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An investigation of change in drone practices in broadacre farming environments

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An Investigation of Change in Drone Practices in Broadacre Farming Environments

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Abstract

The application of drones in broadacre farming is influenced by novel and emergent factors. Drone technology is subject to legal, financial, social, and technical constraints that affect the Agri-tech sector. This research showed that emerging improvements to drone technology influence the analysis of precision data resulting in disparate and asymmetrically flawed Ag-tech outputs. The novelty of this thesis is that it examines the changes in drone technology through the lens of entropic decay. It considers the planning and controlling of an organisation's resources to minimise harmful effects through systems change. The rapid advances in drone technology have outpaced the systematic approaches that precision agriculture insists is the backbone of reliable ongoing decision-making. Different models and brands take data from different heights, at different times of the day, and with flight of differing velocities. Drone data is in a state of decay, no longer equally comparable to past years' harvest and crop data and are now mixed into a blended environment of brand-specific variations in height, image resolution, air speed, and optics. This thesis investigates the problem of the rapid emergence of image-capture technology in drones and the corresponding shift away from the established measurements and comparisons used in precision agriculture. New capabilities are applied in an ad hoc manner as different features are rushed to market. At the same time existing practices are subtly changed to suit individual technology capability. The result is a loose collection of technically superior drone imagery, with a corresponding mismatch of year-to-year agricultural data. The challenge is to understand and identify the difference between uniformly accepted technological advance, and market-driven changes that demonstrate entropic decay.

The goal of this research is to identify best practice approaches for UAV deployment for broadacre farming. This study investigated the benefits of a range of characteristics to optimise data collection technologies. It identified widespread discrepancies demonstrating broadening decay on precision agriculture and productivity. The pace of drone development is so rapidly different from mainstream agricultural practices that the once reliable reliance upon yearly crop data no longer shares statistically comparable metrics. Whilst farmers have relied upon decades of satellite data that has used the same optics, time of day and flight paths for many years, the innovations that drive increasingly smarter drone technologies are also highly problematic since they render each successive past year's crop metrics as outdated in terms of sophistication, detail, and accuracy. In five years, the standardised height for recording crop data has changed four times. New innovations, coupled with new rules and regulations have altered the once reliable practice of recording crop data. In addition, the cost of entry in adopting new drone technology is sufficiently varied that agriculturalists are acquiring multiple versions of different drone UAVs *with variable camera and sensor settings, and vastly different approaches in terms of flight records, data management, and recorded indices. Without addressing this problem, the true benefits of optimization through machine learning are prevented from improving harvest outcomes for broadacre farming.*

The key findings of this research reveal a complex, constantly morphing environment that is seeking to build digital trust and reliability in an evolving global market in the face of rapidly changing technology, regulations, standards, networks, and knowledge. The once reliable discipline of precision agriculture is now a fractured melting pot of "first to market" innovations and highly competitive sellers. The future of drone technology is destined for further uncertainty as it struggles to establish a level of maturity that can return broadacre farming to consistent global outcomes.

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1 INTRODUCTION

Agricultural production systems in Australia are undergoing extensive technological changes with the introduction of digital agricultural solutions, the use of machine learning, drones, and automated vehicle machinery. These technologies have the potential to improve the productivity of broadacre farming in WA by assisting farmers to make better strategic decisions in real-time and with long-term planning (Hu et al 2018; Ayamga et al 2021). This has already been shown for cropping scenarios in WA and Internationally (Armstrong et al 2020), (Van Es and Woodard, 2017). The use of drones has already been shown to be an effective tool for growers in the monitoring and analysis of crops and livestock (Lost et al. 2020; Daponte et al 2019) This is achieved by combining drones, drone sensor technologies, and GPS records management, which allows for the highly accurate monitoring of change and subsequently improved crop management. It is now also possible to closely monitor crop~~s~~ health~~,~~ and soil conditions~~.~~ (Basso, 2020) (Van Es and Woodard, 2017). Drones are now becoming increasingly more affordable and with greater flight and payload capabilities (Upadhyaya et al, 2022; Stehr, 2015). They are being used for many applications across the farm including crop yield, soil and fertilizer management, pest monitoring, and spraying (Daponte et al., 2019).

The emergence of a discipline that encapsulates a holistic discourse on drones and drone technology has brought with ~~is~~it a range of terms, abbreviations, and associated jargon. It also includes a range of dual-meanings and duplicated measurement constraints. For example, some discussions would include a notation of 50 metres in height, whilst others would refer to measurements of 150 feet in height. The two measurements are almost the same, however for the purpose of precision agriculture the exact distance is of great importance. 150 metres is 45.72 metres not 50 metres. In the aggregation of precision data such a difference promotes inaccuracies that, over the life of even a small agricultural crop, could easily have enormous and ongoing financial, agricultural, and environmental implications. Such seemingly minor variances might appear frivolous, however in aggregate form, across years of data, they become enormous problems in the search for broadacre optimization in farming. Drone technology brings the promise of clear imagery to a conversation that has been blurred by inaccuracy and poor resolution for many decades. The ongoing quest is therefore useful if standards are precisely maintained, but potentially dangerous if new quests for increased accuracy brings constant change and comparative data that has reduced accuracy in terms of drone operating heights (Truong, et al, 2019; Petrides, et al., 2017).

The inclusion of acronyms and abbreviations is also important to note and include (Joyce et al, 2021). There are different terms of shortened forms that overlap between different fields of interest. Some have emerged from military terminology whilst others are associated with popular themes and widespread leisure usage (Granshaw, 2018). Even the terms UAV and Drone are somewhat interchangeable. Whilst most people are familiar with the concept of an Unmanned Aerial Vehicle (UAV), the full denotation of Dynamic Remotely Operated Navigation Equipment (DRONE) is less widely applied (Chapman, 2014; Chabot, et al., 2022).

Common Terms and Abbreviations

Term	Description	Source
Machine learning	A computer activity which simulated human learning for an expert task. Self-improvement methods of computers identify existing knowledge obtain new knowledge and new skills, to continuously improve performance and achievement.	Wang, Ma and Zhou (2009**)**
Image Processing	Computer activity which simulated human learning for an expert task. Self-improvement methods of computers identify existing knowledge, obtain new knowledge and new skills, to continuously improve the performance and achievement.	Wang, MA and Zhou (2009)
Image processing	Computer processes whose inputs and outputs are images. In addition, processes extract features from images, up to and including the recognition of individual objects.	Gonzalez (2009)
Segmentation	Segmentation subdivides an image into its constituent regions or objects. Segmentation should stop when the objects of interest have been isolated. Segmentation accuracy determines the eventual success or failure of computerized analysis procedures.	Gonzalez (2009) page 567
Optimization	Optimization is a term used in computer science to describe the pursuit of an algorithm that demonstrates the least bad choice for the purpose of maximising a benefit. It is often used in conjunction with machine learning approaches that use complex systems to determine an outcome based on reliable information and data.	
UAS	Unmanned Aircraft System (Original term – now more commonly superseded by the acronym UAV)	Chabot et al, (2022)
UAV	An Unmanned Automated Vehicle (commonly referred to as a Drone) is a flight capable instrument with directional control used for flight, visual analysis, and in some cases the deployment of payload. It is often used in farming for precision agriculture. They operate either autonomously or remotely rather than having an operator on their spindle.	Chabot et al, (2022)
DRONE	Dynamic Remotely Operated Navigation Equipment – Interchangeable with UAV, it is a flight capable UAV.	Chabot et al, (2022)
DECAY	The planning, organising, leading and controlling of an organisation's resources" to minimise the potential of negative effects on the business activity.	Borgsdorf and Pliszka, 1999
ENTROPY	The gradual erosion of seemingly minor systems, practices and controls that lead to significant harm and misunderstanding.	Coole and Brooks (2009)
GSD	Ground Sampling Distance (GSD) is the measurement between 2 consecutive pixel centres measured at ground level. The larger the value of the GSD image, the lower the spatial resolution of the image and the less visible details.	Chabot et al, (2022)
LIDAR	Light Detection and Ranging, (LiDAR) is also known to represent laser imaging, detection, and ranging. It is a method for determining ranges by targeting an object or a surface with a laser and measuring the time for the reflected light to return to the receiver	Chabot et al, (2022)
NDVI	NDVI is the normalized difference vegetation index (NDVI). It is a straightforward graphical indicator that allows for the analysis of remote sensing measurements to distinguish the occurrence of live green foliage and vegetation.	Chabot et al, (2022)
PA	Precision Agriculture is a management strategy that gathers, processes and analyses temporal, spatial, and individual data and combines it with other information to support management decisions in farming enterprises.	Chabot et al, (2022)
UAV CS	Unmanned Automated vehicle Control System: It is a system that is used to control the UAV in real-time (e.g., remote control or via a GPS built-in computer.)	Chabot et al, (2022)
GCS	Ground Control System: A GCS is a device that is used to interact with the UAV control system and monitors the UAV in real-time. The operator can monitor real-time data relevant to the UAV and record data from sensors that are embedded in the UAV such as ground-based sensors.	Chabot et al, (2022)
RGB	The Red, Green and Blue elements within a whole image can be examined by decoding a colour output into three images.	Chabot et al, (2022)
RePL	A Remote Pilot Licence is required to fly drones under an RPA operator's (or ReOC) and operate 25kg – 150kg UAVs for agricultural purposes	Civil Aviation Safety Authority, (2022)
ReOC	A remotely piloted aircraft operators certificate (ReOC) allows you or your business to trade as a drone service provider. It allows you to conduct a range of remotely piloted aircraft	Civil Aviation Safety

		Authority, (2022)
ML	Machine Learning is the usage of processors and computing to study and familiarise to an event without following explicit directions, by means of algorithms and statistical models to draw inferences from patterns in data.	Chabot et al, (2022)
OBIA	Object Based Image Analysis (OBIA) relies upon pixels that are first grouped into objects based on comparison.	Chabot et al, (2022)
BVLOS	BVLOS or beyond visual line of sight refers to drone operations where the drone or aircraft flies beyond the pilot or spotter's line of sight.	Chabot et al, (2022)
TRLs	Technology Readiness Levels (TRLs) are used to evaluate the adoption and acceptance of transformational technology (e.g., Drones in Broadacre Farming)	Chabot et al, (2022)

Table 1.1: Commonly used Terminology, Abbreviation and Jargon

1.1 Background and Context

These introductory remarks indicate the important factors that have arisen from the changes that evolving drone technology has brought to the attention of the agricultural industry. They are ordered in this introduction as a set of challenges that face the broadacre farming industry. These initial thematic statements are more fully examined in the literature review in chapter 2.

The compounding challenges of improved image resolution

One of the demanding areas which is dynamic in terms of quality is the field of image resolution. Resolution is an essential factor to consider when it comes to object detection methods. Higher resolution means better map reconstruction (Aasen et al., 2015; Saxena et al 2020). The issues associated with resolution dynamics are threefold. Firstly, there is a cost involved in continually upgrading equipment to satisfy the need for greater image resolution. This can be cost prohibitive (Ren et al., 2020). Whilst the expected changes suggest that the quality of images will continue to rise in step with improvements in technology, there are many studies that point to a plateau effect that will promote changes in industry around low-cost imagery (Van Der Merwe, et al, 2020; Hafeez et al, 2022; Jiminez-Jiminez and Ojeda-Bustamente, 2021). Secondly, there is an associated challenge because, for example, the comparison of imagery from crop to crop or from year-to-year present different image sizes and resolutions. This makes the task of accurate comparison difficult for ordinary farm environments. Thirdly, and finally, the storage and access of the associated changing imagery is dynamic, meaning that images in higher resolution formats are more difficult to curate. This change in image format leads to an increase in the volume of data in non-sovereign cloud environments.

In addition, there is a technology barrier restricting the access to high-performance drones such as fixed wing aircraft. Whilst farmers and agriculturalists can easily enter the drone market and acquire relatively inexpensive drone equipment, training, and licensing, the jump from simple four-engine quad drones (eg: DJI Phantom, and Mavic) to fixed wing aircraft ~~is~~ represents a significant leap from popular drone usage to a more sophisticated and more expensive environment. Fixed wing drones however offer the ability to acquire the full mapping of a large agricultural property in just a few hours. However, they also require an independently experienced operator, flying at high speeds, beyond line of sight, and over terrain and adjoining properties that would be outside the purview of the standardized farm property fence lines. Fixed wing drones, like WingtraOne which has a 42MP resolution, full-frame camera, make it possible to achieve the same Ground Sampling Distance (GSD) accuracy, while flying higher and covering more area within a similar portion of time (WingtraOne, 2022). Using drones and various cameras with different resolutions it is possible to capture images from a variety of heights and distances to ascertain the image value for higher resolution image capture than existing low-resolution image practices.

In combination with a higher level of image resolution, a more accurate level of decision-making can be obtained using a Deep Lapproach (Pound et al., 2016). Improved image resolution and positioning allows for an improvement in terms of computer vision, object recognition, and classification (Cazzato et al, 2020; Al Sobbahi et al 2022; Gupta et al., 2014). Using a model-based processing block it is possible to convert images to predictions (e.g., concepts, bounding boxes, etc) and, in this instance, a model can be trained to recognize a unique set of output. Bauer et al (2019) reported on the development of open-source platforms that use computer vision machine learning tools and software to estimate crop production for aerial images.

A comprehensive review of the Lost Filho et al study (2019) highlighted the importance of using drones and other UAVs to detect images for non-invasive crop monitoring and chemical application. The research reported on the possibility of using drones in tandem to guide each other to identify pest hotspots or other areas of interest.

Many of the considerations used in assessing the broad range of drone practices are shifting in terms of acceptance and usage. To measure these changes this study uses a risk and decay approach to identify and include those elements that are decaying or at least not growing in strength or acceptance. Thus, this thesis examines the practices where drone usage is susceptible to entropy in the form of uncertainty, disorder, decline, and decay. This study evaluates the changing nature of broadacre farming in terms of drone practices. Whilst many practices are becoming more strongly consolidated there is a wide range of farming-related drone activities that are less rigorous in holistic terms.

Overall, the inclusion~~s~~ of drones and drone technology in agriculture has signalled the advent of a set of dynamic changes and adaptations that face the broadacre farming community. Since many Australian farms are large in acreage yet small in the number of farm workers, the arrival of a tool that is potentially capable of photographing crops, spreading seeds, spreading fertiliser, as well as spraying specific areas in need of weed~~s~~ management, is likely to be a popular piece of technology / farm machinery. If you then add the ability to take precise crop, assist in shepherding livestock, locate lost animals, and detect feral animals and predators, then the expectation of wide-spread usage and inclusion becomes normative.

Challenges with regulations, licensing and compliance

Despite these accolades, the ubiquity and popularity of drone technology in agriculture is both its greatest motivational driver for technology acceptance and simultaneously its most complicated adversary. The increasing demand for licensing, regulation, compliance, and best practice has shown to be a characteristic that boosts the change in industry of a professional farming community that is fragmented by complexity, cost, choice, and confusion. The practices outlined in this study demonstrate a range of activities that are multifaceted in terms of their regulatory and pragmatic appeal. The integration of drone technology into farming practices has generated interest and appeal, whilst at the same time enduring malpractice, malfeasance, and widespread technical illiteracy in the usage of drone technology. This knowledge area is characterised by such widely differing variables and options that it is open to criticism and exposure to threat and increased risk.

Drones are highly efficient aerial devices that have been used to provide unique information about crop and agricultural data. They can create visual and spectral information from a range of aspects, set at different heights and depths, at different locations, and in alternative environments. Despite advances in technology, the application and usage of drones in broadacre farming is influenced by a range of novel and emergent factors. The application of drone technology is subject to legal, financial, social, and technical limitations. The drone technology is relatively new and, as each new aspect of drone development is released, there are a raft of factors that directly affect the ability to remain consistent within the accuracy demands of the Agri-tech sector. This research is significant because it challenges the agricultural industry to accept and deploy new UAV technology whilst at the same time remaining consistent from year to year and crop to crop in terms of data accuracy. The question for broadacre farming is therefore centred on the question of whether drone footage can be accurately compared each year (despite new camera angles, camera resolutions, drone heights, velocities, and all-weather capabilities.

Recent and emerging improvements to drone technology allow for visual data to include Multispectral, Thermal, GIS, RGB, RH, and Lidar imagery. This re-imagining of the usage of drone technology means that data can be obtained rapidly and efficiently to optimise crop outputs. A key challenge is to improve the accuracy of image gathering through a variety of physical, software, and hardware constraints whilst retaining the authenticity of the data that is collected from year to year despite the ongoing expectations for the development and upgrading of equipment and standards associated with UAVs.

This study will investigate the benefits of different pixel images, different resolutions, and a range of characteristics to optimise the choice of camera, imagery, and data collection technologies. It will examine the limitations of UAV usage in terms of equipment, resolution, and deployment characteristics. The goal of this research is to assist drone users in determining minimum guidelines, standards, and best practice approaches for the optimisation of UAV deployment for precision agriculture and broadacre farming needs.

1.1.1 Unmanned aerial vehicles (UAV) as Drones

The definition of a UAV is an aircraft without an operator on board, which can be operated either autonomously or by means of a remote pilot (Sharma et al 2020; Um et al 2019; Hu et al 2018). The first attempt to deploy a UAV was recorded in 1916 (Taylor et al, 1977) and was originally developed for military purposes. For the last 100 years UAVs have worked their way into different sectors such as commercial, scientific, agriculture, and recreation. A strong emergent sector for UAVs is in remote sensing applications for precision agriculture (PA) (Gnädinger and Schmidhalter 2017).

The last decade has seen a set of user case benefits that have been attributed to the inclusion of drones and drone applications in the field of Precision Agriculture (Gupta et al., 2013; Rejeb et al, 2022; Barbedo, 2019). UAV integration into precision agriculture has allowed for a “middle layer” of improved data quality that was previously difficult to obtain (Manfreda et al, 2018; Khaliq et al, 2019). Whilst the past 50 years of precision agriculture has drawn information from a combination of ground data and satellite data, the introduction of drone technology has provided the agricultural industry with a middle layer of data and information that informs the precision agriculture sector within the broader industry. Past efforts to gain above ground data has mostly been limited to satellites (Shendryk et al, 2020). This has been restricted by several factors such as cloud cover, the age of the satellite cameras and the connectivity limitations with networks of sensors (Lee et al, 2019;Shendryk et al, 2020;Manfreda et al, 2018). In addition, the specific time of day that a satellite comes into range over a given section of land can also be a limiting factor in the collection of specific data (Manfreda et al, 2018). The inclusion of the drone middle layer has redefined the way in which agricultural professionals have been able to validate existing data and improve the level of accuracy and measurement that has previously been limited in precision agriculture.

There are several clearly defined advantages to the inclusion of drones into agriculture. One key advantage is that UAVs can be operated either manually or by a pre-determined flight path. The ability to autonomously operate UAVs and collect data under a broad range of conditions means that the data set of information becomes significantly richer, and significantly more reliable in terms of the collation of precision data. From a long-term decision-making perspective, the inclusion of drone usage has dramatically changed the way in which agricultural yields have become more profitable, more stable, and more productive (Rejeb et al, 2022; Tsouros et al 2019; Ayamga et al, 2021).

The following examples provide a background to some of the key factors, both limiting and advantageous, which characterise the emergent dynamics that will drive change and technology acceptance in this sector.

Drone development and change

Whilst there have been some great strides taken in terms of the military development and application of drones (Coutinho et al, 2018; Khoufi et al 2019; Tran et al, 2022), the large proportion of the emergent drone changes are clearly aligned with the leisure and recreational elements of the drone sector (Macrina et al 2020; Ghasri et al 2021; Giacomini et al, 2022). In the last decade many drones have been released to the market that have had sufficient stability, ease of use, and reliability, so that they have gained widespread acceptance within the popular leisure market. These initial drone offerings were widely adopted by individuals and families for recreational purposes. Drone models such as the DJI Phantom 3 and Phantom 4 drones have provided an entry level set of easy to operate UAVs (Chamata and Winterton, 2018; Mills, 2016) that have allowed for the early adoption and exploration in terms of its advantages and opportunities.

These early drone models were also used to quickly determine areas of interest and the early development of the models saw the release, and rapid change, on a range of important structural changes. These drones were used and tested in a range of settings to determine the important requirements for drone technology to enable them to become widely accepted and to develop into a more mature form of UAV technology. At the same time, it became clear that a range of early limitations required a re-think in terms of their use across a wide range of environmentally different landscapes and outdoor elements (both naturally occurring and man-made).

The Challenge for flight time: Batteries and Performance.

Early models were initially limited in terms of three key criteria. These were battery life, stability, and control reliability (Tanaka et al, 2022; Pasha et al, 2022; Chung et al, 2020). Under perfect conditions, drones would operate within standard flight performance criteria in terms of duration, time in air, take-off, and landing. Where battery life was subject to early fade and termination, it became apparent that it was important to establish a significant number of safety controls to allow for the safe return to the ground of drones from different areas, under different wind and light conditions. This helped to establish the reasonable prospect of landing in a controlled manner that would prevent the UAV from sustaining damage to props, parts and UAV structure (Pasha et al 2022). Damage control became an important area of development to ensure that expensive parts, such as cameras, could survive and continue to operate reliably after crashes, hard landings, landings in water, or other collisions where the parts would sustain damage (Tanaka et al, 2022). Thus, much of the early development centred around the ability to get batteries to last for longer and enable drones to operate in a stable manner in the face of harsh wind and rain conditions. Drones were required to perform reliably in conditions that provided a level of hardship that required, physical, electronic, and communications resilience that extended to include extreme factors of operation (Adão et al, 2017).

Flying at different heights above ground level

One of the key challenges for precision agriculture is to ensure that the data collected at one period holds the equal value at another point in time. For example, if we use a drone to capture an overhead pass of a wheat crop and we want to use that overhead pass to compare with other drone data collections, then we need to understand that the camera should be flown at the same time of the day, at the same airspeed, and in the same direction (Martínez et al., 2017; Tu et al. 2020; Tu et al 2018). Each data capture should have the same camera angle and use the same image resolution for the camera. If followed in this way, then future crop analyses can be immediately and directly comparable.

The challenge to find the perfect camera resolution.

The challenge in an early adopter stage is that as the drone market slowly matures it requires successive models to demonstrate additional or improved features. One area of maturation is in terms of camera resolution. Another is in terms of weight, size, and flying speed (Deng et al, 2018; Tu et al. 2020; Adão et al 2017). Features such as these are constantly subject to improvement and change. This study looks at which elements are maturing and offer growth and stability in broadacre farming. The sale and acceptance of drone technology is not yet considered as a mature marketplace. This study considers this factor from the viewpoint of entropy. It looks at those factors that are in gradual decline, or those which are losing structure, or those which may appear to be in a form of disorder. These factors are difficult to reconcile in terms of drone practices because they invoke uncertainty, disorder, randomness, and ambiguity.

The scenario described above could be applied to any technology. However, in the case of drone technology, the difference is that drones are a recent technology that is finding new sales avenues and markets. For example, in Australia a large portion of the uptake of drone technology has been popularised (and therefore rapidly accepted) through the recreation and leisure field. In conjunction with affordable pricing, drone technology has been rapidly taken up across a wide range of both urban and rural areas. (Radoglou-Grammatikis et al 2020; Tran et al, 2022; Ghasri et al 2021).The drones in this entry level bracket are affordable yet sophisticated enough to allow for early market entry by commercial entities for business opportunities using mapping visualisation and image gathering as part of a wider development of the understanding of the power of data gathered from drones. (Hafeez et al, 2022; Van der Merwe, et al, 2020).

The Challenge of new technology and acceptance.

Many farmers have purchased drones for trial purposes, aware that they may get some benefit from their usage, whilst unaware of the ongoing structures and challenges needed to sustain drone usage in a robust and resilient manner. Some farmers have come together to share usage experiences. The majority are in an undecided category, aware of possible benefits, yet un-prepared in terms of the greater technology demands. Agricultural drone practices demonstrate a less-mature part of wider agricultural technology practices. They are dominated by a few technologies and are rapidly developing without unified values and sustainable practices. It is against this backdrop that this thesis examines the broad variety of drone practises and their varying issues.

1.1.2 Emerging challenges for drones

The vast differences between drones of differing shapes and sizes demonstrates the scattered approach that characterises the wide variety of drones and their adaptations. Some drones are built to perform a pay-load driven purpose whilst others are smaller and more lightweight, seemingly designed around maximum battery life and with a focus on range and sustainable time in the air. Other drones place great emphasis on the flexibility in terms of imagery, with a rage of different images including Lidar, NDVI, RGB, and other indices and features. The broad range of drones and specifications is problematic. New models are emerging rapidly, whilst older drone equipment uses systems and controllers that are more comparable with games controllers for younger children than machinery controls that hold appeal for more mature farming stalwarts.

In November 2022, the Mavic 3 Multispectral drone was released by DJI Agriculture in order to spark the development of precision agriculture across the world (Figure 1.1). This drone uses a two in one camera system which consists of a 5 MP multispectral camera and a 4/3-inch

CMOS and 20MP image sensor RGB camera. The drone has an ultra-long battery life of 43 minutes and can complete a mapping operation over an area of 200 hectares in a single flight duration (DJI Mavic 3 multispectral ,2022). The Mavic 3 can support up to 15 km ultra-long transmission distances compares to the P4 multispectral drone which support a transmission distance of 7 km and a maximum battery life of 27 minutes (P4 multispectral – DJI, 2022).

Figure 1.1 DJI Mavic 3 drone (DJI Mavic 3 multispectral ,2022)

The DJI S1000 is an octocopter drone that weighs roughly 4 kg and has a maximum take-off weight of about 11 kg (Figure 1.2). It has a maximum flight time of 15 minutes. Depending on the specific research parameters, these drones can be outfitted with a variety of sensors to help achieve a variety of precision agriculture tasks.

Figure 1.2 A Ping octocopter drone (DJI Spreading wings S1000)

Zhou et al, in 2020 used a DJI S1000 equipped with a Sony Qx-100 HD camera to compare RGB images of a manned ground vehicle (MGV) and unmanned aerial vehicle (UAV) for recognition of maize seedling.

In 2018, Su et al., deployed a DJI S1000 drone with a low cost Five-bands Mica Sense Red Edge multispectral camera to monitor yellow rust in wheat. The image was acquired between 16-24m with a ground resolution of 1-1.5 cm/ pixel. The research has proven that the use of low-cost multispectral camera, low-altitude UAV platform and machine learning techniques can be used to detect yellow rust when it is in diseased stage. The same author, Su et al, (2019) used a similar DJI S1000 to monitor yellow rust in wheat. A Five-bands Mica Sense Red Edge multispectral camera was mounted on the DJI S1000 and the images were acquired from an altitude of about 20 metres.

1.1.3 Cost of Drones

There is a broad range of drone technology that has a relatively low-cost barrier to entry, with a price range of approximately $1000 to $2000 that provides reliable UAV machinery, a reasonably reliable system of control, and an opportunity to trial a combination of software and hardware that is widely compatible with mobile phone technology, mobile tablets, and laptop machines (Ayamga et al. 2021). The initial cost of drones is enticing but, at the same time, is misleading in its general messaging.

Whilst the initial purchase of an entry level system is affordable, the more widely sought-after applications of drone technologies are both increasingly cost prohibitive (Kuzmenko, 2020), and are misrepresented in terms of the true overall cost of a more fully extensive application of the technology (Joiner, 2018; Kuzmenko, 2020). Specialised features that allow for precise imaging and sensor diagnostics add tens of thousands of dollars and require advanced computer skills, software inclusions, and high levels of piloting skill and experience (Agrotechnomarket, 2017). The cost of equipment does not fully explain or properly address the real costs which include training, breakages, and repair work (Ayamga et al. 2021).

Some farmers find that using a drone is a much more awkward activity than driving a large modern tractor. Whilst farmers easily become familiar with farm machinery, drone technology is inherently more fragile, nuanced, and carries the need for a fresh set of skills (Watkins et al., 2020). Even the entry-level training in Australia for an RePL licence is usually an endeavour of around 5 – 7 days, requires $3000 - $4000, and includes drone failures, crashes and fly-aways as a part of the initial training for drone technology at the fundamental level of instruction.

There are enormous differences in up-front costs for access to drone technology. That separation also extends to the additional costs of hardware, software, training, and additional items that are often not considered but which are highly necessary in standardised drone usage and implementation for broadacre farming.

1.1.4 Licencing and Certification of Drones

The regulatory control of drones in Australia comes under the purview of the Civil Aviation Safety Authority (CASA). There are a wide range of legal considerations relating to the remote piloting of drones that vary according to location, distance from airports, proximity to people, height from ground, and line of sight from the pilot. Other factors to consider include the weight of the drone, the classification of drone, fixed wing or multi rotor options, payload weight, safe flying time, the battery life, the connectivity with a network, and the level of pilot licencing (CASA, 2023). In many cases the use of drones takes place in remote and rural areas where there is a simplified application and enforcement of specific CASA regulations. As a result, many rural drone incidents take place with a strong practice of under-reporting (Ottosen, 2014).

1.1.5 Range and Distance of drones

Drone regulations across Australia are characterised by a broad range of piloting constraints. The weight of each drone, (including the payload) has a widespread effect on where and when a drone can be operated (CASA, 2023). In remote and rural areas there are many occasions when a drone incident takes place and is recovered without the need to inform CASA or any local authorities. The three most significant areas for drone regulations are classified by the Civil Aviation Safety Authority in terms of operating a drone on a farm, in a remote area, and across someone else's property.

