazing event and for all control cells. The fescue pasture measured less dung patches/ha compared to ryegrass. Fescue is more productive during summer and wetter conditions than ryegrass (Milne et al., 1997) and grows in a more upright

and clumpier form (Kerrisk & Thomson, 1990) than ryegrass. The unseasonably wet summer experienced in the current study meant that the fescue pasture had higher growth rates and yield than the ryegrass pasture. This led to clumpier fescue plants which created more shading from the drone compared to ryegrass. Therefore, if the dung was deposited next to a clump of fescue it could be shaded from the drone. This finding was observed in Chapter 3 with the kernel density showing the difference between the systematic method to the drone method on the fescue pasture. Therefore, the different growth characteristics of fescue could explain the lower number of dung patches/ha measured compared to ryegrass pasture in the current study. Sward type and height is an area for further investigation in the detection of dung using drone technology to understand what factors will affect the drone accuracy.

There was a difference in the rate at which the dung patches were deposited within the cells, as shown by the dung patches/ha/hr (Table 4.5). Results show that more dung patches/ha/hr was being deposited in the regenerative treatment compared to the control treatment. This could be due to the higher number of animals stocked in the regenerative treatment (57) compared to the control cells (6). However, as the number of dung patches/ha/hr was higher, the number of dung patches/animal/day was roughly the same for the regenerative and control treatment. This is to be expected as past research has shown cattle will defecate on average 6 to 12 times a day (Weeda, 1967), which is within the range measured in the current study. This shows that the regenerative treatment with the higher stocking density is depositing the same number of dung patches daily as the control, just at a faster rate. This is likely as a result of the number of times the cattle are being shifted to fresh pasture under the regenerative treatment.

The local Moran's I result for all cells (Figure 4.4) shows no difference in the dung distribution between the control and regenerative treatment. Across grazing 1 to 4, the spatial distribution changed from low risk, to non-significant, to high risk of dung clustering. When the local Moran's I test was stratified to each grazing event, it showed that the control treatment dung patches were highly clustered together. The regenerative treatment was more variable, with the dung patches being less clustered together at the start and only highly clustered at the end of the grazing. The Local Moran's I result for each grazing event (Figure 4.5 and Figure 4.6) shows there is more variability between each grazing event which would indicate that there was a change in the distribution of dung to be more evenly distributed through the cell and less clustered under the regenerative grazing treatment compared to the control treatment. This matches previous research, which indicates that under a higher stocking

density, the distribution of dung patches were more evenly distributed than under lower stocking density (Morton & Baird, 1990; Thorrold et al., 1985; DeRamus et al., 2015).

However, this result does not show how great this difference was. The results only indicate a difference in the distribution of dung under regenerative treatment compared to the control treatment. However, it is likely that this change in dung distribution could lead to dung being dispersed over a greater area, leading to higher and more even nutrient return to the soil to be available for plant uptake. More even distribution of dung within a paddock also reduces the risk of nutrient hot spots associated with animal camping areas. Previous research has also shown an association between dung and increased soil water infiltration capacity (Blanco-Canqui et al., 2013). It is possible that more evenly distributed dung could result in less overland flow and a lower risk of nutrient loss. However, more research is needed to measure the difference in dung distribution between the regenerative and control treatment and if this difference influences other factors, such as nutrient return to the soil and overland flow.

4.6 Conclusion

The research conducted in this chapter showed that a drone-mounted camera method can be used to effectively locate and compare dung deposits under regenerative and control grazing management across four grazing events. Results showed no difference in the number of dung patches/ha between the regenerative and control treatments for each grazing event. As the sample size was small, with only four grazings, more research is needed to test further if regenerative and control grazing treatments affect the number of dung patches/ha.

The research showed that pasture type affected the number of dung patches/ha measured and that fescue pasture resulted in a lower number of dung patches/ha. This was due to fescue's increased growth rate in the summer months and the wet summer conditions experienced with the current study resulting in clumpy fescue which shaded dung patches, making them difficult to detect using a drone-mounted camera.

The research also showed a difference in the dung patches/ha/hr between regenerative cells for each grazing and the control cells. This showed that even with no difference in the dung patches/ha, there was a difference in the number of dung patches/ha/hr, due to the number of animals grazing the regenerative cells compared to the control cell.

The local Moran's I showed that dung was not evenly spread throughout the cell based on the differences in the degree of clustering. The results for all cells showed little to no difference in

the dung patch distribution between the control and regenerative cells. However, when the local Moran's I test was applied to each grazing event, it indicated that dung was more evenly distributed through the cell and less clustered under the regenerative grazing treatment compared to the control treatment, a finding which is in line with previous research on the effects of increased stock density on dung distribution. More detailed research is needed to understand what is causing this change in dung distribution associated with the grazing treatment.