These are best described under the following points:

1. A drone operator must not operate more than one drone at the same time.
2. A drone operator must always operate with a Line of Sight to the drone.
3. A special licence is required when using a fixed-wing drone, or long-range UAV that can quickly fly out of sight – known as beyond visual line of sight (BVLOS)

In agricultural terms these points are significant because they relate to farm-specific activities. The first point states that a drone operator must not operate more than one drone at a time. Anecdotally discussions regarding the flying of more than one drone simultaneously have arisen in agricultural terms, since there are occasions (such as in the control of locusts) where a farmer may see great benefit io using multiple drones as part of a timed spraying operation to control emerging larvae and to restrict the rapid emergence of large numbers of locusts. Similarly, many farmers see great benefit in the use of two or more drones as a cost-effective method of mustering sheep. (CASA, 2022)

The second point relates to a drone operator always maintaining a line of sight to a drone. In broadacre farming most of the drone usage will cover large acreages of a single crop variety. The reliance upon a line of sight is problematic since the operator must also just the location of the drone against a background that is difficult to use when it might show a single crop (eg wheat, lupins, or canola). A drone operator should (where possible) use a spotter to keep a connection with a drone as it operates in broadacre settings, and in instances where a large bird of prey (eagle or hawk) may choose to attack the drone and may see it as a rival predator. (CASA, 2023)

The third point relates to the need to understand the more specific requirements for operating a drone in a BVLOS scenario. In the case of high-powered drones and fixed wing drones, the UAV is capable of very high speeds (eg 70 – 80 Kph) and can quickly become lost to the naked eye. In these types of situations, the BVLOS ruling recognises that the operator is unable to continuously monitor the drone flight path. In such instance the drone is operated with a pre-determined map that indicates the intended plan of flight and the drone follows that path in an automatic sense – rather than in response to manual instructions from a drone operator. (CASA, 2023)

1.1.6 Battery life – Power supply

Drone operations and their developing usage is strongly constrained by the life of the batteries that are used to power each device as well as its motors and flight control functions. Larger fixed wing and multi-rotor machines have built in safety margins (often more than 20%) that will allow a drone to maintain flight time. Battery life is the definitive constraining factor, forcing the interruption of large–scale mapping functions as well as limiting how far a drone can fly away from a pilot and still leave sufficient battery power to achieve a successful flight by returning to its point of origin.

1.2 Drone Rules and Regulations

Due to the increased use of drones, several countries have enacted new legislation governing the use of drones and their operators. Every country has established its own laws, which impose very particular constraints. For instance, the maximum flight altitude in Luxembourg, Israel, and Germany is regulated to be 50 metres above ground level, whereas in Belgium, the maximum flight altitude is controlled to be 45 metres (Tsiamis et al, 2019). Every member nation of the Organisation for Economic Co-operation and Development (OECD) has some kind of restriction on the operation of drones that are permitted near airports, populous areas, and buildings or authority.

While most countries have passed laws mandating a minimum distance from airports, a few of nations like Austria, Italy, Korea, Turkey, the United Kingdom, Hungary, Estonia, Belgium, and Luxemburg have not specified a particular distance but rather require a "safety distance." (Figure 1.3)

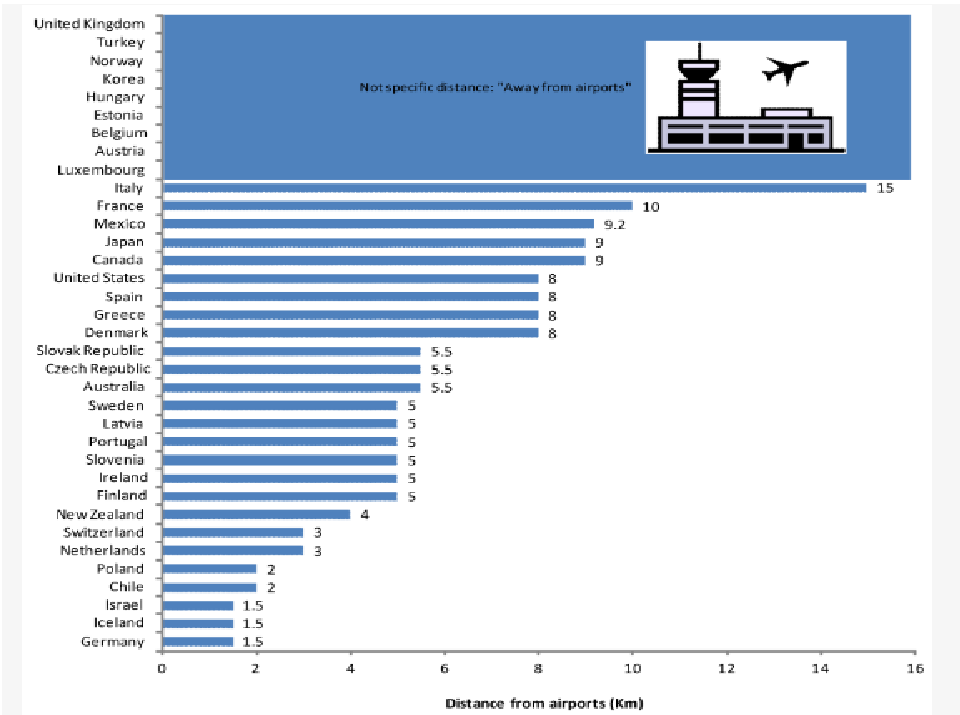

Figure 1.3 Minimum distance of drone flights from airports (Tsiamis et al, 2019).

Rules for Recreational drone operators in Australia (CASA, 2023)

The Australian Civil Aviation Safety Authority stipulates twelve specific rule sets for recreational drone operators in Australia. The first rule is that pilots must not fly their drone higher than 120 metres (4000 feet) above ground level. The second rule is that they must keep their drone at least 30 metres away from other people. The third rule is that they must only fly one drone at a time, whilst the fourth rule states that pilots must keep their drone within their visual line of sight. This means always being able to see the drone with their own eyes (rather than through a device, screen or through goggles. The fifth rule is that pilots must not fly over or above people or in a populous area. This includes beaches, parks, events, or sports ovals where there is a game or event in progress. The sixth rule is that they must respect personal privacy. They must not record or photograph people without their consent as this may breach other laws. The seventh rule is that if a pilot's drone weights more than 250 grams then the pilot must fly at least 5.5 kilometres away from a controlled airport, which generally has a control tower at them. Where possible they should use a drone safety app to find out where they can and cannot fly. Pilots must not operate their drone in a way that creates a hazard to other aircraft, personnel, or property. The eighth rule is that they must only fly during the day, and that they must not fly through cloud or fog. The nineth rule is that they must not fly their drone over or near an area affecting public safety or where emergency operations are underway. This includes situations including a car crash area, police operations, fire or firefighting efforts, and search and rescue. The tenth rule comes into play if pilots are near a helicopter landing site, or a smaller aerodrome without a control tower, where they can fly their drone within 5.5 kilometres. The eleventh rule suggests that if a pilot becomes aware of manned aircraft nearby, they must manoeuvre away and land their drone as quickly and safely as possible. The twelfth rule is that if they intend to fly their drone for work (commercially) then there are rules that they must follow. A pilot must also register their drone and get a licence or accreditation (CASA, 2023).

1.2.1 Licencing and Certification of Drones

In 2016, The Civil Aviation Safety Regulations (CASR) Part 101 legislation introduced a new category of operation called "Excluded RPA" (Civil Aviation Safety Authority Part 101, 2021). Individuals are now permitted under the new Excluded RPA legislation to engage in certain types of flying for commercial gain without getting a Remote Pilot License (RePL) or making an application to CASA for an RPA Remote Pilot License (ReOC). Farmers and other private citizens now have more leeway in how they use drones on their own land because of the new laws. If a person wants to fly drones under 25 kg over their own property, they can also fly as an Excluded RPA.

1.2.2 Drones and Standards

The standards for drones and UAVs are regularly being updated and altered to reflect the changing needs of a world that has more and more UAVs in use (including in broadacre farming). The ISO standard *ISO/TC 20/SC16 Unmanned Aircraft Systems* was established in 2014 to standardise “classification, design, manufacture, operation (including maintenance), and safety management of UAS operations.” The ISO standards committee has 7 standards and 24 projects in development (Ramezani et al, 2022).

Australia participates in this ISO standards committee as an Observing Member. Standards Australia has initiated the formation of a national mirror group (SV-001-01) with the goals of expanding Australia's involvement on the international stage and better representing Australia's best interests in terms of flight safety and drone usage (Ramezani et al, 2022).

Other standards relating to the use of drones includes *ISO/TC 23/SC 6* (Equipment for Crop Protection) / and WG 25 Unmanned Aerial Spraying System (UASS), which covers the rules for the use of drones for aerial spraying. Similarly, there is the *IEC TC 129* standard for Robotics for Electricity Generation, Transmission, and Distribution Systems, which includes the use of drones for power distribution. Both standards are being developed and are under ongoing revision by the International Organization for Standardization (Ramezani et al, 2022).

1.2.3 Australia’s Drone Market

After the United States, Australia had the largest yearly income per capita on consumer drones in 2019. The drone market in Australia currently contributes AUD $5.5 billion (about USD $4.3 billion) to the economy of the country, and it is anticipated that this number will grow to AUD $14.5 billion by the year 2040 (Ramezani et al, 2022; Deloitte,2021). The growth in the Australian demand for UAVs suggests that drone usage is well established in Australia.

By the year 2040, Deloitte estimates a cost reduction of $9.3 billion, with $2.95 billion of this coming from the agriculture, forestry, and fisheries industries, with $2.4 billion coming from the mining industry, and $1.34 billion coming from the construction industry (Deloitte,2021).

1.2.4 Sensors

There are several key applications for the use and integration of sensors into drone technology. The key areas of application for sensors demonstrate the importance of the acquisition of image data through the usage of indices from sensors such as LIDAR sensors and NDVI features. Drone acceptance is reliant upon the overall value of these different sensors, including their technology value, their data value, their limitations, and a range of variations in terms of costs. Some drones are significantly more expensive than others, and this research needs to understand the cost benefit of a wide variety of sensors. Further agricultural research needs to consider the practicality and integration of drone instruments that have a very expensive cost (both for flying and for repairing).

Remote sensing technologies such as unmanned aerial vehicles (UAV) are repeatedly equipped with sensors. These sensors are used to capture images of high resolution as well as temporal resolutions which can help to analyse various characteristics. Drones have a wide variety of potential applications due to their ability to be outfitted with cutting-edge technology, advanced computing capacities, and on-board sensors to assist in crop management (e.g., mapping, monitoring, irrigation, plant diagnosis) (Zhong et al., 2020; Lin and Habib,2021; H. Huang et al., 2021). Sensors can offer information that may be used for risk assessment, such as by updating farmers on cand growth monitoring, water stress, disease detection, weed and yield estimation (Inoue, 2020; Panday, Pratihast, et al., 2020).

Low cost RGB camera equipped drones have proven to be successfully deployed in precision agriculture. In 2016, Lopez-Granados et al, undertook a research study for early season weed mapping in sunflower crops using UAV technology comparing an RGB and a multi-spectral camera. Two specific flight altitudes were copied for the use of UAVs so that they would specifically be operated at heights of 30 metres and 60 metres above ground level. In particular, the flying height at which a drone is operated has a profound effect on the image's spatial resolution, as well as the area captured by each photograph, and the total flight time. When the UAV was operating with the RGB camera at a lower altitude, it was able to acquire imagery with a finer spatial resolution than when it was operating with the multi-spectral camera at the same altitude. Additionally, the number of images required by the RGB camera to cover the entire field at an altitude of 30 metres above ground level was significantly lower than the number of images required by the multispectral camera.

Different specifications regarding the inclusion of sensors in UAV instruments has a considerable impact on the price and associated additions of drone technologies. It is important to point out that the inclusion of a multispectral sensor into an unmanned aerial vehicle (UAV) will incur significantly higher costs than the price of a regular RGB (red, green, and blue) camera. Unmanned aerial vehicles (UAVs) equipped with RGB cameras start at between one thousand and two thousand dollars and are therefore significantly more accessible to farmers (Gašparović et al, 2020). In comparison, the cost of individual multispectral cameras can range between seven thousand and fifteen thousand dollars, and this price does not include the cost of the UAV (De Oca et al., 2018). The less expensive RGB fittings for drones have demonstrated that they are useful for several procedures in farming. The application of low-cost UAV-RGB images has been proven to be successful in estimating barley biomass (Zheng et al., 2018a) and (Zheng et al.,2018b). Emerging sensor devices, such as Lidar, are some of the commonly used sensors in Precision Agriculture (PA). These are particularly useful in the identification of specific types of objects (notably livestock) and are becoming more recognised as appropriate for a range of farming applications.

1.2.5 Visible light sensor (RGB)

The red, green, and blue sensors (RGB) can capture an image in different conditions on both sunny and cloudy days. Before a picture is taken, the RGB sensor guides the camera to determine the amount of light needed to create a well-exposed image (Nikon, 2021). The RGB sensor is then deployed to capture a high-quality image in poor lighting by combining the different optical elements. This includes a special filter that can divide light into various wavelengths and display a clear image onto the sensor (Nikon, 2021; Tsouros et al., 2019).

1.2.6 Multispectral Sensors

Multispectral cameras with remote sensing image technology use Green, Red, Red-Edge, and Near-Infrared wavebands to capture both visible and invisible images of crops and vegetation (Corrigan, 2021). Multispectral cameras work by imaging different wavelengths of light. For example, the Mica Sense Red Edge multispectral consists of 5 images. In such an example each imaging device is equipped with a special optical filter whose purpose it is to allow a certain set of light wavelengths to be captured by the imager (Rise Above, 2021).

The P4 multispectral drone (Figure 1.4) is equipped with multispectral camera that features a total of six imaging sensors, five of which are multispectral sensors and one RGB sensor. The P4M camera (Figure 1.5) has a focal length of 5.74 millimetres, an image resolution of 1600 by 1300 pixels, and the sensor size is 4.87 mm × 3.96 mm (P4 multispectral DJI, 2022). In addition, the P4M camera is also equipped with a sunshine sensor, but reflectance data cannot be obtained directly compared unlike the Sequoia Multispectral camera (Figure 1.6) (Lu et al, 2020).

Figure 1.4 P4 multispectral drone (P4 multispectral – DJI, 2022).

Figure 1.5 P4 Multispectral drones' multispectral camera (Lu et al, 2020).

The Sequoia camera has a total of five imaging sensors including four multispectral sensors and one RGB sensor (Lu et al, 2020). It has a sunshine sensor that can record the illumination information of each image, which makes the process of calibrating multispectral photos much easier. It allows for the reflectance data to be obtained directly.

Figure 1.6: Sequoia Multispectral camera (Lu et al, 2020).

In 2020, Lu et al, compared the difference between the Sequoia multispectral camera technology and the P4 Multispectral camera drones. In term of data collection both the Sequoia and P4M demonstrated similar capabilities, and their spectral values and Vegetation Index (VIs) are highly correlated. Both the P4 and Sequoia sensors had similar qualities, making it possible to use them interchangeably for remote sensing applications that required daily coverage of wide areas with great spatial resolution. Additionally, the authors noted that the Vegetation Index (VI) obtained from both sensors had good precision and were suitable for vegetation remote sensing monitoring.

A recent study by Ashapure et al, (2019) compared RGB and Multispectral images of cotton canopies. The study used a DJI Phantom 4 Pro for RGB images and the DJI Matrices 100 platform with the Slant Range 3p sensor for a multispectral data collection. The result of the study showed that in the early-growth stage of a crop, the RGB-based CC estimation was useful, but later in the season, the MS-sensor-based indices were more accurate. Similar studies in 2019 that quantify vegetation cover in olive groves was conducted by Lima-Cueto et al, (2019). That study suggested that an MS-sensor-based CC had better accuracy compared to RGB – based CC (Lima-Cueto et al, 2019).

1.2.7 Machine Learning

Machine learning (ML) is often used in broadacre farming to analyses information acquired by UAVs. Due to the large volume of information that is acquired from those UAVs, ML can be used to boose the performance and extract knowledge for differing variables within the vegetation.

Deep Learning (DL) models are a subset of the machine learning algorithms that are built up of artificial neural networks that are multi-layered. These models derive their hierarchy and formation from the structure and operation of the human brain. In deep learning the goal is to identify previously undiscovered structures or patterns in the input distribution, so as to allow them to create accurate representations of the data and learn the various characteristics via a hierarchical organisational structure (Deng et al 2014; Al Sobbahi et al 2022; Buters et al. 2019).

UAV-based RS and advanced computational algorithms, including Artificial Intelligence (AI), Machine Learning (ML) and Deep Learning (DL), are progressively being applied to make predictions and solve decisions to optimize the production and operation processes in many farming industries (Amarasingam et al, 2022; Tsouros et al, 2019; Buters et al. 2019).

Object-based Image Analysis (OBIA) is one of the commonly used applications in Precision Agriculture (Buters et al., 2019). The Purpose of OBIA is to discriminate objects within agricultural images acquired from UAVs (Borra-Serrano et al., 2015; Huang, Lan, Yang, Zhang, Wen & Deng, 2020; Blaschke, 2010). OBIA is usually composed of two main steps: image segmentation, and object classification (Blaschke et al., 2014).

In 2018, Liakos et al., reviewed the state of machine learning in agriculture. The review study noted that machine learning plays an important role in several agricultural sectors, such as crop management in the form of yield production, disease detection, weed detection, crop quality, species recognition, livestock management, water management, and soil management.

The Challenge of different software for image analysis

Table 1.2 gives an example of the software tools for flight plan, image processing and image analysis. The table displays a wide and varied range of instruments that can provide a range of photogrammetric equipment that provide for many differing processing areas.

Software Tools for flight plans		
Flight Plan	Image Processing	Image analysis
Altizure DJI	Pix4D mapper	ArcGIS
autopilot	ArcGIS Pro	ENVI
eMotion flight planning	ENVI	MATLAB
DJI Flight Planner	Global Mapper	QGIS
PIX4Dcapture	Open Drone Map	GIMP
DroneDeploy	Agisoft Metashape	ImageJ

Table 1.2: Software tools for flight plan, image processing and analysis (Amarasingam et al, 2022)

1.3 Problem Statement

Farmers who rely on technology to provide precision agriculture solutions are increasingly aggregating expensively captured data that combines different conditions, cameras, drone velocities, shadow distributions, and locational ground truths. These aggregated combinations are sufficiently disparate from each other that the decision-making process is inaccurate and less effective than necessary. When described over time and with the addition of season-by-season comparisons, the use of inconsistent drone-based image capture represents a level of inaccuracy that is likely to impact the yield and efficiency of crops based on precision agriculture decisions. The problem, therefore, is to reduce the number of inconsistencies by means of determining consistently similar measurement areas such as the optimal height and velocity for drone-based image capture.

Image quality can be improved with the use of computer software, however, a study conducted by National Taiwan university suggested that a super-resolved image is often not cleared compared to the image that is directly acquired by a high-resolutions camera (Shih, Hsu, Yang and Chen, 2014).

However, getting accurate recordings on height, resolution and velocity has always been a challenge. There are many factors that need to be taken into consideration that can have a significant impact on image resolution. One factor is the consideration of image capture where there is likely to be adverse weather conditions. This is an area of widespread benefit where the quality of pictures captured on a rainy, cloudy or sunny day will not be the same. The white balance (direction of the sun), focal length and resolutions, stability, flight time, and ground-level can all affect the quality of the resolution from different images (Hu et al., 2019).

Drone practices are being adopted across a wide range of agricultural enterprises however the focus of this study specifically considers broadacre farming where the dynamics of drone interaction is largely premised upon remote areas with large acreages that require drone activity in large cross-sectional areas of land. These emerging practices are developing from a market position that describes UAVs as an area of technology that is yet to reach maturity (Schmeitz, 2020; Ren, 2020). That same developmental position is an observable feature of the UAV industry whereby rules, regulations and guidelines are only loosely formative.

Farmers and agriculturalists are quickly realising the benefit of data and its application in terms of precision agriculture. The demand for precise mapping, Internet of Things (IoT) data, and sensor driven information has galvanised the need for UAVs to take a permanent role in broadacre farming practices. The issues that accompany this new technology are varied and complex in nature. Farmers are increasingly being asked to engage with the computer science of technology but are doing so from a low base of knowledge and experience. This raises key questions about the risks, maturity, and readiness to deploy globally professional solutions in the context of broadacre farming.

A study undertaken in 2020, comparing the difference between low-resolution, high resolution, and super-resolution images, outlined that super-resolution images have a higher accuracy margin compared to low-resolution images and underlines the amount of data that is lost in low-resolution images (Yamamoto, Togami, and Yamaguchi, 2020).

The research reviewed in this thesis will be viewed through multiple lenses. Part of the challenge to solve these challenging differences is to determine the elements where small differences can determine a great deal of crop variance. Images captured by a UAV during different periods of the day, season, and different height levels may benefit from being examined using machine learning. Such examinations aid in understanding the impact of resolution and recording approximate resolutions for image capture.

1.4 Significance, Potential impact, and Novelty

An optimal framework for UAV practices that standardizes specific image resolution, as well as defining the height at which drone operations should be performed, is needed to provide consistency in terms of data and agricultural record keeping. This study will identify issues experienced at ground-level, as well as in the air in terms of height, position, angle, and speed. This would make a significant contribution in capturing a range of images to suit best practice and utility in broadacre farming. Problems arise from the inconsistencies in image resolution and in the inconsistent ways that images are being captured in broadacre farming. The usefulness of the images that are obtained through drone practices can be significantly improved by using a standardised approach to specifying ways to classify the way in which data can be used to improve outcomes in broadacre farming.

One of the novel features of this investigation is the decay and entropy approach to the way yearly crop data is added to the many years of agricultural data. This thesis seeks to expose the way in which decay and entropy can change critical data used in precision agriculture. In an extended for, it may demonstrate a decaying system that will affect future crop decision-making for many decades. There is currently no consistency in the way in which data is being collected and analysed in broadacre farming. For the last three decades in Western Australia the collection of satellite imagery across broadacre farming areas has been collected at the same height and time of day. These consistent practices are highly reliable in one sense, but problematic in another because the quality of the images in terms of their resolution is based upon the quality of cameras that were installed many years ago when satellites were placed into Earth's orbit to observe and record information. New practices using drones are hindered by the opposite challenge. They allow for measurements to be taken at any time of the day, at any speed, at any height or angle, and with a changing guard of camera technology that renders any two image sets highly incompatible because of the lack of a consistent set of image parameters.

This study aims to improve the way in which data is collected and analysed in broadacre farming. The advent of drone usage has brought a raft of options in terms of how data can be collected. This broad set of choices means that agriculturalists in broadacre farming (especially early adopters of technology), are faced with multiple decisions and opportunities. The aim of this study might therefore draw a focus on the ability to assist those using drone technology to achieve some form of standardisation. This study also aims to assist with the development of standards of practice that allow for a consistent comparison across seasons and across years. The changing nature of drone technology has made the task of standardisation increasingly difficult and instead of drawing the Agtech drone community together, has instead brought about fragmentation and accelerated the decay of a consistent set of agricultural practices, especially in precision agriculture where the reliability and quality of the precise measurement has always been the mainstay of the efforts to improve yields, efforts and productivity.

This study seeks to better understand these practices in terms of accurate height measurement, velocity of drones when capturing data, and the resolutions that are accepted that represent a constantly improving set of high-resolution images. This type of knowledge and understanding can greatly assist farmers to save money and time by re-setting the standard means by which data is collected. It will also serve as a guideline to self-operated drone usage in capturing accurate images that can be used for data analysis. However, different sets of cameras need to be explored to get a better understanding of options and choices in terms of the quality of agricultural imagery.

The significance of this study also lies in the application of machine learning techniques to maximize the quality of images. The tools of machine learning could prove instrumental in the advance made in this research area. The novelty of this research has three aspects. The first is to understand the quality of images (Resolution), operating heights, and the flight speed of drones in farming practices. The second aspect is to understand about the usage of drones to characterise the deployment of drones in a meaningful manner, and finally the third aspect is to understand the rules and regulations that provide for a highly fragmented and segmented set of guidelines in the UAV industry.

The study will identify novel approaches to address the ways in which UAV machines capture images in broadacre farming. At the conclusion of this thesis the result will be seen in the development of a revised approach for image-capturing using UAV in broadacre farming.

1.5 Research Objectives

A long-term goal of this research is to determine the most effective techniques for the application and accepted usage of drones in broadacre farming for high yield wheat productions in Western Australia. The research also considers how UAV imagery can best be acquired and compared from season to season after different models, lenses, cameras and upgrades have changed each season. To achieve this goal, the following Research Objectives (RO) are discussed.

RO1: *To identify factors that impact upon the use of UAVs in Broadacre farming*.
RO2: *To identify limitations in UAVs in Technologies, Cameras, Costs, Laws, Acceptance of the technology. This includes the issues of different height standards and resolution standards for measuring crop indices and aggregating crop data.*
RO3: To a*scertain what consistencies are required to make the use of UAV Drones a sustainable practice in terms of precision agriculture.*
RO4: *To ascertain optimisation features that will drive higher yields in precision agricultural terms.*

1.6 Research questions

On the basis of the research objectives and the significance of this study, a set of research questions were devised to provide knowledge and understanding about the practices of drone usage in broadacre farming.

Main Research Question

Q1: "*What are the important factors influencing the development of UAV technology for broadacre farming?*"

Sub questions

Sub questions 1

SQ 1. *What are the ongoing limitations of the development of drone technology?*

Sub questions 2

SQ 2. *What are the important optimization features of image analysis using UAVs?*

Sub questions 3

SQ 3. *What are the important standardisation approaches for using drone technology in broadacre farming?*

1.7 Summary

This project aims to use drone-based object detection for wheat crop and paddock management using drone technology. This research will explore how drone technologies and Machine Learning tools can be uses to identify the optimal physical placement of drones to best allow for decision making in high yield wheat productions in Western Australia. This project considers how UAVs can be best displayed prior to harvest. These systems could be used to map crop changes and other specific object crop altering phenomena. The research will examine the most effective techniques for capturing images under different field conditions. The project will use technology to develop optimum decision-making parameters with reference to specific image reference positioning. It will consider systems for capturing images in wheat crops at different stages of growth and will include a consideration of how to predict objects of agricultural relevance and commercial concern.

This project aligns with existing research within the School of Science in drone usage, image processing and machine learning.

2. LITERATURE REVIEW

This chapter describes three main areas. The first is an explanation of the Selection Criteria that underpins the way literature is chosen, screened, and collated. The second is an explanation of the search-string methodology that was used to select literature that was relevant, aligned with research themes, and valuable in terms of relevance, collaborative appeal, and likely to align with a wider selection of contributing research narratives. In this sense, a deliberate attempt was made to avoid using literature from “one-time-only” authors, and to instead look where the research themes had been developed and consolidated over several research fields of study. The third area outlined is an organised selection of relevant research themes applicable and highly relevant to the specific research direction of this thesis, as well as being drawn (wherever possible) from literature within the past 5 to 6 years.

2.1 Literature Selection Criteria

This section describes the methodology that informs the following section: A systematically driven scoping review was undertaken of the literature on important factors influencing the optimization of UAV technology for broadacre farming. The broad discipline of science sometimes has difficulty in the usage of literature from authors and from research teams who, whilst passionate and qualified, lack two important qualities. The first is that the literature on drones is relatively new and has captured the excitement and intrigue from many authors (Schmeitz, 2020; Maciejczak and Faltmann, 2018; and Straub, 2015). This is both intriguing and problematic. On the one hand, the literature contains a range of works which are unique, single-issue driven, and often specifically related to the author and their research. This makes for a range of fractured and highly dissimilar research vectors which, although potentially interesting, are unlikely to become the subject of in-depth and further defined areas of research. One of the criticisms of the emergent narratives regarding drone practices is that they are highly splintered.

This reflects the very recent beginnings in research terms within this area. Drones have their historical origins in the 1850s, 1920s and 1930s (Azoulai, 2011), however their more ubiquitous emergence is more clearly connected with the 1980s when the US Department of Defence contracted the Israeli company Malat to assist in the development of drones based in larger numbers for defence and surveillance purposes (Goraj, et al. 2004; Azoulai, 2011)

The literature included in this thesis study has been selected because it has been deemed appropriate for the purpose of helping to answer the research questions for this work. Literature has been sourced on the basis that it contributes towards a deeper understanding of drone practices, broadacre farming, and the factors that either limit drone technology, optimise it, or assist in the standardisation of drone technology. This study draws upon the characteristics and features of UAVs to better understand the present state of development and application in broadacre farming. To achieve this goal a specific method has been chosen to identify relevant literature so that it does not include research contributions that form the outlier portion of the research contributions for this field of study. The search criteria, and its associated search string, are therefore important elements of this study in terms of the provision of a body of literature that is current, instructive, and provides a purposeful means by which information and data can be used in achieving the objectives of this study.

The search criteria revealed several themes and phrases that are critical in terms of generating the informed literature for this study. These terms are emergent from the initial background literature and have been tested to demonstrate thematic alignment with the area of research that describes this research study. The following keywords were used to create our search strings:

- UAV, UAS, Drone
- Remote Sensing, Camera, Pixel
- Smart Farming, Agriculture, Broadacre farming
- Development, limitation, Guideline

As a result, this literature review comprises a range of literature that creates a collated aggregate of knowledge from two main research strings.

Search string One:

ti=drone OR ti:(UAS) OR ti=UAV OR ti:(remote sensing) OR ti=camera OR kw:(Farming) OR kw:(Agriculture) OR ti:(livestock) OR au:(battery life) OR kw:(weather) OR kw:(Pixel)

Search string Two:

kw:(Drone) OR kw:(UAV) OR kw:(UAS) AND kw:(Rules) OR kw:(Regulations) OR kw:(Guideline) OR kw:(Framework) AND kw:(broadacre) OR kw:(regional) OR kw:(remote)

OR kw:(farming) OR kw:(agriculture) AND kw:(camera) OR kw:(velocity) OR kw:(Ground coverage) OR kw:(remote sensing) AND kw:(multispectral)

Based on the selected keywords the following search string was assembled:

(~Drone~ OR ~UAV~) AND (~Rule~ OR ~Regulation ~ OR Guideline ~ Framework) AND (~broadacre~ OR ~regional~ OR ~remote~ OR Farming ~ OR Agriculture).

The following databases andpublishers served as data sources: ACM Digital Library, IEEE Xplore, Science@Direct, Springer, Elsevier, and Scopus. After performing the set of queries on the databases, we collected 403 articles. Further filtering was carried out based on a range of inclusion and exclusion criteria. The inclusion criteria focused on articles that were peer reviewed, were published in the last five years, and described at least one drone-related activity within the broad context of broadacre farming. The exclusion criteria focused on articles published before 2018 that were not peer reviewed and/or were not written in the English language. The exclusion criteria also extended to articles not related to farming or agriculture, articles from Blogs, personal websites, YouTube, and Facebook social media sites.

<u>Inclusion criteria</u>

- Peer reviewed.
- Published in between 2018 and 2022
- Describes at least one drone related activity in Broadacre farming.

<u>Exclusion Criteria</u>

- Before 2018
- Not in English
- Not Peer reviewed.
- Not related to farming or agriculture
- Blogs
- Personal websites
- YouTube
- Facebook

The formal literature was drawn from the following databases and key collections of science-based journals.

Formal Literature

	No. of Abstracts	No. after Screening	No. of Full papers	No after screening	Final nos.
ACM	*145*	*90*	*90*	*77*	**38**
Web of Science	*177*	*134*	*134*	*69*	**46**
IEEE Explor	*208*	*156*	*156*	*68*	**33**

Elsevier	*201*	*144*	*144*	*85*	**39**
Springer	*268*	*187*	*187*	*116*	**48**
Science Direct	*98*	*75*	*75*	*43*	**13**
Scopus	*158*	*123*	*123*	*62*	**39**
TOTAL					**256**

Table 2.1 Scoping Literature review and Screening data

This thesis also takes into consideration a range of informal literature sources. Whilst the main provision of literature has been sourced from peer reviewed material and high-ranking journals, a small section of the literature has come from blogs, social media, government reports, and early works.

Informal / Grey Literature

- Youtube
- Blogs
- Not related to farming or agriculture
- Early works/Seminal Works

2.1.1 Literature review Components

The components listed below constitute a broad thematic range of information that was initially collated as part of the initial search string. This collation forms the formal literature that comes from the search strings and demonstrates a specific scoping review that includes clearly specified inclusion and exclusion criteria.

2.2 Drones in Broadacre farming

UAVs are experiencing very high demand in the agricultural sector (Floreano, and Wood 2015; (Borra-Serrano et al., 2015). In agriculture drones were initially used for spraying a chemical, to overcome the visibility problems associated with cloudy weather (Simelli and Tsagaris 2015).

2.2.1 Drone applications in Farming

Crop Spraying and Pest Management

There is a wide range of applications that drones have been applied to in farming. Drones can scan the ground and spray the appropriate quantity of liquid while also adjusting their distance from the ground and spraying in real time (Budiharto et al, 2019, Michels et al 2020; Delavarpour et al, 2023). This ensures that the liquid is evenly distributed. As a consequence of this, there is a corresponding reduction in the quantity of chemicals that seep into the groundwater. This leads to an increase in efficiency and has proven beneficial in reducing environmental and human contamination risks and raising food quality and safety standards (Rani et al., 2021; Salcedo et al., 2021; Sabzevari and Hofman, 2022).

The rapid development and application of agricultural UAVs within rice cultivation is generating considerable commercial and practical interest among rice farmers, particularly for aerial spraying. This is because agricultural UAVs can fly at low altitudes, use low volumes of spraying fluids, and operate with reduced operating costs. In rice crops drones are effective in terms of improved spraying outcomes, reduced energy consumption, and improved harvesting results (Lan et al 2018).

The effect of unmanned aerial vehicle (UAV) spray treatments in vineyards was investigated by Biglia et al. 2022 using a DJI Matric 600 Pro. This study showed that when using conventional nozzles, spray losses could be minimised, and canopy spray distribution could be boosted by using a high-level UAV operating at cruising speed . In this study the drone flight plan was shown to be a critical element in influencing the success of the spray application.

An innovative and practical design and development of a small application system that is capable of being mounted on an unmanned aerial vehicle for agrochemical spraying tasks is presented by Martinez-Guanter et al., in 2019. Additionally, an analysis of the quality of the application and economic costs in olive and citrus orchards is presented and compared to those of a conventional treatment. The research made use of an unmanned aerial vehicle (UAV) model DJI S1000, which had been redesigned and rebuilt with low-cost materials while taking into consideration the payload. The design has proven to be effective in reducing costs, and additionally has the capacity to conduct variable spraying tasks at a variety of places in a consistent manner.

Mapping and soil analysis

In terms of large-scale farming, the effective management of weeds in a timely manner has proven to be essential for maintaining optimal crop yield. To reduce the harmful effect of herbicides, site-specific weed management (SSWM) methods have been deemed as necessary (Lopez-Granados, F. ,2010; Huang et al 2020). To carry out site-specific weed management farmers typically obtain an orthophoto map of their fields. UAVs have been proven to be useful for weed mapping due to their high spatial resolution. (Huang et al., 2021; Wang et al., 2019; Schmeitz, 2020).

In 2020, Huang et al., combined deep learning and object-based image analysis (OBIA) with UAV data for site-specific weed management (SSWM) in rice paddies. The findings of these experiments showed that in cases where remote sensing is carried out by a drone using deep learning, it can deliver accurate support information for SSWM applications carried out in rice fields.

Pérez-Ortiz et al, (2015) collected UAV images that demonstrated improved performance for weed mapping in sunflower fields. To assist in the classification of maize and weeds for herbicide patch spraying, Castaldi et al. (2017) used a fixed-wing drone equipped with a modified Canon S110 camera and operated at a flight altitude of 150 metres above ground level.

In 2019, Wu et al. conducted soil moisture mapping in the *loess belt region* of Belgium (a low plateau forming a flood plain). This study made use of a DJI phantom 4 pro drone equipped with ground-penetrating radar (GPR). The findings demonstrated the potential and benefits of drone based GPR for rapid, high-resolution mapping of soil moisture at the field scale to support, for example, precision agriculture and environmental monitoring. Furthermore, the results demonstrated the potential of drone based GPR for mapping soil moisture at the field scale.

The DJI Mavic 3M drone (DJI Mavic 3, 2023) has demonstrated improved performance in terms of image capture and application. This type of drone has the capability of capturing multi-spectral imagery of crops before fertilising rice, regulating the growth of cotton, or spraying foliar fertiliser on potatoes. The prescriptive maps that are generated by both the DJI Terra and the DJI SmartFarm Platform, which capture variations in crop potential, permit the drone to subsequently conduct variable-rate applications. Users are able to reduce expenditure, increase their output, and reduce the amount of damage they do to the environment as a result of using a sophisticated image-based smartfarm platform.

Agricultural insurance investigation

UAV drones can efficiently carry out jobs in the aftermath of natural disasters due to their agile response time, high-resolution imagery, and high-precision positional data collection capabilities. They possess extended application capabilities for a diverse set of tasks by means of varying devices, flexible configurations, and straightforward system maintenance. Insurance firms can more precisely pinpoint the areas affected by a disaster due using aerial surveys, post-processing and technological analysis of aerial pictures. This approach allows for the comparison with field measurement results. Drones can provide insurance firms with a bird's-eye view of hail damage, allowing them to quickly assess a specific level of damage. In insurance cases it can be important to differentiate whether a field has sustained a 70% (medium) or 90% (catastrophic) level of agricultural loss (Ren et al, 2020).

Mechanical Pollinator

Dropcopter, a start-up business based in New York, has developed a pollen dump drone that assists in the pollination of crops such as almonds, cherries, and apples (Dropcopter, 2021). The company has been using drones to pollinate crops for many years, stating that it has an advantage in terms of saving time and labour as the drones can travel to the area requiring cross-pollination in a matter of minutes. This approach demonstrates the efficient use of pollen pump drone technology where the conventional approach would normally take several hours to cross-pollinate a similar area while driving in a truck (VGN, 2020).

Crop monitoring and Disease detection.

When a tree is under stress, whether it be from an infestation of pests, a lack of nutrients, or an insufficient supply of water, its leaves will change in terms of colour, texture, and condition. These alterations might be observable in the visible light spectrum, such as a change in the colour of the leaf's green pigmentation. They are also able to be digitally recognised in different bands of the electromagnetic spectrum. For example, a shift in the texture of the waxed coating on a leaf may cause a change in the way infrared light is reflected by the leaf (Hogan et al, 2017). The application of imagery acquired by drone footage provides increased information and leads to improved and better resourced decision making for crop monitoring and disease management.

Recent improvements in the use of unmanned aerial vehicles (UAVs) based remote sensing (RS) in precision agricultural techniques have proved essential in improving crop health and management. In many farming industries, remote sensing technology that is based on unmanned aerial vehicles (UAVs) and advanced computational algorithms, such as artificial intelligence (AI), machine learning (ML), and deep learning (DL), are increasingly being used to make predictions, solve problems, and make decisions in order to maximize production and operational processes (Amarasingam et al, 2022, Napier et al, 2023).

An investigation into the use of unmanned aerial vehicle platforms, sensors, and applications for the surveillance of sugarcane fields was carried out by Amarasingam et al, (2022). The research article - discusses the use of unmanned aerial vehicles (UAVs) in the sugarcane industry. Drones were successfully deployed for the management of pests and diseases, the estimation of yields, the measurement of phenotypic traits, the assessment of soil moisture levels, and the evaluation of nutritional status in order to improve productivity and environmental sustainability. The authors state that unmanned aerial vehicles (UAVs) allow for the accurate management of sugarcane and significantly reduce the amount of pesticide inputs. In addition, the research highlights some of the challenges that unmanned aerial vehicles UAVs) face in agriculture, including the need for technological adaptation, high initial costs, inclement weather, communication failure, policy and regulation.

The deadly fungal disease known as yellow rust affects winter wheat all throughout the world (Wellings et al, 2011), and it is responsible for considerable losses in terms of crop yields (Beddow et al, 2015). To guarantee consistent and reliable wheat production as well as food safety, it is essential to undertake thorough monitoring and accurate identification of yellow rust (Wan et al, 2007). Standard procedures currently in use often include agronomists or trained surveyors performing manual inspections of disease symptoms in agricultural areas that are quite modest. As a result of the subjective and annotative approach by surveyors, this procedure is not only expensive but also time consuming and prone to error (Sankaran et al, 2010). There has, however, been recent progress made in unmanned aerial vehicles (UAVs), which can be equipped with hyperspectral image sensors. These UAVs can solve these problems in an efficient and cost-effective manner (Zhang et al, 2019).

Zhang et al., 2019 used a DJI s1000 UAV system in conjunction with a deep learning-based approach for the purpose of automating the diagnosis of yellow rust disease using high resolution hyperspectral UAV photos. According to the finding of the study, combining spectral information with spatial information is a viable strategy for boosting the accuracy of crop disease identification using high resolution UAV hyperspectral pictures.

Schirrmann et al, (2016) was able to create ultra-high resolution orthoimages and surface models of a farm comprising of an 11 hectare wheat field using inexpensive UAV imagery based on an RGB consumer-level camera. From the wheat's initial "booting" stage through to its final "grain filling" stage, the author witnessed the formation of distinct spatial patterns. Other biophysical indicators, including leaf area index, fresh biomass, dry biomass, and plant height, were also met with great success.

Challenge and benefit of drones

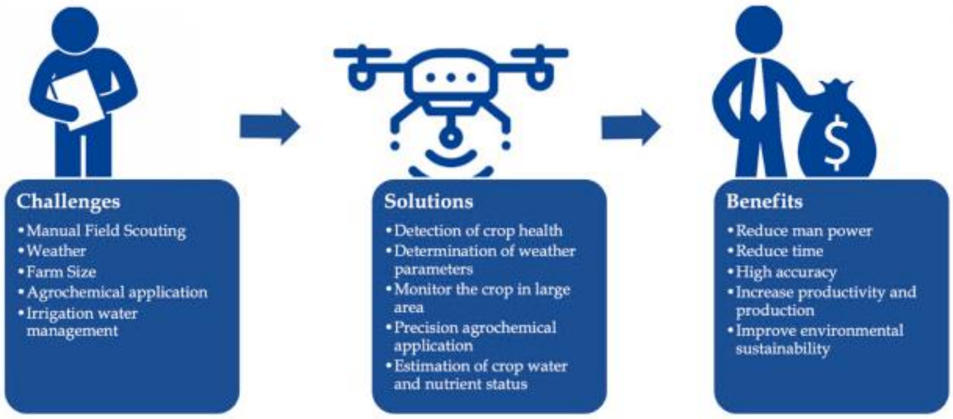

Figure 2.1 Challenges and benefits of drones in agriculture

In the last decade, there has been a significant rise in the usage of drones of different sizes, shapes, and capabilities (Figure 2.1) (Banu, Borlea and Banu, 2016; Colomina and Molina, 2014). They have mostly emerged in different sectors like civilian application, precision agriculture forestry, military, and many other applications (Shahbazi, Theau, and Menard,2014). Figure 2.2 shows the rise of UAV remote sensing from 1950- 2020. The paper from Banu et al, (2016) highlights the global spread of the same issues for agriculture (although through a forestry lens). It shows that in Europe, South and North America, and throughout Asia there is a rapidly accelerating reliance upon precision data as acquired by the UAVs and that are several challenges in terms of image quality, variations in terms of equipment and differences in camera resolution.

A summary of these challenges and benefits from the literature suggests that the issues are rapidly accelerating. The challenges are rapidly growing alongside the similarly fast paced nature of the development of the technology, and that challenges and benefits are a useful expression in defining the hand in glove connection between these two areas of UAV development. There are clearly a range of similarities between forestry and agriculture where shared alignment with benefits and with challenges are clearly articulated (Banu et al, 2016).

The overarching commonality of these challenges and benefits are strongly connected to outcomes issues with precision data, either precision agriculture or precision forestry data. The key information remains focused on the best practice usage of increased accuracy set against existing practices that use past data aggregations.

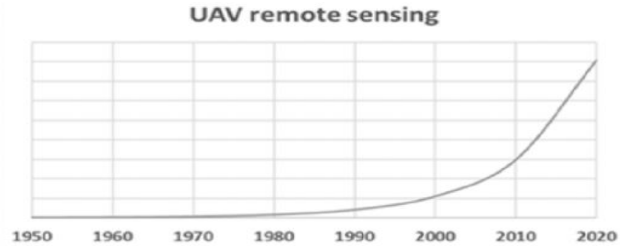

Figure 2.2: UAV remote sensing in the civilian application (Banu, Borlea and Banu, 2016)

The classification of a drone's frame construction is dependent on the number of motor arms it has. In general, the more arms a drone has, the more stable the flight (Kardasz & Doskocz, 2016). Based on the number of arms, drones are classified according to five principal categories (See Fig 2.3)

- **Bicopters** – two engines
- **Tricopters** – three engines
- **Quadrocopters** – four engines
- **Hexacopters** – six engines
- **Octocopters** – eight engines

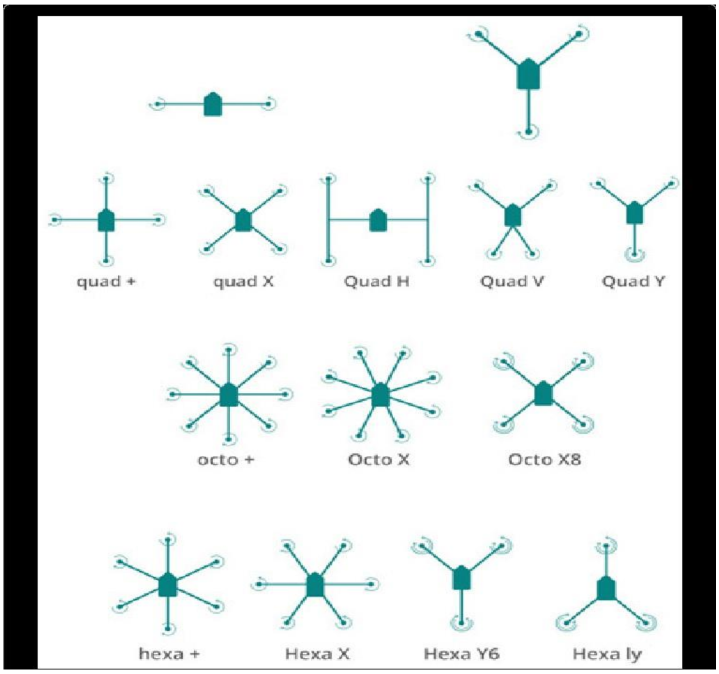

Figure 2.3: Drone's arms (Kardasz & Doskocz, 2016)

In 2016, (Mokros et al) used a quadcopter DJI phantom 3 professional drone to estimate the volume of wood-chip piles. The results were compared with the GNSS (Global Navigation Satellite System) images. The author concluded that there were not many significant differences between the two, and in fact, there was 10.4 % more volume estimated via the drone method with an advantage of collecting data 12-20 times less compared to GNSS, as highlighted in Fig 2.1.

An emerging feature of drone development is that the industry continues to shift upwards to offer more sophisticated drones that are available to market such as the DJI Phantom 4 Pro v2.0 and P4 Multispectral (P4 Multispectral; Phantom 4 Pro v2.0, DJI 2020).

Such drones have a multispectral camera that is designed for agriculture missions or environmental monitoring. The Mavic-mini 2 is a small but powerful drone that weighs 249grams. It is equipped with a 12 MP camera and can fly up to 31 minutes with a wind resistance of up to 29-38 kph (Mini 2, DJI 2020). A more advanced version of the Mavic-Mini 2 is the Mavic Air 2 which is equipped with a 48 MP camera and has a flight time of 34 minutes (Mavic Air 2, DJI, 2021). A recent study by Huuskonen and Oksanen, (2018) has used drones to demonstrate soil sampling. Tu et al. (2020) was able to demonstrate that similarly small-sized drones could be successfully used in measuring horticultural tree structures.

A study conducted by the University of Finland on data and resolution requirements deployed drones for mapping vegetation by means of spatially comparing images from three different platforms (UAV, Aerial, and Satellite). The approach suggested that the UAV images were more accurate than other images (see Fig 2.1). The drones image resolution captured used a combination of 8 MP and 18 MP image resolution (A. Räsänen and T. Virtanen 2019).
In 2017, Gnädinge and Schmidhalter from the University of Munich, conducted a study on precision farming and precision phenotyping to collect information on plant properties and plant health using aerial image detection with UAVs. The study suggested that UAVs not only provide time and cost-saving data for further processing but also allows for flexible and weather-independent data collection (Gnädinge and Schmidhalter,2017)

2.3 Image Resolution

Image resolution refers to the number of pixels in an image. Image resolution is sometimes also described in PPI, which refers to how many pixels are displayed per inch of an image (Herasymenko, 2021; Michigan Library, 2021). Resolution can also be identified by the height and width as the total number of pixels in the image (Jin et al., 2017). For example, images that are 2580 pixels wide and 1944 pixels high (2580 x 1944) contain 5,015,520 pixels or 5.0 megapixels. Pixel density is a noteworthy feature as it governs the quality of an image (See Figure 2.4). Research has demonstrated that the smaller pixel sizes provide both greater accuracy and more detailed information of plants (Hengl, 2006; Hsieh et al., 2001; Jin et al., 2017).

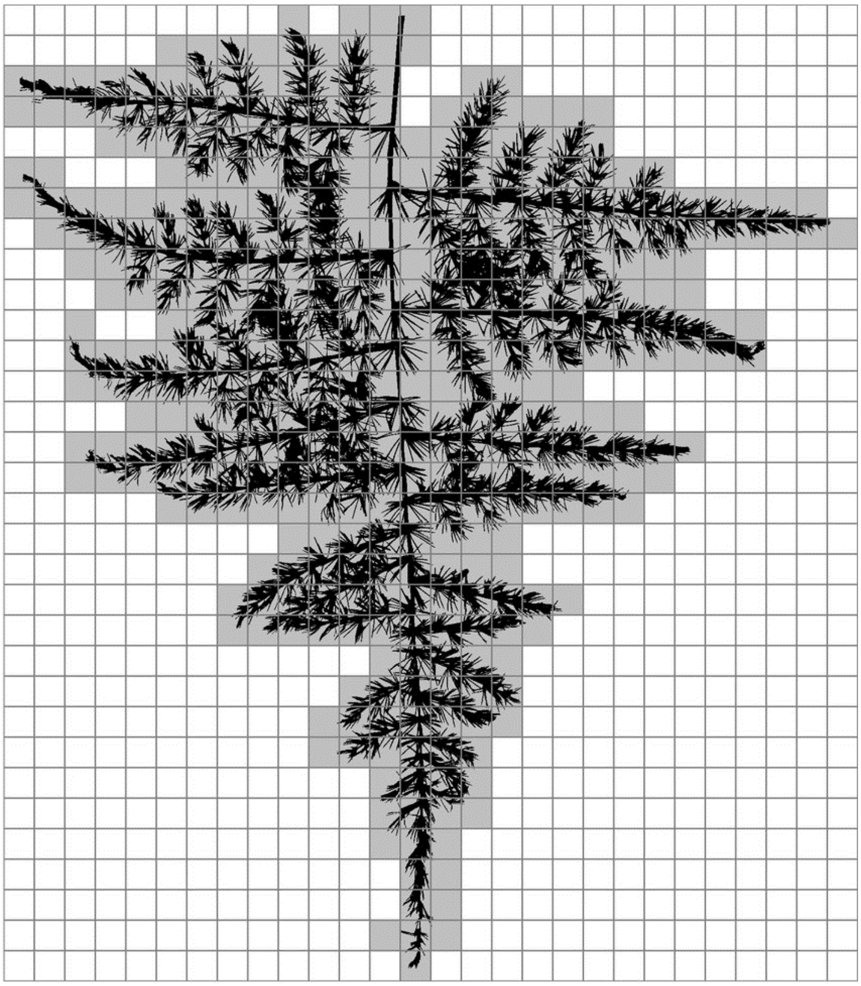

Figure 2.4: Pixel Density on branches and leaves of a plant.

A study conducted at the University of Queensland explored the impact of pixel size on the estimated accuracy of the ground cover (GC) from RGB imagery (Hu et al., 2019). The images captured in this study were either (3456 x 2304 (MP)) or (5184 x 3456 (18 MP)) taken at 1m above the canopy plants. The study proposed that an alternative method like multiple flights with extreme high-resolution cameras (100 MP) or a camera with a long focal lens could be used to obtain more optimal results.

The improvement achieved in computational analysis, electronic sophistication, and software integration has enabled both multi and hyperspectral imaging to emerge as the prevailing tools for gathering data relevant to many different fields in the last decade (Gowen, O'Donnell, Cullen, Downey, and Frias 2017; Lorente, Aleixos, Gómez-Sanchis, Cubero, García-Navarrete and Blasco, 2017; Napier et al, 2023; Dale, Thewis, Boudry, Rotar, Dardenne, Baeten, and Pierna, 2013). The DJI Phantom 4 Multispectral drones have a multispectral camera and a sunlight sensor to deliver an integrated multispectral solution. With a flying time of 27 minutes the Phantom 4 uses an image sensor that includes a standard RGB camera plus separated red, green, red edge, and near-infrared image sensors.

Sandino et al., (2018) researched tea trees in New South Wales studying the aerial mapping of forests that were affected by pathogens. The research was conducted using UAVs, hyperspectral sensors, and artificial intelligence. The individual rates for healthy trees was measured at 95 %, and at 97 % for deteriorated trees. Using hyperspectral three-dimension (3D) imagery, Aasen et al (Aasen et al, 2015) were able to deploy UAS instruments to boost vegetation monitoring.

2.4 Flight Altitudes and Operating Heights

This section covers three main areas of discovery. The first section looks at the different heights that are chosen and used for image capture. The second section looks at similar studies in image capture challenges. The third section looks at how drones demonstrate different capabilities under variable conditions. This is critical in understanding the issues of wind, sustainability, battery life and a wide variety of environmental and introduced conditions (as highlighted in Fig 2.1). This thesis is interested in understanding tests where different flight heights using different cameras and configurations can be used to determine the optimal frame need to acquire high-quality images.

There are various issues regarding optimal height and flight altitudes, as variable parameters can have a direct impact on the Ground Sample Distance (GSD), as well as the average image and image forward overlap. Other issues arise from variations in terms of the velocity or flying speed which can cause a change to the forward overlap when the camera trigger speed is fixed (Figure 2.5).

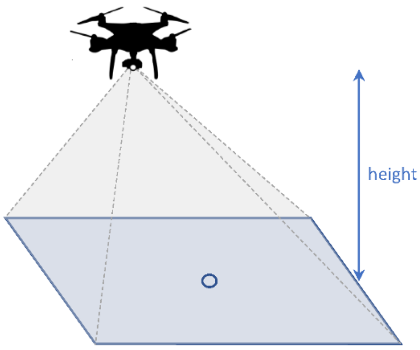

Figure 2.1 Fight height or Ground Coverage

By using an analysis of different CNN architectures and machine learning it becomes possible to train instruments to change according to their analysis of noise levels, mixed pixels and detection rates. The GSD of the drone images can enable visual identification of major substrate types, which is acceptable to use as reference data for training the classifier and accuracy assessment (Congalton, 2001). Such technology would help to determine the effective technique for object detection and to understand the impact, change, and effect on wheat crops using an aggregated approach to objects.

2.4.1 Drone Flying heights for image capture.

When capturing photographs from a UAV, one of the most significant considerations to make is the flight height, also known as ground coverage (GC), because this has a direct impact on the pixel size of the images (Hu et al., 2019; Zhou et al., 2018; Seifert et al., 2019).

In 2019, Hu et al. used ground coverage (GC) as an example trait to show how the major flight attributes could affects the size of images in terms of their pixels. According to the findings of the research carried out by the University of Queensland in Australia it suggests that the most practical height for canopy photos given the limitations (fight time/ battery) is in the range of 20 to 30 m with a 20 MP camera with a focal length of about 50 mm. This research found similar results to Jin et al., who published a study in 2017 that estimated wheat plant density at early could be determined using extremely low altitude UAV footage (less than 10 metres). However, the study also suggested that more research needed to be done to explore the real UAV imagery captured when flying at different heights and including an analysis of other environmental factors like wind, light conditions and sun direction that can affect the image quality (Hu et al., 2019).

In 2018, Zhou et al. compared RGB images obtained from an unmanned aerial vehicle (UAV) and a manned ground vehicle (MGV) utilising the identical camera configuration (Sony Qx-100 HD camera), but the images were captured at different heights. when compared to the UAV image, the MGV image had a distinct advantage in terms of recognition accuracy. The authors note that differences in the height altitude has a direct impact showing differences in image quality.

Images captured at both 25 metres and 50 metres above ground were compared by Seifert et al. in (2019).

The image acquired at 25 metres had nearly 20 times more identify distinct features. These features are described as Tie Points and allow for a comparison between the two above ground heights of 25 metres and 50 metres. This research demonstrated that drone flights conducted at low altitudes significantly enhanced the number of tie points and, consequently, the level of reconstruction detail. The research pointed out that it is difficult to provide optimal values for the flying and sensor settings since every combination of drone, sensor, and post-processing system would be quite unique and would need to be evaluated on an individual basis.

2.4.2 Similar Studies related to image capture

A similar study has been conducted by the University of Queensland using ground coverage (GC) as an exemplar in order to explore its relationship to pixel size. The study suggested that it can be challenging when the GC is less than 25 % in plants with thin leaves (ranging from 2 to 15 mm across). Furthermore, the study also demonstrated that small pixel sizes (e.g <0.1 cm) are significant for accurate ground coverage estimations in wheat plants where the height of the drone is between 20 to 30 metres above ground. As per Waiter et al (2015), Ground Cover (GC) is a key factor in characterizing the temporal and genotypic characteristics involved in plant breeding.

2.4.3 Drone Altitudes and impact on conditions, sustainable flight, and batteries.

This section examines the way in which drones can be affected by the conditions in which they are operated. For example, flying drones at higher altitudes invokes a range of dangers such as wind speeds, increased chance of bird strike, lack of sustained flight from excessive battery strain, and loss of signal and frequency dropouts. These issues also include challenges to maintaining Line of Sight (LoS) and possible challenges arising from lost UAVs and "Fly Away" scenarios.

Seifert et al. (2019), noted that drone flight altitude had a direct impact on both drone-flying time and processing time. This finding demonstrated an impact upon the number of images being captured. In 2020, Biglia et al used a DJI Matrice 600 inspray mode to test different flight modes and spray systems on canopies and vineyards. The study cited that in windy conditions the fine droplets could be diverted and blown away from the intended spraying area by the environmental wind. The study showed that such issues could be minimized, by reducing the drone speed and flight altitude, and by using different types of nozzles. In 2018, Lou studied the effect of drone height on droplet distribution drift on cotton fields. The study showed that flight height had a significant effect on the droplet distribution. The conclusion was determined by an experiment conducted at two different heights of 1.5 metres and 2 metres. The coverage rates at 2 metres were significantly higher than those of 1.5 metres.

To address the limitations of conventional commercial drones, small unmanned aerial vehicles (SUAVs) have adopted nature-based concepts and design principles from flying animals. Tanaka et al (2022), conducted research to address some of the limitations that are faced by the drone industry like flight stability, flight efficiency, collision avoidance, damage mitigation and grasping (grasping and carrying irregularly shaped heavy objects) during flight. The study made use of nature-based designs to develop a drone that was based on the concept and design principles of flying animals.

2.5 Sensors

This section explains many of the different types of sensors that are in use with UAV devices. These include NDVI, Thermal, RGB, Multispectral, Lidar, and Hyperspectral sensory devices.

2.5.1 NDVI

In order to complete the photosynthetic process, green plants use visible light (solar radiation). During photosynthesis, the plants scatter and reflect solar radiation in the near infrared range. This variation in absorption is exclusive to plant life and serves as an indicator of plant greenness (Map information, 2022). The normalised differential vegetation index (NDVI) calculates this difference and provides information about the health and density of plants (Huang et al 2020; Robinson et al, 2017). Research has shown that the NDVI is a useful index for distinguishing between types of evergreen and seasonal forests, as well as between savannahs, dense forests, areas that are not forested, and agricultural fields (Pettorelli et al. 2005). NDVI has become popular in UAV applications because of its ability to differentiate and quantify live green vegetation (Huang et al 2020). In 2017, Tian et al, mapped mangrove forest leaf area index (LAI) and used it to to estimate various vegetation properties using a UAV mounted multispectral camera.