Chapter 5

General discussion

5.1 Chapter summary.

The validation of the drone fitted with an RGB camera (Chapter 3) was able to identify dung patches in pasture grazed under a high and low stocking density and regenerative pasture management. The results showed that the drone-based technology identified, on average, 57% of the dung patches identified by visual assessment (Table 3.2). On average, the drone camera identified 62% of dung patches in the regenerative cells and 44% of dung patches in the control cells (Table 3.2). The kernel density mapping tool showed that the dung patches identified by the drone had a very similar spatial distribution of the dung patches mapped within cells by the manual method, providing further confidence in the drone images for mapping the distribution of dung patches within the cell.

The drone was more effective in identifying dung patches in cells under a regenerative grazing practice, possibly due to the fresher dung patches, as the grazing duration was measured in hours in any one cell. In the cells under the control treatment, animals were in each cell for several days, with a higher risk of dung patches being disturbed by the animal. These findings suggest that measuring dung deposits as close to deposition as possible could improve the percentage of the dung patches identified by the drone method.

Following the validation of the drone identification of dung patches, Chapter 4 compared the spatial distribution of dung patches between control and regenerative grazing treatments. The results show no significant difference in the number of dung patches/ha between the two grazing treatments (regenerative vs control) at any of the compared grazing events. When the comparison was limited to the fescue-based pastures, there was a significant statistical difference between the number of dung patches/ha in the cells grazed following regenerative grazing practices compared with the cells grazed by conventional practices at the fourth grazing event. No differences were found when the analysis was limited to the ryegrass-based pastures or when the data from the two pasture types were compared. The absence of any differences in the number of dung patches/ha was unexpected as past research has shown that at a higher stocking density, there were more dung patches present (Morton & Baird, 1990; Thorrold et al., 1985; DeRamus et al., 2015). However, an explanation can be that the stocking rates between the two grazing practices were the same, which differs with past research.

A key finding of this study was that the spatial distribution of dung under regenerative management showed a lower cluster than dung under the control treatment. This suggests that the high stocking density under the regenerative grazing management resulted in less camping and a more even return of dung to the cells. More even distribution of dung following the regenerative grazing treatment is likely to lead to more even soil nutrient distribution and therefore lower risk of nutrient loss associated with nutrient hot spots within the cells.

5.2 Constraints and potential improvements to the use of the drone-based approach to identifying and mapping dung patches.

During the research project, several limitations were identified, some of which could be addressed by further refinements to the drone-based approach. One of the constraints to the use of drone technology is related to the weather, (i) the general restrictions that weather imposes on the use of drone technology and (ii) the impact of specific weather events on the collection of data in the current study.

5.2.1 Impact of weather conditions on drone use.

The drone could not fly in strong winds or during a rainfall event. This can limit the number of days that the drone could be flown during a study. More importantly, it might not be able to be used on specific dates required as part of the sampling regime. For example, in the present study, data collection was interrupted by the weather which prevented the flying of the drone. This limited the collection to only four out of the six grazing events. Given that our findings indicated that dung should be measured as close to deposition as possible, this limitation could limit the quality of data collected. The fallback position would be to revert to a manual identification of dung patches using the grid approach. The drone can handle winds up to 43.2 km/hr of wind (DJI, 2023), however, even close to that wind speed, the quality of the drone images is likely to be compromised due to difficulty in keeping the drone steady, compared to lower wind speed. The current study did not examine the impact of wind speed on image quality but was very mindful of its impact on the quality of the imagery. Another consideration of stronger winds and greater turbulence was that the drone battery drained more rapidly due to the motors having to work harder to stabilize the drone, thereby reducing the total area that could be covered in a session. The drone used in the current study could not fly in the rain, as it was water resistant but not waterproof. The other issue with rainfall is its impact on the integrity of the dung patch deposited by the animal. The fresher the dung, the higher the accuracy of the drone method.

5.2.2 Impact of weather on pastures and dung patches.

The weather was unusual during this research, with higher-than-normal rainfall throughout much of 2022. Over the summer months, 167mm of rain fell over November and December. Central Hawkes Bay's long-term average annual rainfall is usually between 100 to 120 mm over these months (Chappell, 2023). The higher rainfall experienced during the study period likely led to higher pasture masses with higher moisture content, resulting in dung with a more liquid consistency (During & Weeda, 1973) that did not form easily identifiable discrete dung patches. In contrast, this watery dung left a light covering of dung on plant leaves and in the base of plants rather than on the soil surface. This led to the dung being shaded by the pasture plants, making it difficult to identify with the drone camera. The other limitation related to the liquid dung, was that it resulted in dung being more dispersed over a larger area and caused overlap between multiple dung patches, making it hard to identify if it was a single or multiple dung patch. This suggests that the drone method should not be used during certain times of the year when dung has a more liquid consistency. In contrast, the drone method is likely to work during periods when the dung has a lower water content and forms discrete easily discernable patches.

5.2.3 Identification of dung patches.

At times it was difficult for the drone camera to distinguish between a dung patch and bare soil, particularly when wet and damaged by the grazing animal, as the colours were the same. The lack of colour difference was amplified when the soils were wet and during a grazing event. This led to the mud being the same dark colour as the dung patches. In the summer months, when the soils were dry and there were fewer rain events, the soil colour was much lighter, providing a greater contrast with a dung patch. This finding showed that dung distribution studies should be conducted in drier seasons, to improve detection of dung patches. The percentage of bare soil was not calculated in this thesis as the time frame did not allow the drone to be validated in terms of correctly measuring the amount of bare soil.

5.2.4 Identifying the dung patches from the drone imagery.

Manual identification and marking of dung patches from the drone image also had its challenges, as this process can lead to human error and mismarking of dung patches. This could lead to a higher false negative or positive rate within the cell. The increase in false positives could be from the pasture causing shade, with shading seen as dung patches by the human eye. An increase in false negatives can be caused by the human eye being unable to distinguish between multiple dung patches or wrongly selecting shaded areas as dung patches. An AI programme that can locate dung patches within the drone image could be

developed to reduce the uncertainty associated with using the human eye and the variance that different operators would introduce. AI programmes, through the use of training data to learn what a dung patch looks like within a drone image, would lead to greater consistency in the location of dung patches than are currently possible with the human eye. Such an approach would reduce the number of false negatives and false positives. Although the current research project did not explore AI, as this was outside the scope of the study, the data generated in the study could be used for training within an AI programme, addressing the limitations mentioned above. Hyperspectral imaging would have helped with identifying dung patches, however it was not able to be used in this study due to its high cost and the limited time frame of the research project. Image classification was not able to be used in the current study, due to the large amount of bare ground present, which leads to errors when bare ground is mistaken for dung patches.

5.2.5 Summary.

Despite the limitations identified, the current study showed that a drone is able to detect dung patches after a grazing event with an accuracy of 57%. Improvements in this accuracy are likely if the drone was flown in a drier summer, as there would have been a greater contrast between the pasture and dung, (Trudgill et al., 2010) and the dung would have been more solid (During & Weeda, 1973), making locating and differentiating between one or multiple dung patches easier. Drier conditions would also have meant less pugging and bare soil and less treading of dung into the soil (Collins et al., 2007). Drier weather conditions with little wind also means fewer interruptions to drone flights and more opportunities to fly the drone immediately after grazing when the dung is fresh and easier to detect.

5.3 Study implications.

This novel research provided a foundation for examining the potential of drone cameras to identify and locate the spatial distribution of dung patches under different grazing practices and on contrasting pasture types. The research points to the likely further work to refine the RGB drone camera method, including the use of AI for training to improve the identification and measuring of the spatial distribution of dung in grazed systems. Further research is required to understand the conditions the method works best and what grazing conditions affect measurement accuracy. This could be achieved by testing the method under a greater range of grazing intensities and also under a greater range of pasture heights and different crop types. This would allow further refinements around the recommendations for when drone accuracy will be highest.

This research has made an important contribution to knowledge as it provides a new method of using a drone fitted with an RGB camera to locate and measure the spatial distribution of cattle dung under high and low stocking density. This method provides a cheaper and faster alternative to locate the spatial distribution of cattle dung compared to the existing manual visual grid method. This new method will open up opportunities to study dung distribution by a wider range of people, over a larger area and under more challenging topography, such as hill country. An improved understanding of the spatial distribution of dung under various conditions and different land uses will allow the identification of nutrient hot spots and critical source areas within the grazing area and also the degree to which the grazing practices influence nutrient transfer by the animal, the single biggest factor determining annual nutrient requirements in a grazed system. This research provides the first steps to understanding the dung distribution of cattle dung under regenerative agricultural grazing management and can provide a starting point for other researchers to continue to study dung distribution under this management practice. This could lead to a greater understanding of the effect of regenerative agricultural management on the nutrient transfer factor and potential impacts on freshwater quality.