RED NDVI video and images were obtained by Ghazal et al. (2015) using an autonomous UAV system equipped with a GoPro camera that had its infrared (IR) filter replaced with a custom filtered lens. The author notes that one of the benefits of utilising a GoPro camera is that it not only helps lower the payload of a UAV, but it also eliminates the need to use two cameras in order to acquire images in the visible spectrum and the infrared spectrum. Neupane et al (2021) used a DJI Mavic Air drone equipped with a single NDVI camera to identify and monitor plant disease.

2.5.2 RGB Sensors

The most popular sensors used by UAV systems for Precision Agricultural applications are RGB sensors (Tsouros et al, 2019, Hassler et al, 2019; Delavarpour et al 2023). Compared to the other types of sensors, RGB sensors are cheap and can take images with a high resolution (Matese et al, 2018). They are also easy to use and operate, and they don't weigh much. Also, the information that is gathered is easy to process. The pictures can also be taken under different conditions, like on sunny or cloudy days (Tsouros et al 2019; Yao et al, 2019).

Some of the criteria for selecting RGB sensors includes the choice of different Lens qualities (higher quality lenses produce less geometric distortions). Such choices affect the resolution and quality of the charge coupled device (CCD)/complementary metal oxide semiconductor (CMOS) chips (pixel size and noise level) (Yao et al, 2019; Adão et al., 2017). Many studies have used RGB cameras to obtain the canopy height and biomass of crops like barley, wheat, and black oats (Bendig et al 2014; Acorsi et al 2019;). An RGB imaging system based on an unmanned aerial vehicle was used by Bendig et al. in 2014 to estimate the height of barley, and based on that height measurement, they determined the biomass of the plants. The study showed that the approach used has the potential to be simply implemented by those who are not trained in the field, such as farmers.

In 2019, Acorsi et al, used a DJI Phantom 3 in order to determine the height of black oats and to provide an estimate of their biomass. The study showedthat UAV RGB imaging can be used to predict and study the spatial and temporal variation of black oat biomass, which provides useful information for precision farming. In 2020, Panday et al, made used of a DJI Phantom 3 Advanced to determine the height of wheat, and to make an estimation of their biomass and crop yield in Nepal. Based on the findings of this research, it is possible to predict wheat above-ground biomass (AGB) and yield in a manner that is mathematically reliable by assessing plant height using crop surface models (CSMs) produced from drone photos.

In 2018, Hu et al. compared humanly measured sorghum height with measurements taken by an RGB UAV. The UAV self-calibration system had the best performance overall, with repeatability that was comparable to human measurement. The study demonstrated that high throughput phenotyping of plots using UAV surveys is both practical and reliable. The popularity and wide-spread acceptance of RGB images is largely a product of the much larger selection of RGB drone-capable systems. RGB systems tend to be much more prevalent in low to medium size drones and are regularly used in places where higher-order sensors are not able to be included in the data gathering exercise. A study in Spain, used a drone with an infrared camera to calculate canopy height measurements which suggest that when comparing the UAV images to traditionally acquired field data the heigh measurements were accurate (Zarco-Tejada et al., 2014).

2.5.3 Multispectral UAV Sensors

In addition to RGB cameras, multispectral cameras are one of the most frequently used types of sensors in the family of UAV sensors. This is because multispectral cameras are able to obtain spectral information in the red-edge and near-infrared band at an extremely high resolution, which is useful for applications involving vegetation (Yao et al, 2019; Patrick et al 2017; Iqbal et al, 2018).

In comparison to standard RGB (red, green, and blue) photographs, multispectral photography has the potential to provide enormous amounts of additional information. (Adão et al., 2017, Navia et al., 2016). As per Candiago et al. (2015), multispectral photography captured by unmanned aerial vehicles (UAVs) has the potential to be a very dependable and efficient tool for use in agricultural evaluation and precision farming. To that end, multispectral imaging can provide higher-order imagery, but at a much higher cost in terms of the cost of each drone system.

Khaliq et al, (2019) conducted a study comparing multispectral satellite imagery with UAV-based imagery. The authors concluded that images captured by unmanned aerial vehicles (UAVs) increased the precision of describing vineyard variability and producing maps of crop canopies. Patrick et al, (2017), used unmanned aerial vehicles and multispectral imaging to conduct high-throughput phenotyping of tomato spot wilt disease in peanuts. Cao et al. (2020) analysed the development of sugar beetroot using multispectral images captured by a UAV. Neupane et al (2021) used a DJI Mavic air drone equipped with a single NDVI camera to identify and monitor plant disease. In 2019, Ampatzidis et al. counted 4,931 citrus trees using a DJI Matrice 600 for detection and counting. The technique was tested and shown to be effective in recognising and quantifying citrus trees with high precision of 99.9%. UAV-based RGB and hyperspectral imaging has shown promise for measuring biomass and forecasting output in potato crops, according to a study by Li et al. in 2020.

Thermal and multispectral imaging can be integrated with AI approaches (e.g., deep learning) to identify plant stress(Ampatzidis et al, 2022; Ampatzidis et al 2019; Jung et al 2021; Syeda et al 2021). These studies demonstrate the benefit of more precise monitoring of plant development, stress, and plant health for increased crop and harvest results (Cao et al, 2020; Buter et al, 2019; Neupane et al, 2021).

Based on the literature, drones and high-resolution imagery has proven to demonstrate accurate results, however, some of the limitations in those studies relate to different drone altitudes as well as the integrated deployment of cameras like RGB and Multispectral cameras. For example, in Germany Getzin et al (2014) studied the use of higher altitude flights (250 metres) to capture UAV footage of 7 cm in resolution. Similarly, Chianucci et al, (2014), used a fixed-wing UAV, equipped with an RGB camera and a flight altitude of 130 metres to captured canopy images.

2.5.4 Lidar

Light Detection and Ranging, (LiDAR), is a technique for remote sensing that measures distance. It generates a three-dimensional projection of distant surfaces and objects by combining laser pulses with other significant data that can be acquired by a LiDAR-equipped UAV (Gautam et al 2020; Zhou et al, 2020). LIDAR may be used to assess the height of vegetation as well as its vertical structure (Chung et al, 2019; Tilly et al 2015). In addition to this, it is unaffected by the natural light in the environment (Lin et al 2015). The information obtained from LiDAR on the height of plants is more accurate than that obtained from digital photographs (Madec et al 2017). In Belgium, Lisein et al, (2013) made used of a small drone to capture near-infrared images with a spatial resolution of 7.6 cm for accurately measuring canopy heights. The results suggested that the equipment (Spatial camera resolution of 7.cm and small drone about 2 kg) showed similar measurements to those obtained by an expensive LIDAR-based UAV.

Measurements showing wheat plant height, ground coverage, and aboveground biomass were all acquired using LiDAR in a study by Jimenez et al, (2018). The estimated findings for wheat canopy height revealed R2 = 0.99 and RMSE = 0.017 m, both of which imply better plant height estimation accuracy.
Several research studies using LIDAR to track plant height have shown promising results for crops including rice (Tilly et al ,2014), tomatoes (Llop et al, 2016), Maize (Zhou et al 2020) and cotton (Sun et al 2017).

2.5.5 Other Sensors

2.5.5.1 Hyperspectral Sensors

Hyperspectral imaging, like multispectral imaging, can collect light over a wider range than traditional methods. The differences, however, are in the size of the light bands. Hyperspectral cameras can potentially monitor thousands of narrow bands of light for every pixel in the resulting images. This is in comparison to multispectral imaging, which can only collect light over a narrower range (Adão et al 2017; Lowe et al 2017). This imaging method may be helpful if extremely specific wavelengths of light need to be detected separately. In most cases, hyperspectral images detect light produced by specific biomolecules like chlorophyll (Gevaert et al, 2015; Cilia et al 2014).

The disadvantages of hyperspectral imaging include the typically expensive cost of cameras, particularly the lightweight versions that may be installed onboard a UAV. Deery et al, (2014) as well as Adão et al (2017), have documented the overwhelming quantity of worthless data if the equipment is not correctly calibrated by skilled specialists (Lowe et al 2017; Saari et al 2017). Hyperspectral imaging was used by Cilia et al. (2014) to measure the nitrogen content of maize.

2.5.5.2 Thermal Cameras

Thermal sensors and cameras can collect infrared light radiation from a distance that ranges from 0.75 to 1000 metres, which enables it to provide the precise temperatures of objects within a thermal picture (Hassler et 2019; Adão et al 2017; Costa et al 2013). In the agricultural industry, thermal imaging is most often used to detect stomatal control (Table 2.2) and, as a result, water stress in plants (Costa et al 2013; Katsigiannis et al, 2016; Gago et al, 2015; Gautam et al 2020).

Spectral Category	Sensor Type	Sensor	Color Space/Spectral Band	Carrier Drone
RGB	1 CMOS	DJI FC6310	sRGB	DJI Phantoms
Multispectral	CMOS	SlantRange 3p/4p/4p+	470-850 nm (6bands)	DJI M100
	CMOS	MicaSense RedEdge	475-842 nm (5bands)	DJI M100, S800 EVO
	9 CMOS Mono-Chromatic Sensors	MAIA S2	Same wavelength intervals as of sentinel-2 (9 bands)	
Hyperspectral		SPECIM AFX10	400-1000nm (224 bands)	DJI M600
	CMOS	Headwall Nano-Hyperspec VNIR	400-1000nm (270 bands)	S800 EVO
	9 CMOS Mono-Chromatic Sensors	Headwall Nano-Hyperspec VNIR A/E-Series	400-1000nm (324/369 bands)	DJI M600 Pro
Thermal	CMOS	FLIR Tau 2	7.5- 13.5 μm	S800 EVO, modified Hexacopter
		FLIR DUE Pro R	7.5- 13.5 μm	DJI Phantom 4 Pro
		FLIR Vue Pro R	7.5- 13.5 μm	DJI M600 Pro, DJI S1000+
	1/3” Sensor	WIRIS Agro R	Long Wavelength InfraRed	DJI M600 Pro, DJI S1000
LiDAR		Velodyne VLP-32C	32 channels	DJI M600 Pro
		RIEGL VUX-1UAV		Hexacopter, RiCopter
		Hesai Pandar40	40 Channels	DJI M200 Series, LiAir 200

Table 2.2 Typical sensors available for multi-rotor drones (Pandey et al, 2020)

2.5.6 Object Detection

Object-Based Image Analysis (OBIA) is a method that divides each image into spectrally similar "objects." This makes it possible to classify things not just by colour, but also by shape, size, and how they relate to other things within a given image (Baena et al, 2017). It further supports the use of supervised machine learning (a method that "teaches" a computer what set classes look like by supplying training examples). This type of programme then classifies the remaining pictures by their resemblance to each stated class (Cruzan et al 2016). Monitoring small features of interest requires very high spatial resolution (e.g., individual plants) (Shahbazi et al, 2014; Baena et al 2017).

Buters et al. (2019) used a DJI Phantom 4 drone with automated object-based image analysis software to detect juvenile plant seedlings. The author mentions that OBIA classification from captured imagery also allowed for the accurate tracking of individual target seedling objects through time. This provides a perfect demonstration of the capability of UAV-based monitoring to undertake plant performance monitoring of individual plants at very fine spatial scales.

Jiménez-Brenes et al (2017), used UAV-based 3D modelling and methods to estimate the pruning effect on olive trees. The study makes a specific mention that assessing tree dimensions and quantifying the effects of three distinct pruning procedures on hundreds of trees was made possible by combining UAV-based pictures with an OBIA process.

2.6 Networking, Signals and connections with LoRa and LPWANs.

The connection between LoRa systems and drones has been well established. LoRa and long range wide area networks have proven to be particularly useful in a range of otherwise complex tasks. The use of the Internet of Things (IoT) as a dominant technology is supported for the benefit of networking systems that can operate in rural and remote regions (Park et al., 2018). This combination of LoRa networks with drone usage has thrived and succeeded because it has consistently proven to be a useful set of technologies that can harness the signal power of long-range network radios with the flexibility and area access that can exist because drones can fly to areas that other vehicles and farm workers cannot easily reach (Khawaja, 2019).

In combination, the ability to access a range of IoT sensors via the power of long range LoRa networking with the additional reach and flexibility of access from drone presents a useful solution for farm areas without access to 3G,4G networks. As such it provides for a number of exceptionally sought-after technology opportunities. This type of combinational approach allows for sensor data to be drawn through the LoRa gateway using a potentially large number of sensor nodes (Verman et al, 2013).

Given that there are radio propagation challenges that exist in remote areas of forest and agricultural land, the use of a relatively small drone with a gateway mounted on the drone can collect sensor data from a number of ground-located nodes. This type of arrangement allows farmers to get environmental data over large areas where much of the land area is hazardous for vehicles and others to try and gain access (Khawaja, 2019).

The LoRa gateway / drone combination has been continuously tested to figure out whether the gateway attached on a drone that hovers over farm field can gather data from nodes on the ground. The aim of this work is to help farmers get environmental data over the geographically large farm field, and from locations where it is difficult or dangerous for farmers to access. The use of LoRa provides a double-edged benefit. It can access IoTs in long-range mode but is also a method of gaining long-range access with very low power requirements. The traditional way of farming and the standard farm systems are in the process of undergoing enormous change, where smart farming is becoming an established norm in the battle for access to data and opportunities in remote and rural areas.

The combinational value of LoRa alongside farm IoTs and sensors is of augmented value, with a drone carrying a LoRa Gateway as an example of a data collection system that can access and gather data across a broadacre farming environment irrespective of connectivity with urban staples such as 3G and 4G networks, which are either uneven or not accessible in remote and rural areas of most of Australia's broadacre farming community. Unmanned aerial vehicles (UAVs) make for exceptionally efficient gatherers in the sense of data collection (Boursianis et al, 2020). On the ground sensors can store sensing data which can be collected through drone deployment in locations without fixed communication infrastructure (Caruso et al, 2021).

The increased acceptance of smart farming has brought together broad interest from service providers who are able to visualise the value of using a digital technology strategy to bring together IoT sensors for a wide range of characteristics including asset monitoring, livestock locational retrieval, and water management (Behjati, et al., 2021). The clear value of this type of combination is the ability to gather data quicky and efficiently without endangering other assets such as livestock. When combined with a larger fixed-wing drone, the combinational value extends to provide capability for large scale broadacre enterprises (Gong et al, 2018). This is particularly effective when using fixed wing drones with normalised fly-over speeds of around 95 Kmh per hour (Behjati et al., 2021). The resulting combination gives excellent access to ground-based data and also allows for higher-level data collection for expected high-yield crops such as wheat (Farajzadeh et al., 2019).

2.7 Machine Learning and Software Processing

One of the emerging benefits of UAV deployment for broadacre farming has been the use of machine learning and other software-based applications that allows for a range of drone practices to significantly increase the exercise of precision farming (Taha et al., 2019). This has a direct impact on improved decision-making and, in terms of broadacre farming, is a critical element for improved yield and productivity expectations (Baig et al, 2022).

There is, however, a risk of incorporating images that use pre-processing because they can negatively impact unsupervised ML models by making alterations to images. This can affect the accuracy of the data. Dilshad, Hwang, Song, and Sung (2020) discuss the use of a Heridal dataset using object detection to make suitable corrections for a precise method of increased accuracy. Marusic et al, (2019) suggests that a useful method for reducing this risk is to review images using a human expert approach to form annotated knowledge based on local expertise. By using expertise drawn from those from the specific area knowledge, it becomes useful to rely on agricultural experts from the discipline of precision agriculture. The issue of misclassified machine learning algorithms can also be addressed by using statistical analysis. Ishida et al, (2018) suggests it is an important inclusion to improve the robustness of an approach that uses similar ML techniques. A similar approach is described by Nhamo et al, (2018).

To address the issue of clarity, object detection algorithms such as convolutional Neural Networks (CNN), Single shot detector (SSD) and YOLO (you only look once) are used. Data from drone images is stored in different categories. Some experiments have shown that the Cascade R-CNN is widely applicable across detector architectures, achieving consistent gains independently of the baseline detector strength. (Cai & Vasconcelos, 2021, Dai et al; Gidaris

& Komodakis,2021). For example, different images taken at the same height and velocity will be compared with others of the same height and velocity. There are comparisons of drone images but with different camera configurations and angles. This helps to determine the height, velocity, and the ideal camera setting/angles for standardised best practice in drone usage.

The machine learning approach uses an unsupervised pathway (Gentleman et Carsev, 2008; Lloyd et al., 2021). Data from qualitative datasets can be used to validate the optimisation and to confirm a needs-based approach that can be applied back into farming environments. Issues such as the risk of object detection can be mitigated by means of a TIDE approach (Toolbox for identifying object detection errors) (Guo et al., 2021; Bolya et al., 2021)

2.8 Animal Welfare

One of the emergent vectors for drone usage is in animal welfare. Smart Farming allows farmers to identify and track animals of all types of backgrounds. This allows for farming livestock, but also permits the tracking and monitoring of feral and wild animals (Bolden et al., 2020), as well as protected livestock (McCarthy, et al, 2022). Animal welfare now carries a much higher level of responsibility in Australia as the greater rural area is more directly involved in both livestock and native animal species.

Livestock monitoring

Animal detection in remote areas is a difficult topic which has gained a lot of attention in ecology (Linchant et al, 2015; Hollings et al 2018). It is primarily used for monitoring the movements and location of animals in the wild and can provide ecological and agricultural information (Vayssage et al., 2018). It has application in both livestock and also feral animals.

In 2018 Vayssade et al. designed a system to automatically track the activity of goat using drone camera. The study noted that image analysis may be used to not only determine the whereabouts of the animals, but also their activities, which presents exciting new possibilities for the monitoring of a large number of animals.

In 2021 Alvarez-Hess et al, from the University of Melbourne used a DJI M200 hyperspectral image for measuring pasture depletion in cow paddocks. In 2017, Nasirahmadi et al., implemented a machine for detecting the behaviour of cattle and pigs. A study by Rivas et al, (2018), proposed a method for counting cattle which combines a deep learning model for difficult to access animal locations.

The use of drone technology can be harnessed in order to show a strong level of success with monitoring and locating the movement of livestock. This can be extended to include the monitoring of temperatures, as well as showing specific locational information for different animals. There is a downside to this type of approach in so much as it can be used to monitor and to track animals based on their lack of movement during a given day(McCarthy et al 2022).

Using drone technology has demonstrated success with livestock, monitoring their temperature, identifying and detecting their position, and other factors. However, it has also been shown to have a bad effect on the wellness of animals. For example, if drones are unable to maintain a safe distance from animals, the resulting noise, which includes a distinctive buzzing sound, may have a detrimental effect on the animals' physiological health. This may cause the animals to experience higher levels of stress. If animals are subjected to such an environment for a long time, it may result in health problems since the effects of such an environment may be especially severe on animals who are either pregnant or are caring for young. Studies has shown that drones may sometimes be the victims of bird attacks, such as hawks and eagles. This can result in the animal being harmed, and it can also pose a safety risk, as the drone could end up crashing into a person, a vehicle, a structure, or even a high voltage electrical cable.

2.9 Rules and Standards for operating Drones

The potential of drones has been recognised by nations all over the world, and countries are actively investing in the creation of innovative drone technologies (Ayyapan, et al, 2007). Yet, they are aware of the dangers that may arise from the unrestricted use of drones and have established laws and guidelines for their use for ensuring safety and privacy of the population (Tsiamis et al 2019; Pathak et al, 2020; Clarke et al 2014).

Globally there are a number of challenges for drones in terms of policies, structure and regulations (Pathak, et al, 2020). The current accepted standards in many parts of the world have yet to properly integrate a workable standard for the BVLOS (Beyond Visual Line of Sight) drone operations, in particular at 125 metres height and above (Pathak, et al, 2020). In a worldwide sense, the rules of drone operations in terms of training, licencing and standard operating procedures are all inconsistent. There is a need to establish clear, globally accepted, regulations about standard operating heights operating speeds, and the obstacle avoidance literature.

In Australia, the Australian Civil Aviation Safety Authority (CASA) is responsible for ensuring flight safety and imposing regulations on various types of drone operations, such as those carried out for the purpose of recreation, hobbies, or for profit-making enterprises. The new regulation known as the Civil Aviation Safety Rules (CASR) Part 101 came into effect from 2016, and included a new category of operation known as "Excluded RPA." Under the new law, property holders don’t need approval to operate drones up to 25 KG on their properties. While operating a drone in Australia, it is important to pay attention to the following regulations: You are only allowed to fly your drone during the day, and it needs to be always kept within line of sight. You should not fly the drone higher than 40 metres above the ground, and the drone should be kept at least 30 metres away from other people. You are only allowed to fly one drone at a time.

In the United States of America, the Federal Aviation Administration (FAA) has introduced the New Small Unmanned Aircraft (UAS) Regulation (107), which relates to the flying of drones for commercial or industrial purposes. According to this regulation, a drone that weighs less than 249 grams does not need authorisation to fly, but a drone that weighs between 249 grams and 25 kg is required to be registered with the FAA. The drone must be always in the pilot’s direct line of sight.

The laws and regulations for operating drones in Japan are handled by the Ministry of Land, Infrastructure, and Transportation (MLIT). Drones are banned between the hours of sunset and sunrise and must stay at least 30 metres away from any individuals or property. Drone flights that extend above an altitude of 150 metres need prior authorisation from the MLIT. In Japan, breaking the law can result in a fine of up to 500,000 yen (about AUD $4,000).

In India, the Directorate General of Civil Aviation (DGCA) oversees the drone laws. All drones that are flown in India are required to have valid third-party insurance coverage to cover any potential liabilities that may emerge as a result of an accident. In addition, it is prohibited to fly above any national parks or animal sanctuaries. Flying drones is illegal within 50 kilometres of a country's border. The drone must be equipped with a licence plate containing the name and contact information of the pilot and drone users must be trained drone pilots who are at least 18 years old.

In 2019, Tsiamis conducted an extensive research of comparative studies showing the evolution of laws regarding the use of drones in Economic Co-operation and Development (OECD) nations: Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Luxembourg, Mexico, the Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, the United Kingdom, and the United States of America. According to Tsiamis, only Italy, Latvia, and the Slovak Republic have defined air traffic zones for the use of drones, and the author also stated that the regulatory framework in Canada is stricter than in any of the other OECD nations. On the other side, the legal system in the United States takes a more permissive approach. Within the OECD flight purpose laws differ. There is an onus on remote pilots to have a reason for the use of a drone on a range of countries. Australia, Austria, Canada, Czech Republic, France, Greece, Israel, The Netherlands, Poland, Portugal, Slovak Republic, Spain, Sweden, UK, and USA have flying purpose guidelines, compared to the other OECD nations which do not give emphasis to such guidelines. In 2014, Clarke et al. did a study on the effects that the regulation of civilian drones may have on individuals' behavioural privacy. These apply to populous areas more than in the remote and rural areas often used by farmers.

2.9.1 Governance of Drones and in remote spaces and / or satellite-affected networks

One area of interest is the way in which governance has been arranged in terms of the rules and standards for drones. On the one hand there is an Australian national authority (CASA) which exercises its authority in terms of the regulation of civil aviation. However, the governance arrangements are less obvious for drone users / farmers / pilots that use UAVs in rural and remote areas. Whilst the CASA rules are prescriptive in terms of typical usage within urban and built-up areas, the use of drones in rural settings is less clear, and there is a community of people who will informally use drones based upon their own judgement rather than follow specific rules relating to people with licences, such as REPL, or the selection of drones based upon payload, multi-rotor, or fixed wing categories.

The way in which governance is followed can be seen through two different lenses. On one hand there is a national authority which provides clarity on specific rules and regulation that relate to the usage of UAVs. On the other hand, many farm-related UAV flights are neither documented nor recorded in the same manner that urban UAV usage is carried out. The farming / agricultural community has drone users who fly UAVs for agricultural reasons. This informal self-managed governance is effectively comprised of private actors who may choose to form their own set of guidelines. This is not to describe the remote agricultural usage of UAVs as reckless or hazardous, but rather to acknowledge that the practices followed by many drone users vary greatly from the prescribed expectations of CASA. This new mode of governance is clearly made up of stakeholders who use drones for the purpose of agricultural business, but also share knowledge in terms of hardware software and associated land resources for the purpose of increased profitability in terms of high yield broadacre crops. This can be described as self-organising networks of participation, authority, and cross boundary accountability. (Cook, 2011).

2.10 Training and Licencing

Remote pilot licence (RePL)

In Australia if a person wants to fly a drone that weighs more than 25 kilograms, but less than 150 kilograms, over their own land or work as a remote pilot for an individual or a business that has a remotely piloted aircraft operator's certificate (ReOC)., they can apply for a remotely piloted aircraft licence (RePL). The Remote Pilot License will specify the model and weight class of drones that a pilot is allowed to fly. These are the following: less than 7 kg, less than 25 kg, less than 150 kg (type specific ratings only), more than 150 kg (type specific ratings only). An RePL does not expire. There is no age requirement in order to obtain a RePL.
RPAs (also called drones) are classified by weight and operations. Table 2.3 outlines the different types.

Classifications for RPAs
Micro: 250 g or less
Very small: more than 250 g, but not more than 2 kg
Small: more than 2 kg, but not more than 25 kg
Medium: more than 25 kg, but not more than 150 kg.

Table 2.3 Classifications for RPAs

If an operator falls into any of the following categories, an RePL is not required: Qualified to fly a micro-RPA (weighing 250 g or less) or an RPA from the excluded category: Excluded categories are RPA that are either: more than 250 g but not more than 2 kg more than 2 kg but less than 25 kg (only over your own land).

If a pilot wants to use their drone for commercial purposes, then they must obtain an operator accreditation. This stipulation extends to activities such as selling images or films shot from above, inspecting machinery, buildings, or other infrastructure, monitoring traffic, doing research, or providing security services. The Operator Accreditation is free and is valid for a period of three years. In addition, in obtaining an operator accreditation, pilots need to be at least 16 years old. If they are under the age of 16, they are required to have an authorised adult (someone older than 18) to supervise them.

Depending on the weight of a pilot's drone, they may need to have qualifications or accreditation that supports the specific usage of the instrument being flown.

Micro: 250 g or less

Any RPA or micro drone weighing less than 250g can be flown commercially or for work purposes. A Remote Pilot's License (RePL) or remotely piloted aircraft operator's certificate (ReOC) is not required (see Table 2.4).

Requirements to fly a Micro Drone weighing 250 grams or less	
1	Obtain an aviation reference number (ARN) – you may require an organisation ARN for your business
2	Obtain an RPA operator accreditation
3	Register your drone
4	Only fly your drone within the drone safety rules.

Table 2.4 Requirements to operate a Micro Drone

Very small: more than 250 g, but not more than 2 kg

A pilot may operate a very small drone or RPA weighing less than 2 kg for commercial or work purposes. This is also known as the sub-2Kg exempt category and no RePL or ReOC is required. Examples of businesses that fly under this excluded category may include photographers and film makers, real estate agents, researchers, construction workers and tradespeople, government and community service providers. (See table 2.5).

Requirements to fly a Small Drone weighing more than 250 grams but not more than 2Kgs	
1	Obtain an aviation reference number (ARN) – you may require an organisation ARN for your business
2	Obtain an RPA operator accreditation
3	Register your drone
4	Only fly your drone within the standard operating conditions

Table 2.5 Requirements to operate a Small Drone

Small: more than 2 kg, but not more than 25 kg

A pilot can fly a small drone or RPA that weighs more than 2 kg but not more than 25 kg over their own land for business or as part of their job, provided they do not accept any type of payment for their services. This is called the landowner or private landholder excluded category because the pilot doesn't need an RePL or ReOC. Some of the operations they can perform under this excluded category include aerial spotting, crop, livestock or equipment inspections, land surveying, agricultural operations, carrying cargo.

In Australia a UAV Drone pilot must follow the rules described in Table 2.6

Requirements to fly a Small Drone weighing more than 250 grams but not more than 2Kgs	
1	Obtain an aviation reference number (ARN) – you may require an organisation ARN for your business
2	Obtain an RPA operator accreditation
3	Register your drone
4	Only fly your drone within the standard operating conditions
5	Keep the required operational records
6	Not Accept payment for the services you provide.

Table 2.6 Australian Requirements to operate a Small Drone

Medium: more than 25 kg, but not more than 150 kg.

A pilot may fly a medium-sized drone or RPA weighing more than 25 kg but less than 150 kg over their own property for business or work purposes, so long as they do not take money for their services. This category is known as landowner or private landholder excluded. They must get an RePL for the drone type and model that they intend to fly.

2.11 Classifications of Drones

CASA classifies drones into a range of segmented categories and sizes (types). They can be recognisably described as multi-rotor helicopters, single rotor helicopters, aeroplanes, power-lift vehicles, and airships. Whilst the main category of interest pertaining to this thesis lies within the category of multi-rotor helicopters, the scope of this study also closely considers that the progressive extension for large-scale farming enterprises will also cross-over into fixed-wing drones operating at much higher elevation, and at much greater speeds.

Multi- rotor helicopter

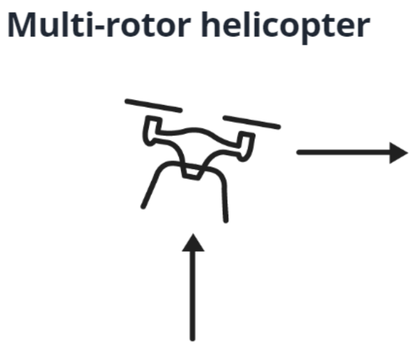

Figure 2.6 Multi-rotor helicopter

This category includes machines that include more than one power-driven rotor that can spin or revolve in a vertical direction. It operates in the same manner as a standard helicopter with a "single rotor," including taking off, landing, flying, and hovering, but it has more than one rotor. Figure 2.6 show a basic multi rotor helicopter.

Single-rotor helicopter

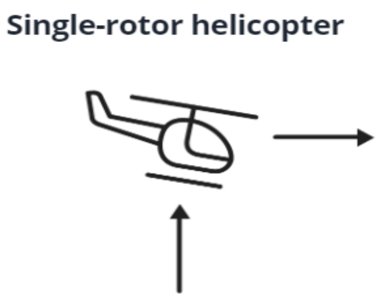

Figure 2.7 Single-rotor helicopter

This type has one power-driven engine (rotor) and looks a bit like a traditional helicopter. It usually also has another rotor on the tail or end of the aircraft. (See Figure 2.7)

Aeroplane

Figure 2.8 Aeroplane

This type of model looks and flies like a regular plane – it has fixed wings. It also takes off and lands horizontally and usually can't hover. (See Figure 2.8)

Power-lift

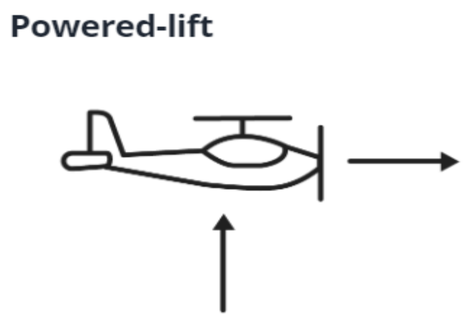

Figure 2.9 Power-lift

This kind of model can take off and land vertically (straight up and down) like a helicopter, but then it can fly forwards like a regular plane. (See Figure 2.9)

Airship

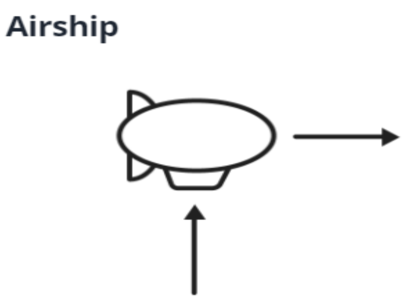

Figure 2.10 Airship

This type of engine is powered and is 'lighter than air' - it can be filled with a buoyant gas and usually 'floats' in the air. A blimp is a good example of an airship. (See Figure 2.10)

2.12 Gaps in the Literature

This literature review has extensively discussed three main factors which can be described as a gap in the literature (Hu et al., 2019)) and also the absence of a standardized workflow focusing on the most frequently used techniques explaining and processing of UAV imagery from agriculture fields (Tsouros, D.C, Bibi, S. & Sarigiannidis, P.G., 2019). A study conducted by the University of Queensland (Hu et al., 2019) has suggested that more research need to be undertaken to explore the real nature of UAV imagery captured at different flight considering the three main factors which are environmental, cameras, and altitude.

Environmental factors

In 2019 Hu et al suggest that factors like wind speed, light condition, and sun direction are some of the environmental elements that can affect the quality of the images. In 2019 Lee & Sim, mention that remote sensing devices are usually contaminated by aerosol particles in the air, and thus satellite images often exhibit hazy or cloudy pixels.

Camera configuration

Some of the camera configurations that need to be considered to acquire a high-quality image are focal length, shutter speed, ISO white balance, camera angle, and camera stabilization. For example, the shutter speed is normally defined as the amount of time that the camera's shutter is open (Schult, 2021). The longer the timeframe,the lighter that can pass through to the camera's sensor. As per Hu et al., (2019) the focal length is directly related to pixel size, and that a lens with a long focal length leads to small pixel size when the flight height is fixed. This research will explore those camera configurations that result in acquiring a high-quality image.

Flight height/ altitude.

The height or flight altitude is an important factor to take into consideration as it can have a direct impact on the quality of the image. For example, A study conducted by Seifert et al., (2019) suggested that low flight altitudes yield the highest reconstruction details and best precision. This research explores different flight altitudes and analyses the effect on image resolutions. In 2014 Getzin et al, suggest that to get a very good image, low flight altitude, low cloud cover conditions, and no direct sunlight light are recommended.

2.13 Risk, Maturity, Readiness, Entropy and Decay

This section of the literature considers five evaluation mechanisms that focus on areas of expected alignment with this research. The introductory information provided in chapter One showed that these five areas held the key to understanding a way to make sense of what is otherwise a complex and dynamic set of variables that are otherwise seemingly disconnected from each other (Boursianis, et al, 2022; Wahab et al., 2018; Hall et al, 2018).

Some areas, such as the cost of equipment, demonstrates the wide gap between entry-level drone instruments and high-level multi-sensory drones that can provide high level productivity data that is world class in terms of broadacre farming (Grieve et al, 2019). There are risks on either spending too much money in a new area of technology or otherwise not investing enough to realise the true benefits of the integration of IoT and sensor analysis across large areas of land with little or no telecommunication infrastructure (Zuo et al, 2021; Dutta et al, 2021).

Similarly, the areas of cost and expenditure are strongly connected with drone expenses that are dynamically changing and have high-end costs that are being rapidly replaced by new technology every few months (Benke et al, 2017). It is clear, even from a cursory examination, that some components of drone-based broadacre farming are a great deal less mature than others (Stampa et al, 2021), and that change is taking place at a relentlessly brisk pace (Tokekar et al., 2016).

The areas of risk and maturity are therefore areas of uncertainty that require an evaluation of technology readiness. In the first instance the readiness needs to show that the technology being practiced in broadacre farming is sufficiently organised so that it can be used with confidence. The use of Technology Readiness Levels (TRLs) is practical in this study because the specific purpose of TRL management is very closely aligned to the transformational elements that are in play with drones in broadacre farming (Mankins, 1995; Straub, 2015; Barari et al, 2015). In particular, the evaluation of TRLs match (loosely) the expected changes that may eventuate in the inclusion of drone technology in order to generate better outcomes for precision farming, especially in terms of broadacre farming. In the second instance there needs to be an evaluation of whether the specific technology will be used using repetition so that the impact of the technology is not so much an element of readiness at one point in time, but rather that it can be deployed in a state of readiness across an entire season, or in the case of broadacre farming for multiple seasons or multiple crops (Balafoutis et al, 2020; Jellason et al, 2021).

Having examined the various factors through the areas of risk maturity and readiness, the final area of entropy is a project feature that is used to determine whether any of the key factors have either stalled, been delayed, or have fallen away from the key broadacre practices. By measuring each factor in terms of its entropy, an area can be evaluated so that it shows its state of currency, and whether parts of the process or parts of the broadacre practices no longer support the specific technology usage (Dainelli and Saracco, 2023). This form of examination is particularly well suited to information systems, and technology uses where the data and information goes through networks and areas where data is stored, aggregated and shared with others (Fanigliulo, et al 2020).

3 RESEARCH METHODS

A number of phases have been structured for the research approach to deliver knowledge and understanding about the practices of drones. This section outlines the research methods for this research study. The methodology has been chosen based on the knowledge drawn from a review of the relevant literature. This includes the research methodology (section 3.1), and the research approach to be undertaken for the study (section 3.2)

3.1 Research Methodology

This study will use a mixed-method approach, which will adopt a largely qualitative approach that incorporates an extensive literature review. It will allow for a high level of understanding of the various parameters that influence accuracy in decision-making using precision agriculture. To better understand the problems that farmers face in gathering valuable data in real-time, the study also includes an examination of the efficacy of a possible framework, by means of a study using the technology readiness levels as adapted from NASA and gaining global acceptance for usage in digital agriculture (Schmeitz, 2020; Agrawal, et al. 2021).

This is a literature-based methodology that draws key insights from a wide range of literature on drone practices and standardisation issues. The literature considered in this study helps to define the challenges of broadacre drone usage and deployment. The approach taken to this literature builds upon a qualitative evaluation of known information. This thesis examines the various literature vectors by description, analysis and comparison. Information is then collated using a thematic approach to ensure that the most activate themes are drawn from the comparison of literature.

3.2 Research Approach

Several phases are implemented for the research approach in order to deliver the stated research outcomes. A brief description of the approach is outlined below. This study will assist in the early recognition of the important labelling terms used, so that a uniform set of descriptors can be formed to allow for the accurate comparison of data acquired from different makes and model of drones. A diagram that describes the research development processes used in this thesis is illustrated below (Figure 3.1).

<u>Research Methodology For Drone Practices and Issues</u>

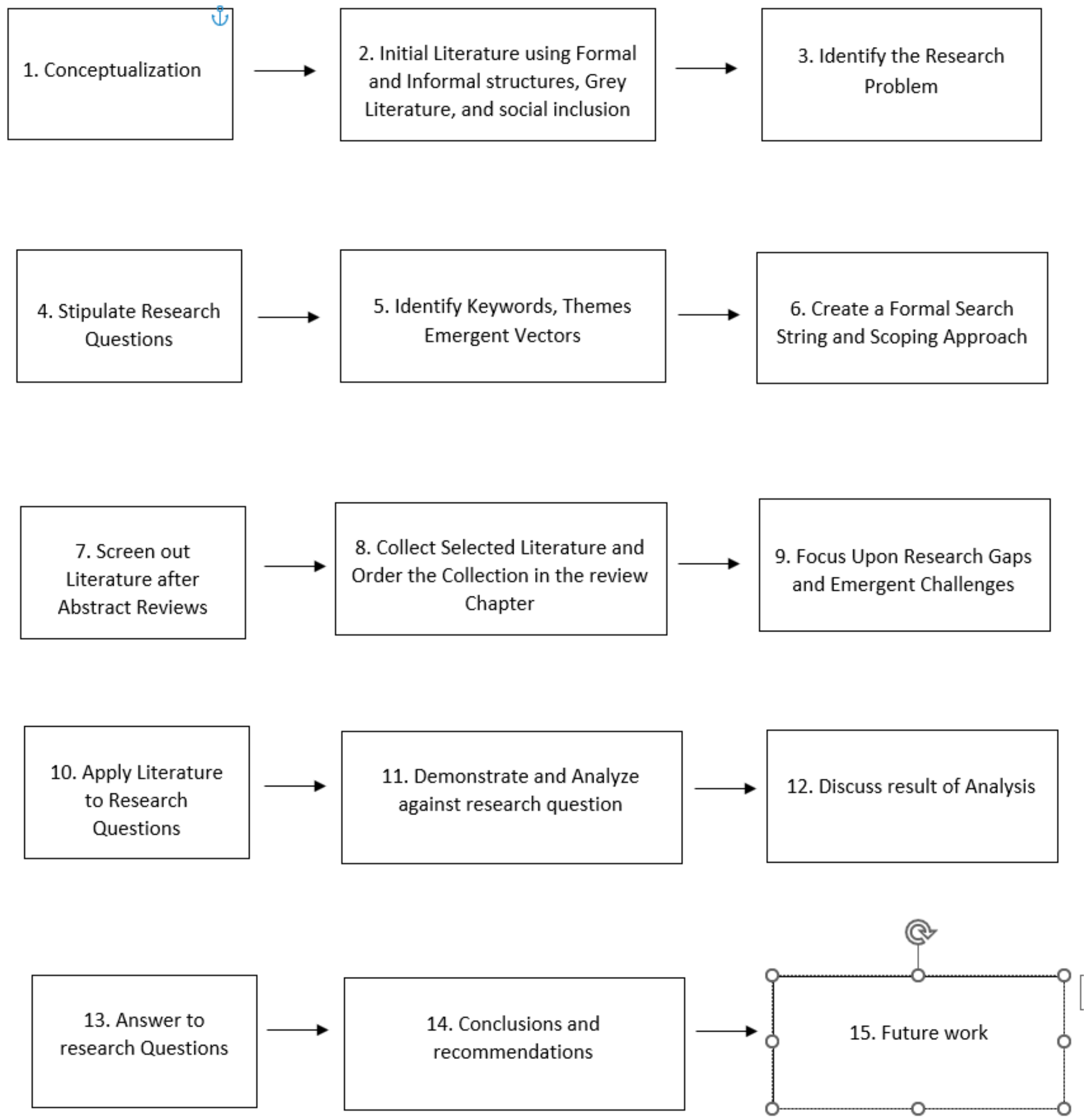

Figure 3.1 A Visual flow chart showing the Research methodology.

To structure each of the emergent themes a process of identification is used to highlight the main areas. There are a number of over-lapping ideas, with some areas more directly connected with technology themes, whilst others are more closely connected with rules, governance and technology acceptance.

From the background information and literature review there are ten firmly emergent themes. These themes can each be directly framed towards the research questions and therefore inform the process through a series of explanatory and illustrative comparisons. This thesis attempts to identify factors of influence. In this sense, the thesis differentiates between small popular elements that have novelty value within leisure and recreation circles from stronger elements that have a profound impact upon the current practices as well as the future developments that are expected to dominate the UAV market as it approaches global ubiquity.

This thesis will identify normalised and standardised practices in drone operating heights. It is anticipated that the different results will provide a snapshot of the range and size of variance between different altitudes. These differences will provide an insight into the types of comparative heights that might form the starting point for the determination of optimised heights for drone flights. Additional questions will consider the different drone equipment currently in use, as well as the relative age and generation of the drones being used. Further examination of the types of camera optics, lens sizes, number of pixels, and focal lengths of different cameras, will take place in order to gather the starting point for questions relating to the optimum type of camera equipment.

Literature Review

This early phase gathers the substantive body of information and data for this research through a review of the body of literature on drones, image resolutions (pixels), governance, networks, data, and privacy issues. The research makes use of the literature to identify gaps in the current knowledge base. Much of the information required to understand this research problem is available in the form of existing reports, government exchanges, and formal research work. The emerging dynamics of this research can be found in two different sources. The first is the technical and regulatory information that comes from the military application and development of drone technology. The second source is from the leisure and recreational usage of drones that has captured the popular accepted rationale of modern technology integration. This study is referent to an agricultural environment that is neither military in nature nor based upon popular recreational technology usage. This study therefore has a challenge in drawing from these two pools of information to apprise a research question that has a unique environmental and social setting.

Research problem and research question

The identification of the problem was based on the literature review, and gaps in the literature, which led to the crafting of the research questions, objectives, and aims of the study. This thesis has been researched through literature-based resources. The approach to the literature in this study has been to use keyword searches to determine emergent themes, and to take those themes and use them to drive search strings that meaningfully draw together a body of literature that describes the attributes belonging to this study. Screening has been used to filter out those papers that belong to outlier themes and one-off authorships.

Methodology

The methodology has been formulated to account for the gaps in knowledge and the shortcomings of existing methods for problem investigation. The collection of data, data analysis, and validations are iterative processes that lead to the development of a frame of reference to support the research question. This is depicted in the chart-based diagram showing the 15-step process (Figure 3.1). The method of analysis and discussion draws from a thematic analysis of individual attributes which are applied jointly and severally to a framework that considers risk, maturity of technology readiness, and entropy as the concluding phases of the research, enabling the formulation of selected and well-ordered answers to the research questions.

4 ANALYSES OF DATA

This chapter draws from the literature to provide answers and to inform the discussion on the key elements that have become the emergent themes, and which clearly demonstrate the areas of greatest interest and dynamic change. There are ten emergent themes and each one has a separate evaluation and analysis.

4.1 Key Areas of Evaluation

There are several critical areas that emerge from a thematic understanding of the known and discovered literature that has been examined in this thesis. Individual thematic segments are discussed separately to each other. Initially the basis for each area of evaluation has been determined through key word and search-string analysis, allowing for Boolean parameters to find, select, and screen out critical elements. The more nuanced selection of these areas is discussed here in the form of ten evaluation points that develop a clear understanding of each area by means of literature, data, information, and by example.

Evaluation point A. Cameras and Sensors

The first area of discussion and analysis concerns the limitations of cameras and sensors. The broad overview of concerns raised through the literature indicates that there are six areas that impact on the efficacy, value and impact of drone usage within farming enterprises. In terms of precision farming, the critical areas of value are related to the ability of a farmer to capture high-quality imagery of a specific area or designated crop acreage and determine specific elements for treatment. This can include high-impact considerations such as weed control, removal of rocks and debris, pest management, water impact and climate change. In these types of segmented examples, the critical value of such drone imagery is dependent upon two main factors. The first is the quality of the camera-driven images, and the second is the ability to repeat the image capture process to allow for comparisons over time.

The literature clearly demonstrates that the quality of cameras in drone instruments changes with different models, cameras, and drone types. This is an issue in terms of comparison because the difference in the image resolution means that crop flyovers from season to season (or from crop rotation to crop rotation) may make comparisons that are inaccurately differentiating some of the key areas. For example, a farmer uses a DJI Phantom IV drone to record a wheat crop in August 2021, and then decides to use a fixed-wing drone in 2022 to more quickly capture the images of that same crop area in August 2022. Although the farmer would be focused on making comparisons in order to make improvements for yield, efficiency and productivity, the differences between a Phantom IV drone and a fixed wing upgrade would be significant. The Phantom IV drone would typically be capturing imagery at a height of 20 metres flying at 30kph using an f/2.8 wide-angle lens and a 12 Mega pixel camera. This would provide a vastly different image set to a fixed wing drone flying at a height of 100 metres with an f/2.4 lens at 70 kph and using a 60 Mega pixel camera.

Comparisons from differing measurements, resolutions, heights and at different speeds all combine to provide a complex range of differences that need calibrating. If the same example also considers additional outside factors such as time of day, cloudy versus clear skies, wind force, and rain, then comparisons can be further mis-aligned. Time factors and shadow impact are key elements that affect such comparisons being of reliable use. As per the analysis drawn from the literature and examples, the flight height can have direct impact on picture quality, flight time, drone stability, processing time, identifying object and crop spraying.

The above example only considers photo and video imagery. If the example is then extended to include other image data such as thermal, NDVI and RGB features, then the comparisons continue to hold a decreasingly disparate set of comparison values. The issue of image compatibility is perhaps best described here as a form of data entropy. Effectively, the dynamic change and rapid development of increasingly different drone features provide elements whereby the process is under decay, and imagery holds different values over time. In a discipline where yearly crop data is critical to the ongoing improvements and changes at the farm management level, image comparisons are subject to a set of data that demonstrates a historically decayed data set.

Lidar sensors are regarded as one of the most significant areas of sensor enhancement that is currently included in drone technology. The application of Lidar sensors demonstrates that future iterations are likely to become standardised with reliable Lidar sensor technology. Current Lidar technology is still in the development phase, and whilst some applications are used well, the great majority of Lidar development has yet to be sufficiently refined so that it can accurately identify and specifically count, and tally numbers such as the number of livestock, numbers of wheat heads, and other key elements that can be well served through more accurate measurement than an extrapolated approximation of a number.

In precision farming, a LIDAR UAV-based system has been shown to have some success; nevertheless, there are several limitations associated with it. The first limitation is the expense of the LIDAR sensor as sophisticated LIDAR sensors are more expensive than other image recognition sensors. Another limitation of LIDAR is that according to some research, it is unable to function correctly when the weather is poor, and the data that it collects may be inaccurate or rendered useless as a result. Scanning a dense area with a UAV-LIDAR system can be complex. For example, the point clouds obtained via the use of UAV LIDAR are significantly different from those acquired through the use of static LIDAR. While using static LIDAR, the distance between the scanner and the object is the primary factor that determines the point density. The target area for UAV LIDAR starts at the surface of the canopy and extends all the way down to the ground below.

In some cases where the vegetation is very dense, the pulses may not be able to reach the ground beneath the canopy. Typically, UAV LIDAR data is not colourized, making it challenging to analyse without the addition of RGB photographs and, due to its complexity, it requires a deep knowledge of the technology and skills to process the data and recognise inconsistencies and inaccuracies.

In the agricultural industry, these types of challenges are further exacerbated by the complicated integration of machine learning with a variety of sensors for purposes such as crop monitoring and livestock tracking, as an example. The accuracy of the sensor equipment's calibration is a crucial aspect to take into consideration.

4.1.1 Thematic Analyses

This chapter discusses several themes as part of the analysis. To assist with this a thematic diagram allows the reader to grasp a single overview of the chapter, and to understand the relationship between the evaluation points and the key issues. The diagram below provides a single view that enables an understanding of a number of complex issues and their relationships with other elements.

The recognition of these differentiated elements is important in terms of the way different technology themes overlap and interfere with each other. The mind map diagram below (Figure 4.1) provides a simple hierarchy that shows the nine major areas that affect drone capability. The individual segmentations show differentiations but are listed together to indicate the connectivity between segments of a similar grouping.

Figure 4.1 A Visual mapping of the key segmentation of analysis

Main Theme	Segmentations
Cameras and Sensors	Quality of the Camera Driven Images
	Ability to Repeat the image
	Change in Technology
	Weather and Environment
Drone Operation, Training and Piloting Capabilities	Drone Operation, Training & Piloting Capabilities
	Need / Confusion about a Drone Licence
	Right to Fly Privately
	Access to Drone Training
	Different Altitudes in Precision Agriculture
	Different Levels of Internet Access

	Access to Robust Computers
Signal Strength, Data Connectivity, Long Range LPWAN, and Mobile networking	Internet or network coverage is low
	Software requires updating
	Drones expected to cover larger areas
	Increasing numbers of adverse weather events
Cost, Time, and Return on Investment	Increasing Demand for Quality Drones
	Lack of Time – Need Time to work
	Length of Time in Training
	Competing Drones
Animal Welfare	Animal Well Being
	Health and Safety
Technology Issues, Battery Life and Drone System Failures	Drone System Failure
	Battery Life
	Bandwidth
Data Privacy, Rules and Regulations	Data Privacy
	Rules and Regulations
Technology Acceptance	Technology Acceptance
	Farmers Engagement with Technology
Device Cross-Usage and Capability Ambiguities	False Sense of Acceptance in Technology
	Picture Quality
	Data Quality

Table 4.1.1 Themes and Segmentations for UAV Drone usage

The multi-functional capabilities of UAVs and drones highlight the importance of understanding the significant segmentations that inform drone usage. The table 4.1.1 demonstrates nine main areas of significance with a further thirty-one areas of discussion and evaluation. Whilst many areas have the possibility of overlap, each individual sub-heading is treated as important, and individual segmentations demonstrate key areas of value. For example, whilst the quality of camera imagery improves at regular intervals as the market adjusts to emerging cameral technology updates, the effects of improved image capture remain controlled and constrained by non-technical elements such as the environment and weather. An improved camera used on a wheat field 12 months after the original images are captured may still provide less than favourable results if the 2nd capture takes place on a rainy, windy day with overcast clouds and variable climactic conditions. The individual segmentations are discussed below to clearly show individual attributes, whilst collating them in subsets that allow for intersections where technology elements are influenced by other constraints and conditions.

The evaluation of key themes from the examination on cameras and sensors has a number of challenges. From these challenges there are four major areas of concern. They cover the changing quality of camera images, the ability to compare images from different cameras, the overall change in sensors and camera-driven technology, and the impact of weather events upon normal drone usage. This is shown in Table 4.1 below.

Key Themes	
1.	The quality of the camera-driven images,
2.	The ability to repeat the image
3.	Change in technology
4.	Weather and Environment

Table 4.1 Key Themes for Cameras and Sensors

Theme 1

The evaluation of cameras and sensors in drone applications draws out four major themes. The first is the issue of quality in terms of camera images. Since the advent of miniature cameras there has been a strong push towards better and more accurate lens applications. In the last decade the quality of the cameras on drones has repeatedly evolved in terms of accuracy and resolution. It is worth noting that a similar change has occurred with the built-in cameras that appear on mobile phones. The early drones produced by leisure and recreation-based companies, such as DJI, had a number of options however the option which has repeatedly improved technically in terms of quality and resolution has been the camera. Early drones had cameras that were only 4Mb in size. A typical drone in 2013 had a 4 MP camera, whereas in 2022 a MiniPro 3 has a 48MP camera. These differences raise several issues. The first point is that every year a new drone or drone assembly is launched, with increasingly better optics and better resolution. This then brings about the problematic option whereby each year broadacre farmers are required to make a new attempt to fly the same areas for farming, but with a different camera with revised optics and different specifications.

Theme 2.

In addition to improved camera resolution, every year there are new models of drones and they do not always have the same camera optics as the year before. In a similar way to resolution, the improvement of camera optics is another changing feature of drone evolution because it changes the way in which drone images become clearer and make better use of imagery in low light conditions. One of the key areas of drone improvement is the ability for small cameras to take high quality photographic images in low-light and shadow-affected conditions. Farmers who take repeated footage of the same land area with the same type of seeding are discovering that the footage that is a year apart is not the same. A camera with different optics will increasingly improve over time as new forms of miniature optically clearer camera lenses improve the quality aspects of cameras that are fitted to drones. Other issues come about because unless the farmer takes the footage at the same height, and with similar conditions, they will suffer the challenges of two seemingly identical pictures taken one season apart. The more recent footage is likely to have a progressively superior camera pixel value and optical clarity, whilst the old one will still operate but will have an outdated, less clear version because it retains a previously standardised camera capability.

Theme 3.

Irrespective of the expectation of yearly upward advancements in camera resolution, there is a similar shift taking place with images, sensors, and other software that is expensive and under continuous improvement. At the same time some poorer farmers fly their drones, whilst they many find that the newer / slightly improved drones provide markedly increased resolutions. There is a market-based expectation of yearly change in drone features that are driven by the competition of competing brands and offerings.

Theme 4.

Despite many people vocalising their opinion about climate change, there are many detractors who do not believe in seasonally adjusted weather patterns. However, there are many drone owners who are unable to fly their drone under medium weather conditions. Some farmers have limited ability in the control of drones, whilst other farmers are exceptionally resilient in their physical ability to work in storms in rain, yet incapable to fly drones in the same weather. For some farmers, the use of a drone takes place on days when there is sufficient spare time from other duties, fair weather with light to no wind, and daylight conditions that are neither overcast or stormy. From here we can conclude that the changing dynamic of drone technology is harming the ability of ordinary drone users being able to take footage from two different cameras if they are more than a few metres apart. The changing guidance on different heights will soon need to issue disclaimers that insist that both usages were (at some time during the day) the approximately same time of day and with the same light conditions. The control of drones is something that appeals to a younger generation of technology users who have trained on video games rather than on tractors.

In summary, the use of cameras and sensors in broadacre farming has three significant barriers that undermine their effectiveness. The first barrier is that farmers and agricultural consultants see the value of multiple sensors and measurement devices but may not understand or even be able to interpret the results of this information in an accurate and thorough manner. Farmers do not generally come from a background in computer science, networking and IoTs, but are now expected to deliver ongoing determinations without sufficient higher-level training in these areas. The second barrier is that many cameras and sensors used in drone technology are constantly being upgraded as this area of technology development dynamically alters its course to include higher pixel counts on technology, and new dimensions of sensing using emergent areas such as LIDAR. This has meant that whilst the precision agriculture movement is now obtaining more accurate data than ever before. Many agricultural consultants are discovering that season after season and year after year the data lacks the ease of a fixed comparative set of values. Data that was obtained in 2020 with a 20-megapixel device at a height of 30 metres above a wheat canopy is being compared with data from 2021 with a 48-megapixel camera using different LIDAR sensors and operating from a height of 100 metres. Each year there is significant adjustment required to ensure that the data can be meaningfully compared with the data from the previous crop or season. The third barrier is the challenge of new technology using IoTs which can be actively exploited using connectivity through sensor networks driven by software such as LoRa and LoRaWAN gateways. This emerging usage of edge systems is again well outside the normal skillset of the farming community and usually requires someone with advanced capability in computer science in order to guarantee successful technology exploitation.

Evaluation point B. Drone Operation, training and piloting capabilities

Whilst the evolution of drone technology improvements remains seemingly unstoppable, a second critical factor is the area of drone operation, drone usage, training and piloting capabilities. Many farmers can demonstrate proficiency and expertise in driving tractors and in using farm machinery. If we make similar comparisons in terms of the control and operation of drones as farm machinery, there are several important differences that are emerging as part of the broader appreciation of skills in terms of farm machinery.

Theme 2

The evaluation of operations, training and flying in drone applications draws out seven major challenges. These key challenges are tabled in Table 4.2

Key Challenges	
1.	Inability to understand sensors
2.	Need / confusion about a drone licence.
3.	Right to fly privately
4.	Access to drone training
5.	Different altitudes in precision agriculture
6.	Different levels of internet access
7.	Access to robust computers.

Table 4.2 Key Challenges for Drone operations, Training and Flying

Drones may be highly useful tools, but not everyone can use them to their maximum potential, which is a harsh reality that may disappoint some individuals. There is no problem making use of them for leisure and recreational purposes. However, to use drones professionally in agriculture, there is a requirement for a specialist user in the discipline of agriculture. This is required in order to acquire the necessary competence to operate each instrument safely and legally, and to use the instrument’s various sensors and cameras at their appropriate level, altitude, and condition. The utilization of these unmanned aerial vehicles for in-field monitoring is therefore ideally suited to pilots who have obtained the proper training. Despite this suggestion, many farmers will consider that the use of a drone on their own property is a private matter and that they feel within their rights to fly a drone on their land, so long as no one else is affected. There is a long historical record of farmers and their immediate farm workers being active in the independent use of UAVs to the individual and non-standardised agricultural practices of the day.

At the more commercially industrial end of the drone equipment range there are UAV instruments with significant payload capabilities. If a farmer wants to use a drone that weighs more than 150 kg for spraying crops, then they will need to obtain a license to operate a drone which may be both expensive and may entail considerable time devotion in order to acquire the necessary competencies to manage the remote pilot skillset. Many such courses are developed based on the weight of the drone, and they often require 40 – 80 hours of instruction (either over 5- 10 days or over a longer period if undertaken in a part-time mode).

In the great majority of cases, farmers would typically need to go to a training location quite a distance away from where they are located in order to participate in these courses. The remote location of many farming enterprises is a barrier to entry for many farmers seeking training for increased payload-bearing drones. Urban training is more widely offered, and distance can be a significant impediment to such appropriate drone training. Unfortunately, access to training does not share the same ease of access as is required for the purchase of a drone. The access to training may be a significant challenge for farming workers. The ability to order and pay for a drone online and subsequently have it delivered is an easy activity to undertake. Thus, the remote location of farm enterprises might not be regarded by farmers as the same level of barrier that prevents people from acquiring a drone to use (both in leisure mode or in the agricultural sense on a farm).

When it comes to operating a drone for either surveying or crop spraying, one of the most important considerations to make is the height above ground altitude of the area being surveyed or sprayed. Since some drones have a unique configuration, such as a different sensor camera, weight, and resistance to wind speed, specifying an optimal framework for height forms a critical part of the professional use of a large-scale payload drone.

As per the literature, a variation of 0.5 metres might have a substantial influence on crop spraying due to environmental factors like wind. It has also been observed that inaccurate data was gathered from a UAV when it was flying at an unusually high altitude with an angle that was directed more 30 degrees differently from its previous travelling line. Drone footage relies on a consistent line of image capture that is acquired under similar conditions, level of daytime shadow, wind, daylight, and other environmental conditions.