5.4 Regenerative management impact on whole system.

While the study did not measure wider differences between regenerative and conventional grazing management impacts on the farm system, drone images allowed a visual inspection to be made between the two treatments (Fig. 5.1). Impacts ranged from the pugging of soil, the opening of the pasture and animals trampling pasture into the soil. These factors are of interest to the current thesis, as they could inform us of other impacts not measured in the current study.

The drone images suggest that the impact of pugging by animals may be greater under regenerative management and higher stock densities than under conventional management and lower stock densities. More rain events (more than twice the seasonal average) meant the soil was continuously wet for long periods and so softened and vulnerable to damage. This was coupled with the high stocking density in the regenerative treatment, increasing the risk of pugging (Beukes et al., 2013). An example of the difference is found in Figure 5.1. It shows that the conventional paddock in the middle has less visible pugging damage than the regenerative paddocks surrounding it. The increase in pugging also increases the risk of sediment loss via overland flow (Donovan & Monaghan, 2021). If sediment loss increases, there is also an increased risk of dung and nutrients being lost from pasture soils to receiving environments.

Pugging damages the structure of soil and creates bare ground due to pasture damage. An increase in bare soil can lead to a lower number of plants to capture the nutrients being returned by the dung patches, therefore increasing the risk of nutrients being lost via overland flow. Pugging also affects soil structure and can lead to a decrease in the infiltration rate and therefore higher risk of overland flow (Donovan & Monaghan, 2021).

Figure 5.1: An example of the physical damage (pugging) to pasture and soil from cattle grazing on regenerative and control treatments. A black outline around the cell identifies control cells. The degree of soil damage is identified by the amount of bare ground within the cells.

Trampling pasture into the soil will influence the amount of carbon being returned to the soil. In this research, it would appear that there was more trampling of pasture into the soil in the regenerative cells. Increased trampling of pasture into the soil could lead to an increase in soil organic carbon and an increase the soil's biological activity. However, an increase in bare soil, may also result in a lowering of soil carbon under this management, so more research is needed to understand the effect of this grazing management practice on soil carbon dynamics.

These observations (Fig 5.1) suggest that when soils are wet, higher stocking densities should not be used as they are likely to increase the risk of soil damage and sediment and dung loss. In summer or dry periods, the higher stocking density related to regenerative management could be used to increase the tramping of pasture into the soil, decreasing the risk of sediment and dung being lost in surface runoff by increasing the amount of pasture that will catch the cattle dung before it can leave the paddock or farm boundary.

5.5 Conclusion.

Overall, this study has shown that a drone-mounted camera can be used to identify dung patches of cattle and also to map the spatial distribution of the cattle dung. As shown in Chapter Three, the accuracy of the drone was, on average, 57% compared to the systematic GPS ground truth assessment. Chapter Four showed that dung distribution tended to be more even under the high stocking density associated with regenerative grazing management, which has important implications for soil nutrient recycling and nutrient loss risk. The study identified that dung detection could be improved by sampling in summer, when there was less risk of pugging damage, a greater colour contrast between dung and background pasture and dung had a firmer consistency. A wider observation of the study was that higher stocking density may increase pugging damage during wet soil conditions and this risk needs to be explored in more detail in future studies.

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Appendix

1.1 R studio code for Sp and Se

```
##Sensitivity and specificity
library(readxl)
library(epiR)
library(ggplot2)
library(tidyverse)

dat$cell <- as.factor(dat$cell)

list<-levels(dat$cell)
temp<-lapply(list, function(x){
  data=filter(dat, cell %in% x)
  tmp <- as.matrix(cbind(data$dis_pos, data$dis_neg, data$test_pos, data$test_neg))
  cell1 <- epi.tests(tmp, method = "exact", digits = 2,
                     conf.level = 0.95)
  s<-(cell1)
  print(s)
})

list<-levels(dat$cell)
temp<-lapply(list, function(x){
  data=filter(dat, cell %in% x)
  tmp <- as.matrix(cbind(data$dis_pos, data$dis_neg, data$test_pos, data$test_neg))
  cell1 <- epi.tests(tmp, method = "exact", digits = 2,
                     conf.level = 0.95)

  se<-cell1$detail[cell1$detail$statistic == "se",]
  sp<-cell1$detail[cell1$detail$statistic == "sp",]

  test <- data.frame(Sensitivity = se$est, Specificity = sp$est)
  print(test)
})
```