When flying a drone in Australia, it is required to be registered with the Civil Aviation Safety Authority (CASA). Operators must fulfil a number of reporting mechanisms that ae best carried out using access to the internet. Such activities and reporting expectations can be frustrating and difficult for some farmers. This is because some farmers may not have access to fundamental technologies such as the internet, and if they use satellite phones, it may be very expensive for them to constantly upload data.

Another vital factor to consider is the complexity of the competing software that is utilised for image processing, mapping, and object recognition. Completing these tasks can often demand several stages before the desired outcome is reached. For example, if a farmer wants to implement 3D mapping of their farms for crop health monitoring or disease/livestock inspection, the first thing that they will need to do is gather the appropriate data using a UAV, which can prove to be the first challenge. The second challenge, which comes after the initial data collection, is to process and analyse the data using a robust computer and the right software and techniques. Sometimes, software does not work as expected, and in situations like this one, it can be problematic for farmers if they do not have the ability to solve these issues themselves. This also implies that farmers would have received the proper training in order to use those applications. Since accidents involving drones have been widely reported in the relevant literature, it is reasonable to assume that farmers will also require the ability to repair drones.

Finally, this section can be summarised by the need to consider a range of limitations placed upon the users of the technology. Drone users are often unable to properly use all of the features on their drones. They are unable to access the different camera sensors or to adjust them to different positions and controls. Farm-based users believe it is their right to fly a drone on their own property. These users feel that it is ok to want to fly a drone on their own property, irrespective of other people or of the law. Access to quality training is difficult, and many farmers will continue to try to fly a drone until it fails or breaks. New drones place big demands on the need for greatly improved computing in terms of hardware and software. This in turn drives the need for network storage, cloud access, and a range of data storage and shared data arrangements. For many farmers the need to share data with others presents a significant trust issue that is difficult for the farming community to reconcile with based on past issues where data has been inappropriately shared or restricted.

<u>Evaluation point C. Signal Strength, Data Connectivity, Long Range LPWAN, and Mobile networking</u>

A third point considers the way in which different farms operate in remote and rural areas, having vastly different access to internet coverage, signal strength for different networks, and long-range considerations where they are effectively isolated from urban technology access. These challenges are important to recognise in the context of technology usage and behaviours that take place irrespective of the expected norms that the commercial marketplace offers to entry level farmers when engaging with drone technology. See table 4.3.

Key Challenges	
1.	The internet or network coverage is very low
2.	Software requires updating.
3.	Drones expected to cover larger areas.
4.	Increasing numbers of adverse weather events.

Table 4.3 Key Challenges for Signal Strength, Data Connectivity and Networking

Most unmanned aerial vehicles (UAVs) have at least a fundamental requirement to be connected to some form of network or internet access (eg: 3G / 4G) in order to function to their full potential in terms of accuracy, mapping alignment, and data transfer. For instance, many versions of drone software frequently make use of access to Google Maps as a primary reference layer for location and mapping accuracy. As a result, the requirement for communications and network access can be a major impediment to data access in terms of precision-agriculture as there is an ongoing and repeated reliance on the need to connect to the internet in order to function correctly. The absence of a reliable network, mobile or internet access in rural locations is problematic in terms of the primary function of data management and precision agriculture outcomes.

Taking this into consideration, there are many instances where farms are not displayed on Google Maps or their equivalent. As such there is a necessity for farmers to manually create maps of their own lands, suggesting an increasing reliance on non-traditional farming skillsets that includes computer and keyboard-driven skills, network and communication skills, and drone operating and camera image acquisition skills.

Farmers who have, in the past, undertaken agricultural studies may have received instructions in terms of basic mapping skills, and perhaps some level of training in terms of accessing internet through standardised mobile networks (3G / 4G) and their network communications systems. However, to suggest that an average farmer will have a strong set of computer-generated mapping skills, GIS skills, and network skills is a challenging concept with an ambitious set of expectations with regard to technical elevation.

A significant proportion of remote and rural farm locations have extensive areas that need to be covered and, in these circumstances, drones can be susceptible to interference from the environment around them. In some instances, there is a high likelihood of UAV instruments losing their connectivity and signal strength. This might make the operation more difficult. If an appropriate pre-flight plan has not been established, it may be difficult to process drone photographs efficiently in environments with poor signal strength.

There are also many recorded instances where it becomes difficult to upload data to the cloud in locations where internet connectivity is poor or unavailable. For instance, if a farmer wants to send some UAV imagery that has been collected from his farms to an associate or hired contractor, or even save them for future analysis, this can prove to be difficult as often high-resolution UAV data is large in size, and it can be tricky for the farmer to transfer them. Cloud and data sharing that relies on connectivity to third party cloud providers is problematic in relation to the integration of reliable drone instrumentation on farming enterprises.

The flow-on effect of network accessibility extends beyond crop mapping. The monitoring of animals and crops, as well as pest and disease inspections, are all vulnerable to disruption from a weak signal. If a farmer is using an unmanned aerial vehicle (UAV) drone to watch his animals in real time, then having a low signal connectivity can be problematic and prove to be a waste of time since the average drone battery does not generally last for a very long period. The reliability to connect in such instances can sometimes be achieved through other network means. This might include LPWAN or LoRa Wide Area Networks (LoraWAN).

When it comes to flying a drone, some of the rules and regulations mandated by the government may turn out to be challenging for certain farmers. For example, agricultural properties that are within a radius of five kilometres of an airport, will be subject to additional regulations on the use of drones. Farmers may also find it challenging to comply with the regulation that states a drone must be within line of sight at all times. If a farmer wants to fly a drone weighing more than 150 kg, they'll need to get licensed to do so, which might be difficult for older farmers to obtain.

This concluding area can be summarised in terms of a baseline understanding of the need for technology that works in remote and rural areas. Many of the current answers to the use of signal and network distribution anchor back to LoRa or other similar systems. LoRa is known for low power, long range, low bandwidth, low security, and low speed. It is not a real-time solution that compares with the 3G/4G speed of drome and sensor needs that occur in built-up and urban areas.

Evaluation Point D. Cost, Time, and Return on Investment

Whilst the upside of drone integration is seen by many in the agricultural business as an exciting area of improvement and opportunity, the discussion of cost and time requires consideration for on-going farm management. This area recognises that stereo-typical farming has its roots firmly connected with standardised farming practices that have not changed much over time. In contract, modern farming practices require significant financial outlay, higher levels of technical understanding across a range of areas, and an investment of time and money into making these changes.

Whilst farmers have historically been encouraged to improve crops, and improve livestock, the introduction of drone technology looks very different and invokes a different set of skills and capabilities. Farmers who integrate drone practices need to appreciate the full extent of the ongoing financial investment, the rapid decay of obsolete technology, the fragility of that technology, and the significant time investment required to achieve professional and reliable implementation. In some cases, these considerations drive the need to have a new drone every year in comparison to the purchase of tractors and other farm machinery that typically can be amortised over several years. The return-on-investment evaluation required for drone implementation is significantly different from traditional farm management practices. Drones hold a mixed set of agreed values because some will claim them as depreciating assets whilst others will classify them as investments. This usually means that the cheaper the drone, the fewer functions it has. Function points in new areas of the globe denote areas of enhanced functionality. Good agriculture drones are cost prohibitive.

In addition to the cost of the drone itself, farmers will need to spend money on equipment like a powerful computer for data collection and processing, a professional image-editing screen, software, advanced sensors/cameras, spare drone batteries, and some costly agriculture processing software if they want to use drones for precision farming. High-resolution images can be rather large and, with the amount of data expected to grow over time, the farmer will need to investigate either traditional storage hardware or online storage options such as the cloud. Furthermore, the cost of electricity, which is required in order for such technologies to operate, is going to increase over coming years.

The obtaining of a drone licence is another area in which the farmer will not only need to invest financial resources, but also their time. The process of acquiring a licence often takes a few days, and some farmers will need to travel to cities several hundreds of kilometres away to undertake the necessary courses. . Farmers will also need to learn how to use a computer for data processing and how to operate complicated software programmes. This would involve more time and incur additional costs. There is a potential risk that the investment and time may be wasted since some farmers may not be able to master the technologies needed to operate a drone.

Due to the inevitable force of Mother Nature, drone crashes are unavoidable, and as a result, farmers may end up needing to purchase replacement drone components or even a new drone. Another problem that has been identified in the literature is the fact that a UAVs are not designed to be flown in conditions where there is a risk of severe weather. For instance, unfavourable conditions such as wind or a cloudy day may interfere with crop spraying or the acquisition of high-resolution images, both of which can result in an unsatisfactory return on investment for the farmer who relies on the drone to increase productivity.

Like many, farms are sometimes the victims of robbery, and the possession of expensive technology might further expose them to risk if additional investments in the farm's security are not also implemented. The increase in remote and rural theft of livestock, unguarded fuel in storage drums, and machinery and tools are important factors in the consideration of additional technology in the form of UAVs and drones. The key challenges are shown in Table 4.4

Key Challenges	
1.	Increasing demand for quality drones – only cheap drones available,
2.	Lack of Time – need time to work.
3.	Length of time in training
4.	Competing drones

Table 4.4 Key Challenges for Costs, Time and Return on Investment

This point can be summarised by considering the cost impact in terms of short, medium, and long term considerations. Short term expenditure in drone systems have a limited life before new models emerge with higher specifications and different and new technology features. Consistency is yet to be established and the drone market has not yet reached maturity. That means that new products continue to emerge yet there is a lack of standardisation and best practices are viewed as few and far between.

Evaluation Point E: Animal welfare

Using drone technology may have a demonstrated to have a lot of success with livestock, monitoring their temperature, identifying and detecting their position, and other things. however, it has also been proven to have an adverse effect on the welfare of animals. For example, if drones are unable to maintain a safe distance from animals, the resulting noise, which includes a distinctive buzzing sound, may have a detrimental effect on the animals' physiological health. This may cause the animals to experience higher levels of stress. If animals are subjected to such an environment for a long time, it may result in the widespread disruption of livestock management, since the effects of such an environment may be especially severe on animals who are either pregnant or caring for young. Studies have shown that drones may sometimes be the victims of bird attacks, such as eagles and hawks. This can result in the animal being harmed, and it can also pose a safety risk, as the drone could end up crashing into a person, a vehicle, a structure, or even an electrical line.

Animal Activism

As per the literature, farmers have recently been the target of undercover filming conducted by animal rights groups. These interruptions have a major impact on farmers, and deceptive footage is published in social media, which results in great emotional distress.

Of concern in recent years has been the increased focus on activism. Farmers of livestock (especially those involved in the sheep and beef live-export industry), have come under increased scrutiny and exposure to activists seeking to push a political cause. The key challenges are listed in Table 4.5

Key Challenges	
1.	Animal Well-being

2.	Health and safety
3.	Exposure and stress of public scrutiny

Table 4.5 Key Challenges for Animal Welfare

This point can be summarised in a precautionary sense. Currently the greatest fear appears to emerge from animal activism, climate change activism, and vegan activism. There are increased and growing instances of activism that attacks or hinders the work of farmers and agricultural workers. Globally, there is a general move towards plant-derived protein sources that are offered as substitutes to traditional livestock farming. Live animal export is a political topic and farmers are realising that traditional markets are slowly being removed as a possible export option because of activism, political will, and the globally re-defining of food and protein sources.

<u>Evaluation Point F: Technology issues, battery life and drone system failures</u>

When technologies operate properly, they can be extremely beneficial and useful. Yet, when they do not work harmoniously, they can, be a complete disaster. There have been various incidents of drone failure, where a drone merely loses signal or begins to behave improperly to the point where it becomes uncontrollable and crashes. As such farmers may find it difficult to rely on such technology. See Table 4.6 for the list of Key Challenges.

Key Challenges	
1.	Drone system failure
2.	Battery life
3.	Bandwidth
4.	Loss of Control / Fly Away

Table 4.6 Key Challenges for Technology issues, Battery life, and Drone Failures.

Another challenging element is the positioning and calibration of additional sensors and cameras. As per experts, if a sensor is not correctly calibrated, it might have a detrimental influence on the quality of the picture or data obtained. Having additional cameras and sensors can add additional weight to the drone, which reduces the available flight time. Furthermore, additional cameras and sensors increase the weight of the drone, reducing its flying duration. These factors complicate the task of experts in developing a uniform framework for drone models.

One of the most significant limitations for UAVs is battery life, which varies from model to model. The normal batteries that come with commercial or low-cost drones do not have a very battery duration, which can make it difficult to operate them on large farms. The latest DJI Mavic 3 Multispectral, for instance, has a maximum flying time of just 43 minutes, allowing the user to survey and map an area up to 2 square kilometres in size on a single charge. However, this may not be sufficient, and the farmer may need to conduct multiple flights in order to map the complete farm.

Not every drone has the technology or sensors to carry certain advanced data for precision farming, for example, a low-cost RGB UAV will not be capable of collecting the same information as a Thermal or Multispectral camera, but the advantage of UAV is that you can customise the drone by installing additional sensors. Hence, an agriculture drone equipped with a specialised camera, or a sprayer, adds weight to the aircraft, which may significantly affect flight performance, which in turn is directly linked to battery life.

The maximum range a drone can fly also varies by model, with the majority of commercial drones having a limited flying range. For example, the P4 Multispectral drone uses a frequency of either 2.4 GHz or 5 GHz. The 2.4 GHz frequency band has a larger coverage area but a slower data rate than the 5 GHz frequency band, which has a faster data rate but a shorter range. If there is no interference, the greatest range of a 2.40 GHz signal is around 1.6 km. which is a relatively small amount for a farm that is hundreds of hectares in size.

This point can be summarised in terms of the technology usage and the increased complexity that is attached to drone practices. Drone failure is a common occurrence. Sometimes the drone failure is a subset of bad weather, whilst at other times a simple drone “fly-away” can take place for technology-driven reasons beyond the understanding and scope of the operator. Indeed, the easy entry low-level multi-rotor drones such as the DJI Phantom and Mavic models are extremely popular but have a level of failure that is unacceptable in a professional sense. When compared to the level of reliability required for a truck or a tractor, there is a disproportionate expectation placed upon the reliability of drones compared to other farm machinery.

Perhaps the most defining barrier to drone practices on broadacre farming are the challenges associated with batteries and battery life. Battery life directly affects the range of each drone, and has associated restrictions in terms of early "return home" functions. Battery life is responsible for the ongoing occurrence of drone failure episodes. The cost of batteries, their life cycle, and their overall performance and reliability have remained a constant barrier to a more fully accepted integration towards drone equipment ubiquity.

Evaluation Point G: Technology issues, Drone system failures and Calibration

Another challenging element is the positioning and calibration of additional sensors or cameras. If a sensor is not correctly calibrated, it may have a detrimental impact on the quality of the picture or data obtained. Having additional camera and sensors can add additional weight to the drone, which would impact the flight time. More cameras and sensors might increase the weight of the drone, reducing its flying duration. This complicates the task of experts in developing a uniform framework for drone models.

This area can be summarised as an emergent challenge driven by increased technology improvements and the associated increase in fragility, complexity and interoperability. As new models are introduced, they trade competitively for market share. However, in the farming and agricultural sector, they are continually restricted by the lack of appetite for expensive UAV technology that is not consistently fail-proof, and which requires an increasingly regular need for calibration, servicing, and maintenance of equipment. If compared to other areas of farm equipment, the integration of drone technology is markedly more demanding and yet to achieve a satisfactory level of consistency, accepted usage, and day to day reliability.

Evaluation Point H: Data Privacy, rule and regulations

Key Themes	
1.	Data Privacy
2.	Rules and Regulations
3.	Data Sharing
4.	Third party data users
5.	Cloud environments and data sovereignty

Table 4.7 Key Themes for Data Privacy, Rules and Regulations.

Data Sharing.

It has always been problematic to determine how data is shared and utilised, as well as who owns the data and whether a third party can be trusted with certain essential data, such as the amount of harvesting that is done throughout each session. There are some farmers who will choose not to disclose this information, which may result in them deciding against using all the technology provided by drones.

Data sharing by the wider farming community is a contested issue. Many farmers have shared crop data in the past with government organisations and departments of agriculture at the state and federal level within Australia. (see table 4.7). In many instances these experiences have driven mixed feelings of trust and cooperation between organisations. Some farmers have felt betrayed at the lack of agreement in the way that their data has been used and shared with other entities, resulting in a disconnection between state government service provisions and farming communities.

There is a similar parallel issue with third party groups and associations that have increasingly infiltrated the agricultural data industry. Third party groups have received similar treatment as agricultural departments because they have used data acquired from farms for their own profitability, on some occasions to the farmer and their business. In some cases, the data acquired by a third party using the sensors on a tractor is stored in an offshore cloud facility and farmers may be required to pay to get access to their own data which was taken from the very farm equipment which they own and operate.

Proximity to Infrastructure

Due to their proximity to airports, some farms may be required to comply with drone regulations. Farmers require a specific licence and are required to notify any drone activities to the appropriate authority in Australia if you want to operate their drone within a 5-kilometer radius of an airport. Some of these restrictions may make farmers wary about investing in drone technology, whilst some farmers simply choose to operate drones without the knowledge of others.

Unlawful Surveillance

The inappropriate applications of drones in agricultural settings have also been taken into consideration. The issues were brought to light in a study by the NSW farmers federation, which stated that a poll of members had found that drones were responsible for thirty percent of unlawful surveillance incidents on farms. For instance, some farmers who can operate drones might take advantage of this situation to spy on neighbouring farms and collect information for their own personal gain.

This area can be summarised in terms of the crossover boundary between regulatory stipulations and on-farm accepted practices. It is clear that many drone practices in farming locations do not align with the codified and organised expectations that are placed upon drone users in urban and built-up areas. At the same time there is little appetite by drone pilots and farmers for regulatory adherence to accepted privacy practices. In remote and rural areas, the misalignment of drone practices with other areas is very different. It is almost impossible for one farm to be aware of another farm using fixed-wing UAV technology and gathering unauthorised crop data and livestock information. Surveillance in this form is extremely challenging. New governance and regulatory changes do not yet sufficiently address the issues with *beyond visual line of sight* (BVLOS) practices that overlap and survey beyond boundaries and established lines of shared mapping and observation (Politit et al, 2022).

Evaluation Point I. Technology Acceptance

There is a significant body of evidence that suggests that drone technology is only partially accepted in terms of broadacre farming. In one sense the farming community (especially the broadacre community) is split in terms of size and scale. The very large broadacre farming enterprises tend to be early adopters of drone and UAV technology. They can afford to invest in a range of high-tech options based on the financial size and strength of their broadacre operations. These operators have overcome many of the networked and signal-related challenges through the implementation of backhaul networks, new software defined network offerings such as Starlink and a range of other emerging network options (Martos, 2020). Many will have sophisticated systems, using LoRa Wide Area Networks, or other proprietary systems such as SIGFOX (Wang et al, 2020).

Key Themes	
1.	Technology acceptance
2.	Farmers engagement with technology

Table 4.8 Key Themes for Technology Acceptance

In contrast, medium to small operators consider the integration of UAV technology as difficult in terms of the upskilling networking and training required. See Table 4.8. Traditionally, broadacre farming can cover large areas – yet there is a divide between those enterprises taking large acceptance steps compared to others who are unavoidably lagging behind. This is based on several factors including shared services, cost implications, technology acceptance and technology skills.

This area can be summarised as a dichotomy of technology uptake where the industry holds an uneasy balance between the desire for precision agriculture and yet is uncertain about the ongoing cost of the upskill in terms of trusted areas where the reliance for support lies with other sectors that have previously not been closely associated with agriculture. This dichotomy is further aggravated by a continuing discourse regarding trust, information, and shared data. This touches on cultural boundaries and demonstrates a separation between the sharing of traditional farm machinery in hard times (e.g. when a harvester breaks down) and the hesitancy to share technology items where there is uncertainty about the storage and data location of valuable crop and livestock information.

Evaluation Point J. Device Cross-usage and Capability Ambiguities

Key Themes	
1.	False sense of technology Acceptance
2.	Picture quality
3.	Data Quality

Table 4.9 Key Themes for Data Privacy, Rules and Regulations.

The research investigated in this thesis shows that there is a wide variety of drone usage that crosses existing boundaries. (See Table 4.9). The delineation between leisure drones and professional drones is unclear. The DJI range of UAV instruments has (like many other brands) rapidly changed its product line so that new models of all shapes and sizes have capability and resolution beyond earlier expectations. The advanced features of even a low-cost drone for under $1000 AUD now makes it possible for anyone (including those in agriculture) to enter the market with ease, and to test the application of drone technology with relative financial ease.

There are three main concerns. The first is whether the low cost of entry misleads would-be professionals in agriculture to assume that the applied use of drone technologies will be easy to implement. The second concern is that these low-cost adopters will mistakenly equate the accuracy of inexpensive drone instruments with the opportunity to acquire a significantly larger, and exceptionally accurate, data collection of farm data that can provide substantial benefit in terms of precision agriculture. The third concern is that whilst small drones (sub $1000) provide a false sense of technology acceptance in terms of ease of use and perceived usefulness.

For example, the picture quality, resolution, and flight capability of a DJI Mavic Pro combines affordability alongside exceptionally high photographic image resolution. A very high level of photogrammetric imagery and picture resolution is now possible. However, the immediate application of this size and type of instrument should be evaluated in terms of the far greater extension of the technology in the form of higher-level instruments that provide enormously beneficial data with a considerably greater demand for three main adaptations. The first is the requirement to upskill farm workers in terms of mapping interpretation and its associated IT skillset. Taking drone footage and stitching together large sections of mapped areas requires increased skills in software application, alongside an accompanying requirement for hardware uptick in the form of visualisation, processing, and storage technology. The real cost of basic entry into the applied use of drone technology in farming enterprises is significantly underestimated in terms of price, training, technology skill, hardware requirements, software requirements, and support.

This area can be summarised in terms of the traditional reliance upon season after season data. Farming communities have traditionally relied upon reference to the history of previous crops and previous seasonal yields and productivity measures. The rapid change in technology instruments (in some cases several changes take place within a single season or crop cycle) creates uncertainty. Most farming communities are resistant to immediate change, preferring to opt for a slower rate of change. The rapid uptake, upskill, and dynamic upheaval of sensor data drives the discourse towards the fear of too much technology or at least technology and data that is dependent upon the advice of others who are non-traditional in terms of previous past sources of consultation, advice and agricultural support.

4.2 Summary of the Analysis of Data

This chapter has examined a broad range of factors. During the analysis and discourse around the principal question of the important factors influencing the application and acceptance of UAV technology for broadacre farming, there are six areas that stand out as the more critically significant themes involved with the research. The analysis demonstrates that there are six areas that form a more prominent part of the discussion on drone practices. These six areas are cost, complexity, ongoing dynamic change, governance, drone failure, and technology acceptance. The following chapter discusses each of these six areas in greater depth. The method of discussion in chapter five works through four guiding frameworks in the area of risk, maturity, technology readiness, and entropy.

5 DISCUSSIONS

This chapter looks at the issues raised in terms of analysis and orders them in terms of the priorities raised through the research questions of this thesis. The main areas of discussion are based on a progression of ideas that examines risk, maturity, technology readiness, and entropy. Through these outlines the key emergent themes are cast. The result is a focused discussion on the more critical areas of behaviour in the usage of drones. The main areas of concern are those connected with matters of criticality. In each of the four discussion areas the themes that are discussed are evaluated on the basis of their criticality towards the use of drones in broadacre farming.

5.1 The general Research problem and the Gap in knowledge

This study has exposed a wide range of issues that highlight areas that impact upon drone practices in broadacre farming. The chapter 4 analysis is both edifying and instructive in guiding this study to the specific areas of greatest impact and greatest influence. The analysis sections describe the pathway that makes it clearer as to how the six thematic vectors of greatest interest and concern are interconnected with the fundamental challenges that face farmers in their pursuit of agricultural data and information.

This study has examined a broad range of issues. From all of the thematic vectors there are six major areas of concern. These are discussed in greater detail so as to develop beyond the thematic analysis and to seek to apply broader meaning to each area and to contextualise these issues so that they can inform this research and address the research questions.

5.1.1 Cost

The first discussion area is cost. Farmers have an easy entry into drones with a relatively low barrier to becoming involved. However, that involvement rapidly changes in terms of complexity, technology, training, regulations, reliability and overall return on investment. Farmers who invest in high-level drone technology are regularly incapable of realising a return on the investment.

Despite the low entry barrier, the key limitations of upskilling into drone usage for broadacre farming are linked to the significantly higher costs of fixed wing drones, and heavy payload, multi-rotor UAVs. These investments require a re-configuration of technology priorities that extends to include drones, operator training and licencing, the need for at least one spotter or assistant, high specification desktop capabilities with large screen viewing, graphics card interface, and drone image mapping software. To properly facilitate these changes there is a need for high-level internet access with improved bandwidth. The upgrade in most cases will include the need for an additional member of staff with IT skills, networking skills, and capability around drones and software analysis. From this position the next set of options might be to share data with a 3rd party or to consolidate the data into a secure storage system that can provide the ability to interrogate the data at a sufficiently organised data management level so that the broadacre operations can derive significant benefit from a precision farming standpoint.

Even if an operation chooses not to set up their farm to the extent outlined above, the decision to use high-level drones will still encounter significant expenditure in the form of outsourced operators, data storage, data management and data retrieval. All of these costs are variable in terms of the application, size, and scale of each broadacre operation. However, the cost of this type of high-level drone set up are inescapable whether they come in the form of internal technology set up or a model that outsources the drone usage side of the operation.

Another consideration is that these costs are associated with ongoing changes and updated technology. The significance of farm records and the best practice for precision agriculture relies upon decision-making that forms a reliable data set based upon ongoing measurements throughout each season. The financial commitment to high-level drone usage holds an obligation on the farmer to continue with wide-spread usage with a commitment to its permanency.

In contrast, the opposite consideration to this proposition is that some broadacre farming enterprises will consider the size and scale of their operation and decide not to make such a commitment in terms of cost and equipment. Farm operations that attempt to take a low-cost option into the deployment of drones will have limited success, using uneven data networking and will endure a range of compromised elements within the technology usage and partial transition. The compromised approach also includes an ongoing set of challenges in terms of technology knowledge, equipment fragility, and increasing portions of obsolete technology.

The literature suggests that, from a return on investment (ROI) stance, the holistic commitment to drone practices and drone usage is the only approach that is likely to deliver a reasonable

ROI. The commitment to drone usage in isolation only makes sense if there is an accompanying commitment to the data management and visualisation / mapping requirements at the same time.

Many agricultural discussions use John Deere as a useful case study that depicts a global data-sharing practice (especially in the US) of farmers buying expensive technology, seeing their sensor data be transferred to a private (in this case John Deere) cloud platform, and then finding themselves forced to effectively buy back their own data from the very provider that sold them the initial farm machinery. The literature points to a number of such cooperative arrangements that gather data from farmers and then re-arrange the data to sell back to the farmer. A useful comparison could be drawn from a sheep farmer who sells their sheep to the market and then goes to the local butcher to buy a piece of lamb for dinner.

There are additional micro costs that should also be included in this discussion. They include safety workshops; CASA governance and regulatory requirements; training and registrations; security considerations (both cyber and physical); and dust-proof areas for drone maintenance and cleaning. These additional smaller costs assist in explaining that the commitment to drone technology is difficult to separate into one or two costs, but rather the commitment relies upon a wide range of different elements being exercised together.

5.1.2 Complexity

The second area is one of complexity. This study demonstrates that there is an increasingly large variation in the numbers and types of sensors that can be used. Farmers will be familiar with sensors in terms of the many devices that are used in and on tractors and harvesters to provide immediate data at the point of harvest or the point of seeding in many broadacre operations. The integration of drone technologies would allow for sensor deployment at a different level of quantum and scale.

Whilst high-level multi-rotor and fixed wing drones do carry different camera sensors that can provide a range of sophisticated data and measurement, the introduction of drone usage allows for widespread ground sensors provide a range of soil and ground level metrics. These can be activated as drones pass overhead and the data can be silently gathered directly onto a LoRa gateway via a LoRaWAN (Wide Area Network). The application of such sensors means that the entire broadacre operation can become operationally active for a range of different ground sensors that provide regular information in low bandwidth long range format. If required, this can be accessed daily in terms of crop management, water, disease, pests and other attributes. The use of widespread ground sensors adds the opportunity to provide rich, specific sources of data that enable a very high level of accurate decision making in real-time. This inclusion raises an issue for farmers and farm workers as to how to understand the complex variable nature of sensors as well as understand the need to have high level computing.

5.1.3 Changing Camera Technology

The third area for discussion revolves around the constantly changing camera technology associated with drones. If the goal of precision agriculture is to be able to make high-level decisions, then the reliance for accuracy must also take into account the challenge of differing measurements obtained through different cameras. Australian farmers have had access to satellite imagery for decades. However, the quality of the imagery has been poor in terms of pixel resolution.

Drone usage provides for significantly higher levels of image resolution. However, this is somewhat offset by the challenge presented by new models of drones with ongoing increases in different sensors from RGB to NDVI and Multi-spectral sensing. Each successive new model has a higher specification of camera with a higher pixel count, a different F stop, and different sized lens. Farmers (or their technologists) need to constantly recalibrate and adjust to suit for a data set that can be compared.

These issues remain firmly centred on changing levels of camera technology, in concert with drone footage that has been taken from different heights, at different angles, and in different parts of the farm. These changes in heights mean that one map taken in a previous year will visually, show widespread differences. There is an ongoing need to standardise and adapt to a fixed set of drone operating heights and camera selections to avoid comparing two different sets of data that have very different measurement assumptions and constraints. This issue can be further exacerbated in terms of the understanding and deployment of sensors from a computing background. Long range systems such as LoRaWAN can be set up by others, but there are often ongoing set up issues associated with the network side of the technology. This is less onerous than full scall drone deployment, but still retains an element of technological skill and training to ensure that the technology is working seamlessly.

5.1.4 Rules, Regulations, Guidelines and Procedures.

The fourth area is that of governance. This includes rules, regulations, guidelines, and procedures, Drones that are flown remotely, and with no large likelihood of being seen by others are regularly flown under a private set of rules (based on being flown over private property). Some of this activity is legal and is sanctioned under the rules for use on rural and agricultural holdings. However, the great majority of the drone rules require a suitable person with a high--level pilot's licence to fly drones. This point is important because new regulations are constantly evolving all the time. Urban systems are gearing up for widespread drone usage for parcel and package delivery in cities. In remote and rural areas, the key issues for governance include the proximity to small airstrips, as well as the emerging rules and laws about drone operation. In particular, the emerging rules and legislation pertaining to BVLOS (Beyond Visual Line of Sight) drone operations are seeking a uniform response to a set of globally accepted rules. The need to address BVLOS issues is a critical part of Australian broadacre farming and requires a successful arrangement to the satisfaction of other countries.

5.1.5 Drone Failure

The fifth consideration is that of drone failure. Taking into consideration the already heavy emphasis placed upon the need to address new forms of technology, this area recognises that drone technology is inherently more technically based than perhaps traditional machinery used on farms. Whilst some farmers and drone operators have a dislike for new technology, others are capable of embracing both the need and the commitment necessary to learn how to safely operate drones. Appendix 8.2 shows globally a large number of agricultural scenarios where drones have crashed with some notable consequences.

Drone failure, however, has a number of precedent factors that are more widespread than crashes from pilot error. These include unfavourable weather conditions, signal loss and signal jamming from nearby devices (non-drone telemetry-related sources). In the South West of Western Australia there are a large number of reports where large birds (especially birds of prey such as eagles and hawks) have attempted to attack and interfere with drones at high altitudes (Junda, Greene and Bird, 2015).

Drone maintenance and drone upkeep is an area that is relatively new to farmers and broadacre technology agriculturalists. One of the recognised issues for large scale farms looking to deploy drone technologies is that there is a significant requirement for the cleaning and upkeep of drones. Broadacre farms are harsh environments for expensive drone UAV technologies., and the upkeep of motors, rotors, batteries, and cameras requires steady hands and a dedicated "clean room" that is free of dust, chaff, and moisture. Some drone parts are subject to oxidation and there is a need to commit to maintenance on a regular basis to ensure that drones fly at their optimum to ensure safety and performance.

5.1.6 Technology and Engagement

The sixth area looks at technology acceptance and farmer engagement with drones. There are always a small number of farmers who fly drones and are engaged in the development of the technology. The question is, what will happen or change for all of the other farmers. There are concerns from traditional farmers that the use of drones is too reliant on technology and not reliant enough on traditional farming practices. Some farmers have concerns about the use of drones with livestock and there is evidence of frightened animals suffering after drones have been used in proximity (Yaxley et al, 2021).

There is little doubt that drone technology has captured the imagination of the agricultural community in a broad sense. At the individual level, the opinion is divided between farmers holding different views. Some are concerned for animal welfare while others are concerned with costs. The overarching hesitation seems to come from farmers who do not wish to lose sight of the more traditional farming practices. Whilst the business of growing crops and raising livestock has been going for thousands of years, the advent of drone technology raises issues about training, skills and knowledge that may appear counter-intuitive to traditional farm operators who have known their craft for decades.

The acceptance of drone technology requires more than a few enthusiastic young farmers showing off their technical skills. The challenge is to embed a culture of acceptance that has the same general benefits of farming community trust as other areas. In general, farmers look out for one another. They will advise other farmers of the presence of foxes, feral pigs, broken fencing and a range of challenges. However, the advent of drone technology brings a different trust paradigm. In this scenario, farmers are expected to understand and tolerate drones flying over private property, over livestock, and identifying new sources of engagement and intrusion. The literature suggests that farming communities (including broadacre operations) are split into two, divided groups. Once the development becomes more widespread the acceptance will change. In the meantime, the issues of acceptance most likely to hinder and influence drone technology usage will be rules, regulations, governance, privacy and security interests.

5.2 Risk

Having examined the six areas that demonstrate the most impact in terms of drones in broadacre farming, this segment studies these individual factors in terms of ongoing, future and residual risk. A full risk register was created and populated based upon known risks as discovered from the literature review. The register lists 50 risks and tracked each risk in terms of likelihood and in terms of impact (See Appendix 7). Note that each line item is tracked based upon the impact to the drone practice. The risk register includes a standardised probability versus impact comparison, using a 5 x 5 matrix as the visual descriptor, with the risk score developed based upon those line items with the highest levels of probability and impact.

Using this system, the area with the highest risk ratings were determined and are discussed in this segment. There was one risk with a rating of 20, six risks with a rating of 16 and one risk with a rating of 15. They represent the eight risk items with the highest risk level based on the 50 risks from the register. (See Table 5.1) The complete register can be seen in Appendix 7.

Top 8 Risks	Technology Issues	Challenge	Probability	Impact	Risk Score (P x I)
1	Rules and Regulations	Too complex – people do what they want on their own land.	5	4	20
2	multi-spectral image processing	Required to apply more complex pre-processing method	4	4	16
3	lack of drone-related software	Lack free open source	4	4	16
4	storms and bad weather	Inability to fly drones in bad weather	4	4	16
5	cost of fixed wing drones	Very large expense	4	4	16
6	cost of heavy payload drones,	Large expense, + training, hardware, software	4	4	16
7	machine learning skills	Better computers, extra software, computer skill	4	4	16
8	Farmer Engagement	Willing to adopt drone tech knowledge for precision farming	3	5	15

Table 5.1 Summary risk register (Top 8 Risks) drawn from Register in Appendix 7.

This segment discusses the 8 top risks derived from the risk register in Appendix 7. The risks listed here are ranked as priority items because the literature reviews mentioned these items in terms of risk and in terms of expected change and transformation in the way that UAVs are integrated into society. Whilst the most prominent areas of transformation are in built up and urban areas, there are several challenges from new regulations that will have adverse effects and bring about limitations in drone usage in rural and remote areas. Some new areas are based on operating presumptions around dangers and interactions with people, and do not translate well into broadacre farming environments.

Risk rating 20:

One risk scored a rating of 20. This risk is described as the challenges of Rules and Regulations and their increasing complexity for drone usage. The literature review determined that, in Australia, the rules and regulations that control the usage of UAVs and drones are perceived to be complex and onerous. There are large numbers of farmers and grower groups who have cited that, whilst in urban areas the usage of UAVs is quite strictly controlled. They have raised concerns that on farm properties (many of which are large and privately separate from built up areas), some drone operators do whatever they want when it comes to drone usage. There is no oversight of drone operation in these areas, and many accidents (many under-reported) have occurred in remote and rural parts of Australia. Other issues relating to this risk include issues of damage, livestock harm, privacy and security. There are several individual references to the challenge of BVLOS rules (Beyond Visual Line of Sight) which go unreported on many private farm acreages.

Risk rating 16:

There are six risks with a rating score of 16. These include multi-spectral image processing; a lack of drone-related software; storms and bad weather; the cost of fixed wing drones; the cost of heavy payload drones; and machine learning skills and equipment. Two of these risks relate to costs and the barriers to entry in to the market. One risk relates to extreme weather conditions, and three risks are concerned with image processing, a lack of software, and issues about the development of machine learning using drone technology. All of these risks are connected strongly with the early discussions about gaps in terms of drone entry and engagement in UAV usage in. The benefits of a risk assessment of this nature are that change, and transformation can be measured.

In the case of the two risks that highlight excessive costs, the change can be measured over time. Risks that present in terms of costs are best measured over a period of time. The key metric for expenditure on expensive drones and on cost prohibitive features such as drones with 25 kilogram payloads, is to consider the return on investment. The key elements are the life cycle of the drone, and evaluating the point in time when the drones being used are sufficiently close to being obsolete and either need replacement or need a change in technology direction.

The three risks that identify with software, image processing and machine learning are elements of the computer science segmentation. They draw in perceptions of difficulty for traditional broadacre farmers because they require a person that have a technology skill set that enables and can interpret software for the benefit of broadacre farming productivity. At the same time, they are all representative of a technology challenge, requiring access to online internet connectivity, cloud storage, and structural programming skillsets. They are inherently risk-based because they require people and products that do not normally exist in or around the surrounding areas where we might expect to find broadacre farming. Individually they score highly as risks. In combination they represent the largest combination challenge to the drone-related factors that affect broadacre farming.

The risk cited against storms and bad weather highlights the attention given (through drone-related literature) to climate change and extreme weather events. One of the reassuring elements of the two main satellites that pass over much of Western Australia every 12 hours is that they keep the same orbit, follow the same routine, and are not physically affected by local individual weather events. In contrast, the use of UAVs to take footage and measurements is far more constrained and needs to follow specific guidelines in terms of wind speeds, extreme weather in form of rain and hail, and the important feature of tracking, returning and landing safely during windy events.

<u>Risk rating 15</u>

The one risk rated at a score of 15 concerned farmer engagement. This risk cites the risk of restricted farmer engagement citing the need to convince broadacre farmers to be willing to adopt drone technology for the benefit of precision farming. The risks around engagement with technologies are well founded because they are (in some cases) perceived to be counter-intuitive to traditional farming methods. Part of the secret of engagement with technology is the ability to join together traditional practices with modern changes from technology to form a single objective. In one sense, the shift to encourage farmer engagement is dependent upon existing farmers taking an interest in drones so that their own farm activities can benefit from the experience.

The use of risk evaluation in the normalised method of evaluating probability and impact is a clever but simple task which draws out the key elements of concern based upon existing literature discourse. It is easy to extract and has an ongoing role in terms of allowing risks to be continually evaluated since they rise and fall as different transformations in agriculture take place.

5.3 Maturity

Given the obvious evidence that modern drone development has a short history of just 30- 40 years, it should not be surprising that there is a discussion about the maturity of an evaluation of broadacre farming that uses and exploits drone technology. The commercial usage of drone technology that incorporates mapping, sensor management, online data management and remote networks is closely linked to the development and ubiquity of the internet, mobile wireless telecommunications, and modern applications of agile systems and machine learning.

The discussion of factors affecting drone practices is uniquely beneficial because drone technology is relatively new. Where technology is operating under more established conditions, the maturity of drone technology would provide many more distinctions. If we consider the drone practices individually, we can identify that some areas are more mature than others. For example, the maturity of multispectral drones has not reached a level of sufficient maturity so that users would settle into a specific reliance upon the one type or style of instrument. Instead, the literature depicts a long, but progressively dynamic, list of changing styles with many variations on different spectra, different sizes and operating capabilities. In contrast, when we look at the literature on payload drones, we can see that the reliability and deployment of payloads is nearing maturity, given the widespread acceptance in the fields of emergency medicine, parcel delivery and remote supply purposes. The advances in heavy lift drone mobility are clearly regarded as significant milestones in Africa and in the Middle East to the point where the World Economic Forum has expressly announced their heavy lift programs as having reached a global level of maturity (WEF, 2021).

The drone development in small drones and in payload drones are described in the literature as those drone elements that are nearing maturity. The high-level technology driven instruments used in precision agriculture are clearly described as less mature and demonstrate a dynamic set of developing changes in sensors, camera types, pixel values, and operating flight altitudes. These are areas of drone development that are developing with uncertainty and less organisational structure than other elements within the stable of drone technology UAVs.

5.4 Technology Readiness levels

Technology readiness is a significant measurement in areas where a relatively new form of technology is being applied into an area of business. From a business perspective, there is a need to judge the level of preparedness so that the cost of the transformation, and the challenges with the transformation, are anticipated in advance. Advanced drone applications (such as the fixed wing and heavy payload options discussed in this study) have the potential to invoke great change, however they can also bring about unnecessary complications if they are introduced without planning for their acceptance and impact upon other existing practices which may be required to change.

The use of unmanned aerial vehicles (UAVs) in precision agriculture has been shown to have some success in a variety of applications, including crop monitoring, livestock monitoring, disease and pest inspection, and crop spraying. More farmers are becoming aware of the many benefits that may be achieved by using these unmanned aerial vehicles in agricultural. Nonetheless, there have been several limitations found with UAVs. The major concerns are clearly connected with the very cost prohibitive nature of technology that has a low level of technology readiness.

Technology Readiness Levels (TRLs) are useful in identifying the areas where, as a result of transformational change, the introduction of new technology alters the way that other, more normalised, practices are continued. In broadacre farming, there is an established system of record keeping that relies on a historical comparison of past crops in terms of yield, production, climate, frost events, weeds, pests, diseases and weather. The use of UAVs provides records that are more detailed in almost all of these areas. Data can be extracted at the times the enterprise wants to extract them. They will typically be more accurate, more detailed, more specific, and more reliable. However, they will also be more complex. One of the important questions that a TRL assessment generates is whether farmers are ready to interpret a richer, more complex set of measurements and records, and whether that change draws away from past traditional records and systems. In some cases, the introduction of complex and more accurate information makes other systems become ignored or obsolete. That can affect the overall performance of a farming enterprise if those systems are perceived as less useful. One of the functions of a TRL assessment is therefore to check for entropy in the form of transformation-driven areas that decay or become misrepresented.

5.4.1 A TRL Model Assessment

This segment draws upon the NASA system of technology readiness in developing a chart describing the technology readiness levels (TRLs) for drone usage in broadacre farming (Mankins, 1995; Straub, 2015; Barari et al, 2015). To describe the TRLs for drones in broadacre farming a number of processes and levels of achievement were identified as part of the thematic descriptors used in the initial segmentation of the literature review.

> "*Technology Readiness Levels (TRLs) are a systematic metric/measurement system that supports assessments of the maturity of a particular technology and the consistent comparison of maturity between different types of technology*" (Mankins, 1995).

TRL (Technology Readiness levels)

Technology Readiness levels (TRLs)	
TR1	Technology Research
TR2	Technology notion /idea
TR3	Proof-Of-Notion
TR4	Technology Proof
TR5	Drone types – different maturity levels
TR6	Sensor Maturity
TR7	Rules and Regulations
TR8	Software Maturity – Integrated Precision Ag data and real-time information analysis
TR9	UAV system Operational Maturity
TR10	Demonstrated Operations

Table 5.2 Technology Readiness Levels for Drones in Broadacre farming (Adapted from Mankins 1995)

The interpretation of TRLs is important to understand. Commercially, some of this work is done by a cooperative firm that charges a fee for consultation. This type of consultation involves an interpretation of new data for the purpose of improving productivity, yields, and profitability. The description below explains the process and includes some specific inclusion for drone practices in broadacre farming.

In Table 5.2, the adapted NASA TRL Model has been applied with the following explanatory notes:

TR1. Technology Research

Fundamentals were noted and reported. In broadacre farming specific large-scale areas of land were prepared and treated for use. Seeding and harvesting schedules were selected and locked into place. The application of UAV-based data is acknowledged as potentially useful in the context of a broadacre farming opportunity. The overall attributes for technology research are clearly indicative of the ongoing expectation of a continued race to develop UAV technology across the areas of camera resolution, increased indices usage, battery life and extended flight, and sensor development and network capabilities. The broadacre farming needs in the immediate future are driven by the lack of technology maturity, and the literature evidence shows that there are competing differences between technology advances and regulatory improvement. TR1 is likely to see ongoing rapid change and development in UAV technology, which will drive high level impact into the profitability of broad acre farming.

TR 2. Technology notions and ideas

Development of a concept and/or a use case scenario. Here the conceptualisation requires a broadening of past practices to include a much larger pool of data / information. At the same time, there is a conceptual commitment to using that data, in real-time, to obtain the maximum benefit from the information. The conceptual change required for UAV development is strongly connected to future skills. In the current state, there is clear evidence of a skills shortage in qualifies drone pilots as well as the ability to analyse sensor data and imagery for the purpose of generating information that is suitable for future proofing precision agriculture. TR2 is likely to see increased growth in line with skills development, which will assist broadacre farming to improve its maturity within the acceptance of high-level UAV technology in broadacre farming. The impact of broadening UAV practices has the potential to grow the UAV business into a reliable sub section of broadacre farming.

TR 3. Proof-Of-Notion

This is a critical function analysis and/or experimental demonstration of the idea. Here the integration of broadacre mapping and the determination of specific areas of attention is based on expectations from initial sensor mapping and discovery. This involves revised performance expectations, technology deployment, implementation timing, and alignment of time commitments to suit seasonal (e.g., optimum seeding) timeframes. As new sensors come to fruition in a commercial sense, the ability to leverage from a new set of data will have enormous impact and will drive considerable change. LIDAR technology, and its related areas of recognition, are likely to have a significant impact on the development of new high-level UAVs that will be able to detect a range of features including accurate numbers of feral cats, feral pigs, as well as the accurate detection of stray livestock. The impact of this type of proof of notion is likely to generate enormous savings in livestock losses, as well as providing opportunities for future sills and job changes in the different usage of UAVs in broadacre farming.

TR 4. Technology Proof

This requires a generic design that demonstrates performance that is consistent with potential uses and enables the development of new concepts. It involves the integration of drone usage, LoRaWAN networks across the whole area, data collection and access, and installation of visualisation hardware and the establishment of CS workstations. Whilst the economic benefits of Long Range platforms such as LoraWAN show obvious merit, the more advanced technical development of UAV technology has chosen to look at 5G/6G platforms and the advent of wide spread Low Earth Orbiting satellites (LEOs) The likelihood of change from LoRa-based technology development is lower than other areas, and the impact of this area of UAV technology is likely to sit of the fringe of rapid development in broadacre farming.

TR 5. Drone type

This identifies the different design of UAVs such as Wing-fixed, multi-rotor (quadcopters, hex-copters and octocopters), a selection of fixed wing overhead mapping and analysis drones, combinational heavy multi-rotor drones for LIDAR, as well as spraying payloads for weeds, pests, fertiliser treatments. This also requires access to spare parts and machinery redundancy features. Changes in design features for different flyable versions of UAVs is increasing because the development has other growth sectors outside of agriculture are driving change and innovation. The applications for UAVs are gaining wide acceptance for issues such as parcel delivery, fast food delivery, and a range of service and repair maintenance usages. The next generation of UAVs are likely to follow new design arrangements in terms of rotors, range, and payload variations. There will be a new generation of fit-for-purpose UAVs that will emerge. This will have expected spin-off benefits for broadacre UAVs and will generate global acceptance and market maturity of the overall UAV definitions of drone types and variations.

TR 6. Rules and Regulation

This outlines the precision farming drone regulations. It involves an acknowledgement of overlapping surveillance, issues on BVLOS challenges, proximity to airstrips and other infrastructure, as well as the required training for pilots and spotters. This generates an acknowledgement from CASA for readiness to operate UAVs according to intended plan. CASA is predicted to make significant changes in the rules and regulations that govern UAV usage. Some of these will have an impact upon the agricultural sector. In specific terms the most impactful areas are the ability to fly and control multiple UAVs with a single controller and/or licensed operator, and the changing of regulations governing the BVLOS sector. In concert, these two areas will generate large amounts of agriculturally specific change. The challenges of these two areas remain within CASA oversight, however if driven alongside consumer demand, are likely to change future capability for agriculturalists and operators in broadacre farming.

TR 7. Sensor Maturity

This requires the identification of sensors that have been used without incident (or with incident levels within acceptable range) for precision farming. Sensors are fully calibrated, and data access becomes operational from combined UAV and ground sensor systems using LoRa and LPWAN infrastructure. The rapid development of the global IoT market is strongly associated with UAV development. For example, the development of LIDAR technology has widespread commercial applications – that stretch from broadacre farming to smart fridges. Sensor technology, once embedded into the market, are likely to drive innovation and change in broadacre farming UAV usage. It is, however, and area with a high cost of development, and will require the urban IoT sensor development to emerge in order for the agricultural sector to see and realised the applied benefits.

TR 8. Software Maturity

In this process there is the need to identify the software design / algorithm that has been used and tested for each specific purpose. This involves an acknowledgement that the algorithms perform to include all data (including past historical information and seasonally relevant records). One of the challenges for the Broadacre farming sector is that the cost of analysis is seen as a solution that requires third party involvement. In this state, the development of the Agtech industry has a large skills shortage. The key challenge is to create new software that allows for high-level analysis that can be achieved without the need for software analysis that requires computer science expertise. The impact of new easy to use software can enable farming communities to engage in the analysis side of farming with considerably greater levels of confidence, which will drive technology acceptance, engagement, and expenditure.

TR 9. UAV system Operational

This process examines the UAV System design with different modified sensors and involves being thoroughly tested against requirement and operating scenarios. The operations are checked for extreme weather conditions including rain, wind, bushfire to ensure maximum operational inclusion across a range of environmentally challenging conditions. A key attribute that underpins the whole of farming approach to UAVs is the reliability and resilience features that have so far not matched the corresponding levels of robustness by traditional farming machinery. This challenge is a factor holding back the operational levels of commitment. Technology readiness of a whole of farm UAV solution is clearly dependent upon the ability of drones to supply daily performance and to achieve the expectation of ongoing usage under rugged conditions in variable climate-driven weather environments.

TR 10. Demonstrated Operations

In this process there is a review of the studies demonstrating the usage of UAV that has been used without incident (or with incident levels within acceptable range) for precision farming. There is a further review process involving the testing for decay and signs of entropy based on a fully operational system deployment. There is a probability that many of the existing standards and regulations require review and re-imagination to meet the broadacre farming vision of the future. These issues include flight operation standards, operator rules, privacy rules, and security issues. The technology barriers of UAV implementation in broadacre farming relate to existing practices that need t change and become nimble in the face of global technology acceptance. The impact of these barriers could slow the maturity of the UAV industry. Many existing farm practices face considerable change from traditional precision farming methods. Whilst new UAV technology seems likely, the acceptance of probable tech innovation that is cost prohibitive will offset some of the impact of UAV development for broadacre farming using UAVs.

5.4.2 Model Assessment Limitation and Precautionary items

Based upon the 10point TRL outlined above a number of limitations and precautionary notes then require inclusion to act as standardised cautionary planning preparations:

1. Batteries and flight time.

The time in air of drones is largely dependent upon battery life. In some cases, this is in regard to low-flight crop and pasture review, and in other situations it is related to payload and overall weight and impediments. There is a need to identify what constitutes safe operating procedures and what restrictions on flight range generate additional requirements for batteries and spare parts in preparation for redundancy.

2. Drone flight Range

The range of flight for some drones is a critical area of comparison. Larger fixed wing drones will complete flights without line of sight (BVLOS) and will complete the task in a fraction of the time for standardised multi rotor UAVs.

3. Rule and Regulations

The rules and regulations of drones are, at best, confusing and at the least, sufficiently different that they required a series of questions in order to answer any given question correctly. New requirements for BVLOS and alignment with both CASA nationally and local shire authorities. There is a level of entropy with past practices taking place on private land to the exclusion of other safety and guidance procedures from CASA and other authorities.

4. Height

Operational flying altitudes are established and agreed upon. The range of heights at which drones can fly demonstrates the widespread inconsistencies and fosters an ongoing challenge in terms of whether farmers operating drones are, in fact, sufficiently qualified and/or informed to use drone technology. Flight altitudes require strict adherence to ensure that post-flight data analysis compare data from on day in similarity to the same altitude on subsequent data collection days.

5. LIDAR

LIDAR sensors are regarded as one of the most significant areas of sensor enhancement that is currently included. Some corrections will evolve to allow for nuances on LIDAR deployment such as cloudy days, wind speed, camera optics.

6. RGB camera

Critical procedures for the cleaning of lenses, testing of gimbals and other fragile UAV elements. A dust free environment is required which is often insufficiently addressed in farm workshops and maintenance areas where farm machinery is included.

7. Thermal camera – tested for specific heat-signatures for map clarity and optimisation ofThermal camera sensor data.

8. Wind speed

Environmental factors such as wind have proven to be problematic for unmanned aerial vehicles (UAV). For instance, wind has been shown to affect UAVs in their ability to acquire high-resolution images by making the vehicle unstable while it is in the air, which can also sometimes lead to the drone crashing. When it comes to crop spraying, wind has also been shown to be a disadvantage, since the chemical might be carried away from the area that it is designed to target. Wind can also have an effect on livestock monitoring, as it causes the unmanned aerial vehicle (UAV) to adjust itself in response to wind interference, which can lead to a delay in either the processing of data or the detection of the target.

9. Weather

Cloudy conditions have an effect not only on the data quality obtained from a UAV but also on the drone signal strength. This may prove to be problematic, particularly in regions where fog is common or during the winter weather. Cloudy weather, with its reduced visibility, will also have an effect on the streaming of live data from a UAV when utilising the UAV for object identification or mapping, sunlight might also be problematic.

10. Drones can't be used for all type of pest detection.

Some crops cannot benefit from the use of drones. For instance, if there was a necessity to utilise an unmanned aerial vehicle (UAV) to detect slugs in strawberry planting, the process would endure a challenging time doing so because slugs are nocturnal organisms that rarely come out during the day.

11. Complexity of machine learning.

Many investigations have shown that the software or methodology utilised for mapping or object detection and avoidance (OBIA) was custom designed specifically for the researchers' projects. This might prove to be a significant obstacle for many farmers who may have little or no experience with computers. Ensure training and skillsets are matched to allow for access and interpretation of data (in real-time).

12. Additional Equipment

In order for a farmer to perform a precise analysis of the data obtained from a UAV, they will need to make additional investments in equipment such as a powerful computer, a screen designed specifically for professional image processing, internet access, storage hardware, and expensive agriculture software.

5.5 Entropy and Decay

In this section the discussion draws on the areas of risk, maturity, and readiness to examine the level of impact and influence that is evident from the combined examples and areas that pertain to drone practices. This discussion deliberately examines the three areas of risk, maturity, and readiness through the lens of entropy so that these factors can be compared in a single framework, rather than as a loose collection of otherwise disparate elements. If compared more openly, the issues that relate to costs are difficult to compare with issues about governance or technology acceptance.

This study includes entropy because there is a specific need to examine transformational change in terms of the challenges to that change. This segment is interested in the areas of disorder, uncertainty, exclusion (of past systems and practices) and areas where practices have decayed or are showing signs of decay.

By considering these different factors as part of an inquiry into the entropy of drone practices, it will provide farmers and drone practitioners with a clearer way to make conclusions that position the discussion firmly in the area of items that are uncertain or in disorder and will also show those factors that are more closely aligned with progress, productivity, and functional change. The evaluation principles using entropy and classifying areas of decay versus progress can be regarded with greater veracity because they directly connect with the key scientific questions that relate to information systems and the transmission of information and effective communication.

The discussion of factors has three areas of validation that is supported by the evidence from the literature. This discussion looks at an evaluation in terms of: technology risk to broadacre farming; the maturity of accepted drone practices and accepted usage; and the technology readiness of each factor. This evaluation looks at the individual factors on an item-by-item basis, but also considers the items in combination as part of a holistic evaluation of the risk profile of drone farming as a varied practice, rather than a specific technology enterprise.

The Risk Register in Appendix 7 also included a column entry for each identified risk in terms of a check on entropy and decay (see Appendix 7). A discussion of that assessment highlights the following areas of discussion.

Entropy and Decay assessment on UAVs in Broadacre Farming			
Key Issues	**Challenges**	**Entropy / Decay problems**	**Increasing or decreasing**
Weather Events	Inability to fly safely in bad weather	Increasing: Climate Change	⇑
Cost on Fixed Wing Drones	Cost Prohibitive – wear and tear	Cost may exclude redundancy yet equipment is critical to the required transformational change	⇑
Cost on Large Payload drones	Cost Prohibitive – wear and tear	Cost may exclude redundancy yet equipment is critical to the required transformational change	⇑
Cost of Thermal Camera	Cost Prohibitive – new changes every 6 months	Can end up running older cameras if not updated every season	⇑
Rules and Regulations	Complexities emerging in line with maturity adaptations	Expected reversion of private land - independent use of UAVs	⇑
Bird Attack	Birds of prey (Eagles and Hawks etc) see UAVs as a threat and recognise theme as a species of bird.	Reversion to illegal practices destroying protective species of bird	⇑
UAV Spraying	Overspray of treatments to neighbouring properties	Due to Climate change	⇑
Multispectral camera and software	Increased features and complexities	Requires software updates as new algorithms will adapt to broader data.	⇑
Camera Calibration	Inaccurate data capture	Size and weight of sensors keeps changing	⇑
Farmer Engagement	Willingness (or lack of) to adopt new technology	Requires positive socialisation and distribution	⇑
Planned Flight arrangements	No standardised guidelines	Requires community group and GGA alliance to exploit and grow strategy	⇑
Lack of Software	Lack of free open-source software – monopolies forming	Increased allegiance with universities to publish new areas of R and D	⇑
Machine Learning Skills	Lack of skills	Pressure on TAFEs and Universities to develop more grads with AI and Machine Learning.	⇑

Table 5.3 Entropy and Decay assessment on UAVs in Broadacre Farming

The issues raised in the above table (Table 5.3) are useful in understanding the separation between technology that works in a reliably stable manner for long periods of time, and the technology which requires a higher level of examination and maintenance in order to deal with issues of entropy and decay. These above identified areas demonstrate that there is a likelihood of entropic systems decay as the transformational change to include UAVs in broadacre farming takes its next steps. These entropy trends require ongoing assessment and vigilance to reduce their occurrence. Socialisation is key to many of these solutions because public and community support are critical factors for almost all of the major items on the assessment. Drone technology is more problematic in terms of the required integration into farm enterprises because it is reliant upon many supporting infrastructural considerations. Unlike mainstream farm machinery, drone technology is by comparison a far more fragile proposition. It is dependent upon support mechanisms that are physical, technical, and human-centred.

5.5 Summary of Discussion

This chapter outlined the specific areas that represented challenges to broadacre farming. In several examples these changes were measured against other similar areas of consideration. The alignment against the four areas of risk, maturity, technology readiness and entropy provide a strong set of identifiable factors that can be acted upon to better prepare the industry for the transformational change that comes with the adoption of UAVs into the broader application in broadacre farming. The broad differences that are identified in these challenges demonstrate that the principal area of convergence is clearly reliant upon emergent technology and the need for sufficient maturity to allow seamless integrate with existing farm machinery practices.

6 CONCLUSION AND RECOMMENDATIONS

This chapter summarises the key parts of the research carried out in this study. It answers the research questions and delivers specific concluding observations regarding the findings that are made in this study. The chapter also makes a number of recommendations in regard to future work in the areas of Standards, Government Policies, and Best Practice. This study concludes its research through the overarching finding that the adoption and broader inclusion of UAVs on broadacre farming represents a transformational change.