1.2 R studio code for ROC curve

```
#ROC curves
####

#generate the dataset
##############################
gps <- c(rep(1, times = 1560), rep(0, times = 1105))
drone <- c(rep(1, times = 911), rep(0, times = 649), rep(1, times = 911), rep(0, times = 194))
cell <-c(rep(1, times = 2665))
type <-c(rep("Regenerative", times=2665))
data <- data.frame(cell,type, gps, drone)

gps <- c(rep(1, times = 856), rep(0, times = 1983))
drone <- c(rep(1, times = 797), rep(0, times = 59), rep(1, times = 797), rep(0, times = 1186))
cell <-c(rep(2, times = 2839))
type <-c(rep("Regenerative", times=2839))
data1 <- data.frame(cell,type, gps, drone)
xtabs(~gps + drone, data = data1)
data <-rbind(data, data1)

gps <- c(rep(1, times = 1292), rep(0, times = 2089))
drone <- c(rep(1, times = 1146), rep(0, times = 146), rep(1, times = 1146), rep(0, times =
943))
cell <-c(rep(3, times = 3381))
type <- c(rep("Regenerative", times = 3381))
data1 <- data.frame(cell, type, gps, drone)
xtabs(~gps + drone, data = data1)
data <-rbind(data, data1)

gps <- c(rep(1, times = 1083), rep(0, times = 2242))
drone <- c(rep(1, times = 1050), rep(0, times = 33), rep(1, times = 1050), rep(0, times =
1192))
cell <-c(rep(4, times = 3325))
type <- c(rep("Regenerative", times = 3325))
data1 <- data.frame(cell, type, gps, drone)
xtabs(~gps + drone, data = data1)
```

```
data <-rbind(data, data1)

gps <- c(rep(1, times = 3871), rep(0, times = 4257))
drone <- c(rep(1, times = 3099), rep(0, times = 772), rep(1, times = 3099), rep(0, times =
1158))
cell <-c(rep(5, times = 8128))
type <- c(rep("Regenerative", times = 8128))
data1 <- data.frame(cell, type, gps, drone)
xtabs(~gps + drone, data = data1)
data <-rbind(data, data1)

gps <- c(rep(1, times = 1975), rep(0, times = 3385))
drone <- c(rep(1, times = 1934), rep(0, times = 34), rep(1, times = 1934), rep(0, times =
1451))
cell <-c(rep(36, times = 5360))
type <- c(rep("Regenerative ", times = 5360))
data1 <- data.frame(cell, type, gps, drone)
xtabs(~gps + drone, data = data1)
data <-rbind(data, data1)

gps <- c(rep(1, times = 2245), rep(0, times = 3245))
drone <- c(rep(1, times = 2094), rep(0, times = 151), rep(1, times = 2094), rep(0, times =
1151))
cell <-c(rep(37, times = 5490))
type <- c(rep("Regenerative ", times = 5490))
data1 <- data.frame(cell, type, gps, drone)
xtabs(~gps + drone, data = data1)
data <-rbind(data, data1)

gps <- c(rep(1, times = 4041), rep(0, times = 5092))
drone <- c(rep(1, times = 3908), rep(0, times = 133), rep(1, times = 3908), rep(0, times =
1184))
cell <-c(rep(38, times = 9133))
type <- c(rep("Regenerative ", times = 9133))
data1 <- data.frame(cell, type, gps, drone)
xtabs(~gps + drone, data = data1)
```

```
data <-rbind(data, data1)

gps <- c(rep(1, times = 857), rep(0, times = 1882))
drone <- c(rep(1, times = 748), rep(0, times = 109), rep(1, times = 748), rep(0, times =
1134))
cell <-c(rep(41, times = 2739))
type <- c(rep("Control", times = 2739))
data1 <- data.frame(cell, type, gps, drone)
xtabs(~gps + drone, data = data1)
data <-rbind(data, data1)

gps <- c(rep(1, times = 1542), rep(0, times = 2450))
drone <- c(rep(1, times = 1475), rep(0, times = 67), rep(1, times = 1475), rep(0, times =
975))
cell <-c(rep(46, times = 3992))
type <- c(rep("Control", times =3992))
data1 <- data.frame(cell, type, gps, drone)
xtabs(~gps + drone, data = data1)
data <-rbind(data, data1)

gps <- c(rep(1, times = 1017), rep(0, times = 2387))
drone <- c(rep(1, times = 857), rep(0, times = 160), rep(1, times = 857), rep(0, times =
1530))
cell <-c(rep(51, times = 3404))
type <- c(rep("Control", times =3404))
data1 <- data.frame(cell, type, gps, drone)
xtabs(~gps + drone, data = data1)
data <-rbind(data, data1)

gps <- c(rep(1, times = 1314), rep(0, times = 2612))
drone <- c(rep(1, times = 1207), rep(0, times = 107), rep(1, times = 1207), rep(0, times =
1405))
cell <-c(rep(56, times = 3926))
type <- c(rep("Control", times =3926))
data1 <- data.frame(cell, type, gps, drone)
xtabs(~gps + drone, data = data1)
```

```
data <-rbind(data, data1)

#xtabs(cell ~gps + drone, data = data)

##Make variables "factors"
data$cell <- as.factor(data$cell)
data$type <- as.factor(data$type)
data$gps <- as.factor(data$gps)
data$drone <-as.factor(data$drone)

#ROC with all data (Regenerative and Control)
m <- glmer(gps ~ drone +
           (1 | cell), data = data, family = binomial)

data$predicts <- predict(m, newdata = data, type = "response")

roc_empirical <- rocit(score = data$predicts, class = data$gps,
                       negref = "0")
plot(roc_empirical, values = T)

#ROC curve with Regenerative only
data %>%
  filter(type == " Regenerative ") %>%
  roc("gps", "predicts", percent=T, plot=T, ci=T, grid=TRUE, print.auc=TRUE)

  roc_empirical_ Regenerative <- rocit(score = data$predicts[data$type==" Regenerative "],
class = data$gps[data$type==" Regenerative "],
                       negref = "0")
  plot(roc_empirical_ Regenerative, values = F)

#ROC Curve with control only
  data %>%
    filter(type == "Control") %>%
    roc("gps", "predicts", percent=T, plot=T, ci=T, grid=TRUE, print.auc=TRUE)
```

```
roc_empirical_ Regenerative <- rocit(score = data$predicts[data$type=="Control"], class =
data$gps[data$type=="Control"],
                    negref = "0")
plot(roc_empirical_ Regenerative, values = F)
```

2.1 Description of grazing date and drone images taken

Cell	Date of grazing	Date of drone flight	Cell	Date of grazing	Date of drone flight
1	20/12/2022	22/12/2022	22	28/12/2022	30/12/2022
2	20/12/2022	22/12/2022	23	24/12/2022 - 27/12/2022	28/12/2022
3	21/12/2022	22/12/2022	24	29/12/2022	30/12/2022
4	22/12/2022	22/12/2022	25	29/12/2022	30/12/2022
5	22/12/2022	24/12/2022	26	29/12/2022	30/12/2022
6	22/12/2022	24/12/2022	27	30/12/2022	30/12/2022
7	23/12/2022	24/12/2022	28	30/12/2022	1/01/2023
8	23/12/2022	24/12/2022	29	27/12/2022 – 30/12/2022	1/01/2023
9	20/12/2022 – 24/12/2022	24/12/2022	30	30/12/2022	1/01/2023
10	24/12/2022	24/12/2022	31	31/12/2022	1/01/2023
11	24/12/2022	26/12/2022	32	31/12/2022	1/01/2023
12	25/12/2022	26/12/2022	33	1/01/2023	3/01/2023
13	20/12/2022 – 24/12/2022	24/12/2022	34	1/01/203	3/01/2023
14	25/12/2022	26/12/2022	35	27/12/2022 – 30/12/2022	3/01/2023
15	26/12/2022	28/12/2022	36	1/01/2023	3/01/2023
16	26/12/2022	28/12/2022	37	2/01/2023	3/01/2023
17	27/12/2022	28/12/2022	38	2/01/2023	3/01/2023
18	24/12/2022 - 27/12/2022	28/12/2022	39	2/01/2023	3/01/2023
19	27/12/2022	28/12/2022	40	3/01/2023	5/01/2023
20	27/12/2022	28/12/2022	41	30/12/2022 – 3/01/2023	3/01/2023
21	28/12/2022	30/12/2022	46	30/12/2022 – 3/01/2023	3/01/2023

2.2 R Studio code for KW test

```
# Import libraries
library(readxl)
library(ggplot2)
library(tidyverse)

if(!require('dplyr')) {
  install.packages('dplyr')
  library('dplyr')
}

if(!require('janitor')) {
  install.packages('janitor')
  library('janitor')
}
############
head(dat)

dat$tx <- as.factor(dat$tx)
dat$treatment <- as.factor(dat$treatment)
dat$tx1 <- as.factor(dat$tx1)
dat$rain_b <- as.factor(dat$rain_b)
dat$rye <-as.factor(dat$rye)

levels(dat$treatment)
levels(dat$tx)
levels(dat$tx1)
levels(dat$rain_b)
levels(dat$rye)

###############
#by treatment (overall)
group_by(dat, treatment) %>%
  summarise(
    count = n(),
```

```
    mean = mean(dung, na.rm = TRUE),
    sd = sd(dung, na.rm = TRUE),
    median = median(dung, na.rm = TRUE),
    p25 = quantile(dung, probs= 0.25, na.rm = TRUE),
    p75 = quantile (dung, probs= 0.75, na.rm=TRUE),
    max = max (dung, na.rm=TRUE)
     )
#by treatment and cell group
group_by(dat, tx, treatment) %>%
  summarise(
    count = n(),
    mean = mean(dung, na.rm = TRUE),
    sd = sd(dung, na.rm = TRUE),
    median = median(dung, na.rm = TRUE),
    p25 = quantile(dung, probs= 0.25, na.rm = TRUE),
    p75 = quantile (dung, probs= 0.75, na.rm=TRUE),
    max = max (dung, na.rm=TRUE)
  )
#by treatment and cell group, with control treated as one group (not 1-4)
group_by(dat, tx1) %>%
  summarise(
    count = n(),
    mean = mean(dung, na.rm = TRUE),
    sd = sd(dung, na.rm = TRUE),
    median = median(dung, na.rm = TRUE),
    p25 = quantile(dung, probs= 0.25, na.rm = TRUE),
    p75 = quantile (dung, probs= 0.75, na.rm=TRUE),
    max = max (dung, na.rm=TRUE)
  )



p <- ggplot(dat, aes(x=treatment, y=dung, color=tx)) +
  geom_boxplot()
p + theme_classic()
```

```
q <- ggplot(dat, aes(x=tx, y=dung, color=treatment)) +
  geom_boxplot()
q + theme_classic()


q <- ggplot(dat, aes(x=tx1, y=dung, color=tx1)) +
  geom_boxplot()
q + theme_classic()
#######
#Describe the rest of the data
######
#By treatment
group_by(dat, treatment) %>%
  summarise(
    count = n(),
    mean = mean(stock, na.rm = TRUE),
    sd = sd(stock, na.rm = TRUE),
    median = median(stock, na.rm = TRUE),
    p25 = quantile(stock, probs= 0.25, na.rm = TRUE),
    p75 = quantile (stock, probs= 0.75, na.rm=TRUE),
    max = max (stock, na.rm=TRUE)
  )

group_by(dat, treatment) %>%
  summarise(
    count = n(),
    mean = mean(time2, na.rm = TRUE),
    sd = sd(time2, na.rm = TRUE),
    median = median(time2, na.rm = TRUE),
    p25 = quantile(time2, probs= 0.25, na.rm = TRUE),
    p75 = quantile (time2, probs= 0.75, na.rm=TRUE),
    max = max (time2, na.rm=TRUE)
  )

group_by(dat, treatment) %>%
  summarise(
```

```
    count = n(),
    mean = mean(rain, na.rm = TRUE),
    sd = sd(rain, na.rm = TRUE),
    median = median(rain, na.rm = TRUE),
    p25 = quantile(rain, probs= 0.25, na.rm = TRUE),
    p75 = quantile (rain, probs= 0.75, na.rm=TRUE),
    max = max (rain, na.rm=TRUE)
  )

group_by(dat, treatment) %>%
  tabyl (treatment, rain_b)

group_by(dat, treatment) %>%
  tabyl (treatment, rye)

#by treatment and cell group
group_by(dat, tx, treatment) %>%
  summarise(
    count = n(),
    mean = mean(stock, na.rm = TRUE),
    sd = sd(stock, na.rm = TRUE),
    median = median(stock, na.rm = TRUE),
    p25 = quantile(stock, probs= 0.25, na.rm = TRUE),
    p75 = quantile (stock, probs= 0.75, na.rm=TRUE),
    max = max (stock, na.rm=TRUE)
  )

group_by(dat, tx, treatment) %>%
  summarise(
    count = n(),
    mean = mean(time2, na.rm = TRUE),
    sd = sd(time2, na.rm = TRUE),
    median = median(time2, na.rm = TRUE),
    p25 = quantile(time2, probs= 0.25, na.rm = TRUE),
    p75 = quantile (time2, probs= 0.75, na.rm=TRUE),
    max = max (time2, na.rm=TRUE)
```

```
  )

group_by(dat, tx, treatment) %>%
  summarise(
    count = n(),
    mean = mean(rain, na.rm = TRUE),
    sd = sd(rain, na.rm = TRUE),
    median = median(rain, na.rm = TRUE),
    p25 = quantile(rain, probs= 0.25, na.rm = TRUE),
    p75 = quantile (rain, probs= 0.75, na.rm=TRUE),
    max = max (rain, na.rm=TRUE)
  )

group_by(dat, tx, treatment) %>%
  tabyl (tx, rain_b, treatment)

group_by(dat, tx, treatment) %>%
  tabyl (tx, rye, treatment)

#by treatment and cell group, with control treated as one group (not 1-4)
group_by(dat, tx1) %>%
  summarise(
    count = n(),
    mean = mean(stock, na.rm = TRUE),
    sd = sd(stock, na.rm = TRUE),
    median = median(stock, na.rm = TRUE),
    p25 = quantile(stock, probs= 0.25, na.rm = TRUE),
    p75 = quantile (stock, probs= 0.75, na.rm=TRUE),
    max = max (stock, na.rm=TRUE)
  )

group_by(dat, tx1) %>%
  summarise(
    count = n(),
    mean = mean(time2, na.rm = TRUE),
    sd = sd(time2, na.rm = TRUE),
```

```
    median = median(time2, na.rm = TRUE),
    p25 = quantile(time2, probs= 0.25, na.rm = TRUE),
    p75 = quantile (time2, probs= 0.75, na.rm=TRUE),
    max = max (time2, na.rm=TRUE)
  )

group_by(dat, tx1) %>%
  summarise(
    count = n(),
    mean = mean(rain, na.rm = TRUE),
    sd = sd(rain, na.rm = TRUE),
    median = median(rain, na.rm = TRUE),
    p25 = quantile(rain, probs= 0.25, na.rm = TRUE),
    p75 = quantile (rain, probs= 0.75, na.rm=TRUE),
    max = max (rain, na.rm=TRUE)
  )

group_by(dat, tx1) %>%
  tabyl (tx1, rain_b)

group_by(dat, tx1) %>%
  tabyl (tx1, rye)

#######
#Boxplots of the other variables
q <- ggplot(dat, aes(x=rye, y=dung, color=tx1)) +
  geom_boxplot()
q + theme_classic()

gplot(dat, aes(x=time2, y=dung, shape=tx1, color=tx1)) +
     geom_point() +
     geom_smooth(method=lm, se=FALSE, fullrange=TRUE)

#By treatment and cell
kruskal.test(dung ~ tx1, data = dat)
pairwise.wilcox.test(dat$dung, dat$tx1)
```

```
q <- ggplot(dat, aes(x=tx1, y=dung, color=tx1)) +
  geom_boxplot()
q + theme_classic()
#by rye and tx1

kruskal.test(dung ~ rye, data = dat)
spairwise.wilcox.test(dat$dung, dat$rye)

q <- ggplot(dat, aes(x=rye, y=dung, color=tx1)) +
  geom_boxplot()
q + theme_classic()



kruskal.test(dat$dung[dat$rye==0] ~ dat$tx1[dat$rye==0], data = dat)
kruskal.test(dat$dung[dat$rye==1] ~ dat$tx1[dat$rye==1], data = dat)

pairwise.wilcox.test(dat$dung[dat$rye==0], dat$tx1[dat$rye==0], p.adjust.method = "none")
pairwise.wilcox.test(dat$dung[dat$rye==1], dat$tx1[dat$rye==1], p.adjust.method = "none")
```

2.3 Dung patches per ha for each treatment for each grazing

Grazing event 1			Grazing event 2			Grazing event 3			Grazing event 4		
Cell	**Treat**	**DP/ ha**	**Cell**	**Treat**	**DP/ha**	**Cell**	**Treat**	**DP/ ha**	**Cell**	**Treat**	**DP/ ha**
1	R	993	10	R	636	19	R	901	30	R	1400
2	R	1602	11	R	1203	20	R	1855	31	R	2528
3	R	3098	12	R	2049	21	R	1231	32	R	2731
4	R	533	14	R	2198	22	R	1693	33	R	1741
5	R	1119	15	R	670	24	R	883	34	R	1794
6	R	1623	16	R	2071	25	R	1971	36	R	2246
7	R	667	17	R	1454	26	R	2660	37	R	2217
8	R	1289				27	R	838	38	R	1724
						28	A	1314	39	R	2827
									40	R	2019
Range		2565			1562	Range		1822	Range		1427
Median		1204			1454	Median		1314	Median		2118
9	C	471	18	C	758	29	C	738	41	C	1227
13	C	1602	23	C	1487	35	C	1208	46	C	1892
Range		1131	Range		729	Range		470	Range		665
Median		1036	Median		1123	Median		973	Median		1559
Overall Median		1204			1454	Overall Median		1231	Overall Median		1955