This study aimed to identify factors of influence, limitations, areas of optimisation, and areas of standardisation. It specifically examined the use of drone technology as a means to improve the way data is collected, analysed and applied into broadacre farming. The advent of drone usage has brought a series of options in terms of how data can be collected. This comprehensive set of adoptions means that agriculturalists in broadacre farming (especially early adopters of technology), are faced with multiple decisions and prospects. There are many different options considered in this study, and a general observation is that not all options are compatible with each other. What is required is a higher degree of standardisation and the development of best practice so that a uniform approach can allow for collectively enhanced agricultural benefits.

The aim of this study might therefore draw its principal focus on the ability to assist those using drone technology to achieve some form of standardisation. This study aimed to assist with standards of practice that allow for consistent comparisons across seasons, crops, and rotations. The changing nature of drone technology has made the task of standardisation become increasingly difficult and, instead of drawing the drone Agtech community together, has instead facilitated a fragmented set of engagements. The same divisions have prompted an accelerated decaying of traditional and consistent agricultural practices. This is especially important in precision agriculture where the reliability and quality of the precise measurement has always been the mainstay of the efforts to improve yields, efforts and productivity.

6.1 Answering the Research Questions

Based upon the findings of this research there are four specific areas of concern that relate to the research and which represent the key approaches needed to answer the research questions that form the key objectives of this study.

The Principal Research Question

What are the important factors influencing the of UAV technology for broadacre farming?

Key Findings

Based upon the findings of this study there are four critical factors that influence drone practices in broadacre farming environments. <u>The first is the issue of Cost and Return on Investment (ROI).</u> This study has found that although there is a low cost of entry to begin using drones, the more sophisticated technology adoptions require considerable cost and outlay to implement and to establish. Whilst UAV technology has bespoke pricing; the underestimated area of concern is clearly in the area of its supporting infrastructure.

Broadacre farming is becoming increasingly more aligned with technology, however the implementation of drone technology for broadacre purposes requires large-scale upgrades in software, hardware, skills, training, computer and data literacy, networking, and technology acceptance. It requires a team of people rather than the work of an individual, however the benefits of broadacre farming at scale are so significant that despite the enormous financial commitment, the expected ROI is well within the limits of what might be expected to improve the profitability of a broadacre farm.

<u>The second factor of influence is in the uniform development of acceptable rules and regulations.</u> UAVs have emerged from two uniquely driven areas. The first is the military sector and the second is the leisure and recreation sector. Both are immeasurably different from one or other, yet they have, collectively, driven change and advancement in a very short space of time. For agricultural use, drone technology has had an uneven footing, with popular recreational drones being trialled and tested throughout Australia in recent years. These have created the perception of a two-tier appreciation of the technology. At the first-tier level there are drone manufacturers that sell drones for under $1000. This has enabled a widespread adoption of "first time" drone enthusiasts. The second-tier level is characterised by sophisticated fixed wing drones, multirotor heavy payload drones with erudite camera options and high-speed methods of mapping and scanning large sized broadacre farms.

To functionally service these tiers there is a need for a more uniform approach to regulations, as well as rules and engagements that are meaningful, authentic and represent an honest appraisal of drone usage behaviour in the agricultural sector. Many farmers fly drones on the basis that they operate on private land and do not need to comply with regulations as long as they operate on private property in remote locations. In reality, there are many different approaches that require stronger codes of practice, as well as agreed approaches to key challenges. Agricultural drones are often large instruments, designed and operated to fly at high speed for efficient mapping and to enable long travel distances. There are also unresolved issues regarding surveillance, security, privacy, and community agreement. Furthermore there are animal activists who criticise drone usage as a hazard to livestock, neighbouring property owners who decry the overlapping nature of aerial drone photogrammetry, and uncertain acceptance of the provisions for drone operation in regard to the challenge of Beyond Visual Line of Sight (BVLOS) rules and guidelines.

The third factor of influence is the issue of training and skills. The development of UAV integration into broadacre farming requires an understanding of the various skillsets required. These skills go well beyond the singular operation of drones. This research finds that the broader set of requirements in terms of skills and training involve an understanding of computing, hardware, software, mapping, security, networks, and network systems. The full benefits of drone usage allow for LoRa Wide Area Networks (LoRaWANs) so that drones can interact with sensors on the ground. An enormous portion of broadacre farming takes place outside of 3G and 4G mobile network coverage. The use of long range solutions such as LPWANs (usually LoRa networks) is critical to the optimisation of data gathering across a large–scale farming enterprise. Drone operations gather sizeable amounts of information and data which needs to be acquired, stored, and analysed. In some cases, the data is better stored in 3rd party cloud systems. In other cases, it is the farmer who must develop their own cloud storage system and must manage the integration of the security and privacy sharing of that data. Overall, there is a greater dependency on computer science-based skills that accompanies the integration of drone systems on broadacre farming enterprises.

The fourth factor of influence is technology acceptance. This finding describes the reluctance of the community as a whole to accept the benefits of drone usage over and above the concerns with privacy, security, animal welfare, and lawfulness. It is clear from the literature that drone usage is a contested idea that does not have the complete support of the wider community. There is room therefore, for a greater level of socialisation in drone usage that allows for deeper inclusion. There is also no doubt that the criticisms raised about privacy and surveillance are genuinely concerning and must also be addressed. The knowledge that many farms follow drone practices that operate according to their own rules is perhaps unhelpful to the broader set of values. To more profoundly obtain a wide level of technology acceptance this research finds that the adoption and adherence to codes of conduct, codes of practice, and uniform rules and regulations should be more actively pursued.

Sub Question 1. *What are the Ongoing limitations in the development of drone technology?*

This research study has highlighted eight key areas that limit the development of drone technology. This question was an important inclusion for this research, since it assisted in the deeper understanding of the limitations of drone practices in farming. <u>The overarching limitation at the broadacre farming level is in financial outlay</u>. This is both an initial impost as well as an ongoing challenge because drone usage has ongoing developmental costs that continue to require upgrade and re-alignment with emerging precision farming practises. There are many cases where the size and scale of broadacre farming requires drone integration to such a high level that the inclusion of UAVs are considered to be cost prohibitive for medium to small scale farming enterprises. That is not to say that they hold no benefits at all. Smaller farming operations (sub-broadacre categories) should adopt a different approach, using smaller drones and accepting the benefits of more easily understood data such a RGB images and simple maps that give excellent information for farmers with lower technical applications due to lower size and scale of operation. This type of differentiation is important because large scale broadacre farming carries a higher level of data and sensor-driven information.

<u>The second limitation was a specific challenge with LIDAR technology.</u> This is a current challenge that can be demonstrated in terms of accuracy whereby LIDAR sensors can have difficulty in recognising specific features. They are less accurate in environments where there is dense vegetation or abundant undergrowth, and they have difficulty in recognising precise head count such that they cannot be relied upon to guarantee and to recognise an exact number of livestock in a given area or location. Nevertheless, LIDAR is a sensor with a potentially great future once the recognition-side of the technology becomes capable of providing definitive accuracy in patterns, livestock, and object recognition.

<u>A third limitation is in the area of thermal sensors.</u> In this area many of the multispectral features demonstrate limitations in summer temperatures where key differentiators are difficult to obtain during day-time drone flight. Again, as with LIDAR technology, these limitations mat be resolved in the near future. Thermal sensors offer inexpensive tracking and movement capabilities because in colder weather conditions they represent extremely accurate options for

the movement and condition of both livestock and feral animals. They remain problematic during high summer temperatures where the thermal characteristics of livestock are indistinguishable against the heat of property and ground cover.

A fourth area of limitation is the 'lag' between hardware and software. Recent developments in drone technology show remarkable potential for sensory knowledge at an extremely high level. At present, the general population does not have access to an equally sophisticated level of software development as it does with hardware. This limitation is in train and is predictably likely to catch up with the hardware demands in the near future.

The fifth limitation that this research has found is in terms of battery innovation. Drones in general continue to be limited in terms of total flying time by their battery life. The recent innovations with smart batteries have narrowed the gap in terms of extended flying time, however drones remain limited in terms of their range away , and returning to, a set destination on the basis of limitations in battery technology.

The sixth limitation that emerged from this research concerns weather events. There is statistical evidence that there is an increase in the number of adverse weather events, and drone technology has yet to become as fully robust as required to operate under these parameters. There is evidence of robust military machinery, however within the agricultural sector the choice of drone instruments still carries limitations for drone usage during extremes such as heavy wind, rain, and hail. Drones do not operate well in bush fire scenarios, and often compete for airspace with water bombers, helicopters, and emergency machinery. Drones have the potential for immense benefit during adverse weather events but are yet to find an appropriate agreed set of operating conditions to be of high-level assistance. They ae capable of providing critical real-time information without the need to place individual humans in physical danger.

The seventh limitation is associated with specific rules for flying. Currently the extended operational purpose for broadacre drone usage needs the ability to fly beyond the visible line of sight of an operator. There is currently an emerging set of reforms addressing the issues for operating drone beyond the visual line of sight (BVLOS), however it remains unresolved, and once organized, it will provide certainty and release some of the entropic disorder to the way that drone operations are applied to broadacre farming enterprises.

The eighth limitation for drones is the absence of 3G and 4G mobile wireless internet coverage. In urban areas this technology allows for a very complex integration of services. In the remote and rural areas where the great majority of broadacre farming takes place, there is an absence of 3G and 4G mobile coverage. Over time this may be rectified however, based on current roll-out information, the likely coverage requirements are not consistent with the major telecommunications companies and their commitment to more densely populated areas. Whilst many farms have 3G and 4G access at the farmstead, the wider coverage over a typical broadacre operation is absent. The commitment to 3G across Australia will be withdrawn by mid 2024, however the required infrastructure for 4G and 5G capability is still in need of substantial development in remote and rural parts of Australia.

Sub Question 2. *What are the important optimization features using UAVs?*

This research study identified two main areas in need of improved optimisation features. They are both connected in terms of object detection. Drones have demonstrated the ability (at low speed) to detect objects such as plants and trees in sufficient time to avoid a collision. Similarly, drone cameras have demonstrated the ability to recognise a range of objects such as feral animals predators such as foxes, and differing varieties of livestock. Whist the general ability of drone cameras to recognise shapes has reached near maturity, the specific ability to recognise and count objects remains unfulfilled. There is substantial ongoing research work in this area, and the impacts are likely to benefit a range of scientific endeavours including artificial intelligence, neural networks, and many additional research areas. As previously described the work on LIDAR sensors is one of the areas that forms the basis for optimisation in drone usage.

Sub questions 3. *What is the challenge for repeated locational drone footage in agriculture?*

This research study found that the rapid improvements in camera visibility have allowed drones to provide an extremely high-quality level of footage and imagery. This advance has allowed agriculturalists and precision agriculture experts to differentiate many features, finding pests, identifying diseases, and assisting with soil management. The benefits of such advances are clearly of great value. This level of rapid development however comes at a price in terms of agricultural records and crop management. Since each new drone now comes with an improved set of optics, improved battery life, and improved aerial stability, there are a number of variations in the way in which information is gathered and analysed. Early drone usage would typically operate at a height of 25 metres above ground level. Subsequent seasons and years have seen different altitude such as 30 metres, 50 metres, 60 metres, 100 metres and so on. In order to remain accurate for yearly and seasonal comparisons, the drone farming industry needs to strike a balance in terms of agreed values. It must standardise to an agreed operating height for the benefit of comparative images and the consistent quantification of farm records to enable high-level precision farming and best practice decision-making. Drone footage (to remain purely accurate) should ideally be collated whilst operating at the same height, taken at the same time of day, with the same velocity, and under as similar conditions as possible.

The new challenge for what is rapidly becoming an enormous repository of done footage and UAV image management, is to retain imagery that is highly compatible with other footage. Whilst there are ways to adapt and re-order some footage, the most significant revision will be best serviced by an accepted set of accepted values for drone altitudes, camera angles and operating speeds. In that way, a consistent set of comparative values can be used to create a new generation of highly accurate plant and livestock data.

6.2 Future Work

This research has identified several important areas requiring further investigation and study. In the first instance, there is an urgent need to look at the way in which drone usage in broadacre farming aligns with the overall needs of the Australian UAV community. Clearly the future of UAVs and drones will extend well beyond existing current practices. It will reach into areas of data collection and mapping that are significantly more detailed than current systems and data collections. The way in which that data is acquired, stored and shared is a matter of urgency because it affects industry and business at the corporate level, and affects individuals and families at the personal level. The integration of shared agricultural data with information systems, stored data systems, and agricultural cooperatives underpins the successful future of the agricultural industry.

6.3 Final Conclusion

With all of the changes and enhancements that are outlined in this thesis, there is a greater aspirational endeavour that should be encouraged. The use of technology to improve productivity and efficiency is obvious in terms of its benefits. However, the single most powerful enhancement that can accompany the benefits of technologies such as drones, is the fulfilment of uniformly accepted digital trust. There is great opportunity for global improvement, whether at the micro level, or with the achievement of the 17 United Nations sustainable development goals. They are all dependent upon digital trust.

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8 APPENDICES

This section arranges a set of data and data sets and tables that provide key touchpoints for the comparison and understanding of key values. Many data items are inconsistent between different regions, governments and nation states. Each appendix should be read with a clear understanding of its origin, its intended audience, and its reliability.

8.1 Appendix 1.

UAV investigations reviewed: April - May 2021

Event Date	UAS Type	Location	Record only occurrence Text
20 Mar 2021	DJI Mavic Mini	Stockport, Greater Manchester	The UAS was being used to film a moving car. However, the UA collided with the side of the car and fell to the ground. It suffered substantial damage when it was then run over by the car.
30 Mar 2021	Parrot Anafi USA	Cassington, Oxfordshire	The UA struck overhead telephone wires and fell to the ground.
30 Mar 2021	Parrot Anafi	Cassington, Oxfordshire	During a night takeoff, the UAS collided with an unseen telephone wire approximately 20 m above ground level
31 Mar 2021	DJI Unknown	Trellech, Monmouthshire	While taking photographs of a building, the UAS clipped the branch of a tree and fell to the ground.
31 Mar 2021	DJI FPV	Waskerley, County Durham	The pilot was flying the UA over a hillside. He lost control of the UA and it fell to the ground.
04 Apr 2021	DJI Phantom 4 Pro	Holywell, Flintshire	The UA was flown to a height of 55 m for handling checks when power to the motors was lost. It descended rapidly colliding with the ground close to the take-off point.
04 Apr 2021	DJI Inspire 2	Covent Garden, London	The UAS was in a stable hover while the operator was looking at the screen. The UAS flew into a nearby building before falling to the ground.
11 Apr 2021	Align T-Rex 500x	Little Stoke, Bristol	The UA, a model helicopter, was being flown from a playing field. The operator hit the rescue button on the transmitter, the button jammed, and the UA did not respond. It disappeared into a housing estate and was not recovered.
14 Apr 2021	DJI Matrice 300	Guildford, Surrey	During night training operations, a warning appeared on the control unit that the UAS was not receiving data from the gimbal payload. The operator was bringing the UA in to land when, at a height of around 10 m, the payload dropped to the ground.
14 Apr 2021	Sky Falcon P93	Salisbury Plain, Wiltshire	The UA made an uncommanded climb while in a height-holding manoeuvre. The remote pilot shut down

			the engine and attempted to recover the UA which resulted in a hard landing.
15 Apr 2021	DJI Unknown	Sawtry, Cambridgeshire	The pilot, who was visual with the UA, misjudged its trajectory and it hit a tree despite the UA's collision avoidance having been turned on.
17 Apr 2021	FPV Inflight Protek certified HD	Newquay, Cornwall	The UAS was conducting commercial photography shoot some 15 m above the cliff top near Newquay when the control feed cut out and the pilot lost control. The UA struck the cliff top, rolled down the cliff into the sea and was not recoverable.
21 Apr 2021	DJI Phantom 4	Swindon, Wiltshire	Shortly after take-off, control of the UA was lost. It flew into a fence and sustained damage to three propellers.
23 Apr 2021	DJI Mavic 2	King's Lynn, Norfolk	The UAS was being used to for aerial photography. During manoeuvring the UA struck a tree and fell to the ground
24 Apr 2021	Radio Controlled Glider	Near Abingdon, Oxfordshire	From a model flying club, the pilot was flying his model glider at 50 m above the ground towards him. It However, it flew past him, disappeared, and was not recovered.
27 Apr 2021	DJI Mavic 2 Pro	Gainsborough, Lincolnshire	The propellers of the UAS struck the branches of the tree causing it to fall onto a parked car.
02 May 2021	DJI Matrice 210 V1	Bury St Edmunds, Suffolk	The operator started the rotors, and the UA took off to a height of about 5 m where the response checks were carried out. After the first check the UA turned but did not respond to control inputs and struck a tree. The UA sustained substantial structural damage.
06 May 2021	DJI M300 RTK	New Malden, Surrey	The UAS was being operated in the hours of darkness in support of a police operation. Whilst manoeuvring to land it collided with some unseen telephone wires causing it to fall to the ground and collided with a parked car. All propeller blades, a propeller arm, leg, and camera mount were broken in the accident.
19 May 2021	DJI Phantom 4 Pro V2	Brent Cross, London	After surveying from a height of approximately 10 m, the pilot flew the drone to a height of 30 m when, without warning, it flipped over and fell to the ground. The UA came to rest on a rubble plie approximately 50 m from any person. The pilot reported that, on inspection, it appeared the battery connector had melted.

8.2 Appendix 2.

UAV incidents from around the World

Event Date	Location	Record only occurrence Text
16 Feb 2023	US Border	10,000 Cartel Drones Detected Crossing US Border Last Year
4 Feb 2023	Dublin Airport	Dublin Airport drones: Ryanair calls for Government action to prevent further disruption
29 Jan 2023	Isfahan defense facility	Iran says drone attack targets defense facility in Isfahan
27 Jan 2023	Las Cucharas prison in Ponce	Drugs and phones by drone in prison
29 Jan 2023	Dublin Airport	Drone sighting causes flights to be suspended at Dublin Airport
23 Jan 2023	Ukraine	Ukraine's battlefields look like World War I but with a new and terrifying addition
23 Jan 2023	Islamabad airport	Authorities alerted after drone comes close to UN aircraft.
23 Jan 2023	Canada	Canada issues report on 2021 police drone's collision with a plane descending to land
23 Jan 2023	Quebec Prison	Drone intercepted at Quebec prison
23 Jan 2023	St. Mary's Stadium England	Another English pro soccer match halted by a drone in the stadium
22 Jan 2023	India – Pakistan Border	Punjab: Drone with 5 kg heroin shot down near India-Pakistan border, two held
16 Jan 2023	River Thame England	A 28kg (62lb) drone crashed into a boat at the Henley Royal Regatta, narrowly missing its occupants, before sinking in the river Thames
16 Jan 2023	Bournemouth England	A MAN has been fined by the courts for flying a drone at the beach in restricted airspace during the Bournemouth Air Festival
15 Jan 2023	Koko head trail (USA)	Drone interferes with helicopter rescue at Koko Head Trail
4 Jan 2023	South Carolina Prison	3 accused of using drone to smuggle contraband into South Carolina prison
23 Dec 2022	Townsville Correctional Centre Queensland Australia	Drone used in attempt to smuggle $250,000 worth of drugs into Townsville Correctional Centre
20 Dec 2022	North Texas	North Texas criminals using drones to drop drugs onto prison grounds
12 Dec 2022	Jasper National Park Canada	Man fined $10,000 for flying drone near forest fire in Jasper National Park

12 Dec 2022	Gatwick Airport	Gatwick Airport's 'drone sightings' that closed runway for three days in Christmas 2018
16 Nov 2022	Oman	Official says oil tanker hit by bomb-carrying drone off Oman
30 Oct 2022	England	Up to six mystery drones spotted over UK nuclear plant in possible ‘malicious’ event

8.3 Appendix 3.

Drone crashes in Australia

Event Date	Location	Record only occurrence Text
15 Jan 2021	New South Wales	Loss of control and collision with terrain involving DJI Inspire 2 remotely piloted aircraft Darling Harbour Sydney, New South Wales on 15 January 2021
21 Nov 2022	Perth	Perth drone show: Remote controlled aircraft crash into Swan River during City of Light
30 Sep 2022	Queensland	Wing delivery drone crashes into power lines in Australia
23 Jun 2022	Sydney	Drone crash in Sydney hotel injures guest
25 Jun 2014	Geraldton	CASA plans legal action over drone crash in Geraldton
19 Feb 2016	New South Wales	CASA TO INVESTIGATE DRONE CRASH AT AUSTRALIAN WAR MEMORIAL
28 Sep 2019	Wyndham Airport Western Australia	In-flight break-up involving Airbus Zephyr unmanned aerial vehicle, near Wyndham Airport, Western Australia, on 28 September 2019

8.4 Appendix 4

Global Press Documentation of Drone Incidents

All drone incidents documented by the press worldwide

Map of global drone incidents by Dedrone Anti-Drone / cuas solution. (2023). Retrieved February 19, 2023, from https://www.dedrone.com/resources/incidents-new/all?bd17d27c_page=1

Date	Location	Industry	Incident
January 29, 2023	Ishafan, Iran	Government/Military	Israel carried out a drone strike on an Iranian ammunition factory
January 22, 2023	Kakkar, India	Government/Military	Punjab: Drone with 5 kg heroin shot down near India-Pakistan border, two held
January 21, 2023	Southampton, United Kingdom	Stadiums	Southampton and Aston Villa players rushed off pitch as drone flies above St Mary's
January 19, 2023	Kingston, ON, Canada	Prisons	Contraband seized at Bath Institution after suspected drone drop
January 19, 2023	McAllen, TX, USA	Government/Military	Texas DPS encounter 'drone incursions,' recover make-shift ladders used to scale wall
January 17, 2023	Kingston, ON, Canada	Prisons	Contraband seized at Joyceville Institution
January 16, 2023	Rawalpindi, Pakistan	Airports	A drone came dangerously close to a UN plane at 3,400 feet near the runway of Islamabad airport
January 16, 2023	Horden, United Kingdom	Law Enforcement/First Responders	Bungling County Durham cop crashes drone into house during major operation
January 15, 2023	Tamil Nadu, India	Private/Non-Coporate	Man fined for filming private forest area of Anamalai Tiger Reserve using drone
January 5, 2023	Gravenhurst, Ontario, Canada	Prisons	Man charged after drone with prohibited items crashes near Beaver Creek Institution
January 1, 2023	Gurdaspur, India	Government/Military	Border Force Fires At Pak Drone, Pushes It Back Across Punjab Border
January 1, 2023	Brasilia, Brazil	Law Enforcement/First Responders	Federal Police shot down four unauthorized drones that flew over the Esplanada dos Ministério during President Lula da Silva's inauguration ceremony
December 27, 2022	Taiwan	Entertainment/Media	Drone crash on Netflix set causes ‘serious disfigurement’ to actor’s face
December 26, 2022	Val-de-Reuil, France	Prisons	Suspicious drone flights over Val-de-Reuil prison
December 25, 2022	Delhi, India	Energy/Utilities	Drone crashes on track, Delhi Metro halts for 1 hour on Magenta Line

December 21, 2022	Daoke, India	Government/Military	BSF shoots down Pak drone, seizes 4.3 kg contraband in Amritsar
December 17, 2022	Asheville, NC, USA	Private/Non-Coporate	It's not a joke or funny' Drone harassing children, staff & therapy horses at Eliada Home
December 15, 2022	Jaffa, Israel	Law Enforcement/First Responders	An assassination was foiled: a drone with an explosive device, on the main street in Jaffa
December 12, 2022	Kelantan, Malaysia	Prisons	Three arrested for attempting to smuggle tobacco items into Machang prison using drone
December 11, 2022	Bennettsville, SC, USA	Prisons	Deputies: Drone delivering contraband to correctional facility; two arrested
December 9, 2022	Auckland, New Zealand	Private/Non-Coporate	Drone spirals, crash-lands near popular Auckland bar after hitting bird
December 4, 2022	Kingston, ON, Canada	Prisons	Contraband seized following suspected drone drop at Joyceville Institution
December 4, 2022	Amritsar, India	Government/Military	BSF Shot down a drone with a payload of 2 kg heroin near the international border in Amritsar
December 4, 2022	Baltimore, MD, USA	Airports	FAA: Spirit Airlines crew found unusual drone flying beneath their plane at BWI airport
December 4, 2022	Naha, Okinawa, Japan	Airports	Airport in Japan's Okinawa Pref. disrupted by possible drone sighting
December 2, 2022	Warkworth, ON, Canada	Prisons	Another drone drop suspected after drugs, tobacco seized at Warkworth Institution
November 28, 2022	Amritsar, India	Government/Military	Two Pakistani drones shot down by BSF, 10kg of heroin recovered
November 28, 2022	Delhi, ON, Canada	Law Enforcement/First Responders	Drone spotted hovering around people’s homes in Norfolk County
November 26, 2022	Mexico	Law Enforcement/First Responders	A Cartel Used Armed Drones and a Plane to Bomb Police
November 26, 2022	Jalisco, Mexico	Law Enforcement/First Responders	A Cartel Used Armed Drones and a Plane to Bomb Police
November 24, 2022	Jammu and Kashmir, India	Government/Military	Drone Drops IEDs, Rs 5 Lakh Cash In J&K’s Samba
November 24, 2022	Gold Coast, Queensland, Australia	Stadiums	Axl Rose Slams ‘Drone Pirates’ at Guns N’ Roses Shows
November 24, 2022	Bavla, India	Government/Military	Three Arrested for Flying Drone During PM Modi’s Visit to Bavla, Gujarat
November 23, 2022	Algeciras, Spain	Prisons	Drone smuggling contraband crashed before entering prison's
November 16, 2022	Lahore, Pakistan	Law Enforcement/First Responders	Police were called to investigate a drone crash near the Orange Line automated rapid transit metro station
November 12, 2022	Dallas, TX, USA	Airports	US B-17 Bomber & P-63 Kingcobra Collide Over Dallas Executive Airport Due to A Drone?
November 3, 2022	Mission, BC, Canada	Prisons	A drone dropped a firearm at the medium-security Mission prison, causing a lockdown
November 3, 2022	Montreal, QC, Canada	Airports	When on final approach to Montreal Trudeau Airport, an airline pilot reported seeing a drone fly at 2,000 feet just 400 feet underneath his aircraft

November 3, 2022	Ferozepur, India	Government/Military	3rd drone spotted near Pak border in 2 weeks
November 2, 2022	Raska, Serbia	Government/Military	Serbian Army comes out with details after the downing of a drone in the Mt. Kopaonik region
October 28, 2022	Ranbir Singh Pura, India	Government/Military	Drone-dropped Weapons Recovered Along IB in Jammu; 2 Arrested
October 24, 2022	London, United Kingdom	Airports	EasyJet plane comes within '10 feet' of drone in 'close encounter'
October 20, 2022	Sweden	Government/Military	Swedish Royal Armed forces dealing with incident involving drone activity over military facility
October 14, 2022	Susort, Norway	Energy/Utilities	Norwegian police investigate drone sighting over the Kaarstoe gas plant
October 4, 2022	Denmark	Energy/Utilities	For the second time in a week: Drones spotted near North Sea gas fields according to Danish Police
October 4, 2022	Dera Baba Nanak, India	Government/Military	Drone hovered nearly 10 km inside Indian territory above Abbad village
October 2, 2022	Wuhan, China	Private/Non-Coporate	An investigation confirmed a woman's report of a drone invading her privacy and photographing her home
October 1, 2022	Wildflecken, Germany	Government/Military	Suspicious drones seen over German military sites training Ukrainian soldiers
September 30, 2022	Parkland, FL, USA	Construction	A drone used by a subcontractor to inspect a residential roof crashed
September 30, 2022	Logan, Queensland, Australia	Energy/Utilities	Thousands of people were left without power for up to 3 hours after a food delivery drone crashed into powerlines
September 29, 2022	Rio de Janeiro, Brazil	Stadiums	Botafogo vs. Goias pro soccer match was interrupted by an unauthorized drone flying over the stadium
September 28, 2022	Denmark	Energy/Utilities	Mysterious Drone Activity Spotted at Danish Gas Field in North Sea – TotalEnergies
September 28, 2022	Washington D.C, USA	Government/Military	White House Partially Evacuated After Drone Enters Restricted Area
September 28, 2022	Palma de Mallorca, Spain	Law Enforcement/First Responders	Drone operators fined for use in Royal Family security zone
September 25, 2022	Seattle, WA, USA	Stadiums	Falcons-Seahawks game momentarily delayed after unidentified drone flies over Lumen Field
September 25, 2022	Seattle, WA, USA	Stadiums	Drone delays Seahawks-Falcons game in 4th quarte
September 24, 2022	Seattle, WA, USA	Stadiums	A rogue drone over Husky Stadium caused a 10–15-minute delay in the Washington Huskies vs Stanford Cardinals college football game
September 24, 2022	Nasik, Maharashtra, India	Law Enforcement/First Responders	Residents were ordered to turn over all private drones after police spotted unauthorized drones flying near defense establishments
September 23, 2022	Al Jahra Governorate, Kuwait	Prisons	Three drones attempting to drop contraband into the Sulaibiya Central Jail complex were discovered by security personnel
September 23, 2022	Glasgow, United Kingdom	Airports	Flights to Glasgow Airport forced to divert after suspected drone sighting
September 19, 2022	Amritsar, India	Government/Military	Pak drone airdropped pistol and drugs near Amritsar
September 14, 2022	Montreal, QC, Canada	Airports	Police and security were dispatched to Montreal Airport to investigate a drone reported flying near a runway

September 13, 2022	Sawtooth National Forest, Idaho, USA	Law Enforcement/First Responders	Drone Flies ‘Extremely Close’ to Firefighting Helicopters in Idaho
September 13, 2022	Oslo, Norway	Airports	Norway's airport owner Avinor reports 50 drone incursions per month at Oslo airport alone, resulting in delays, costs, and traffic rerouting for passengers, airlines, and the airport
September 9, 2022	Jasper, AB, Canada	Law Enforcement/First Responders	Illegal drones temporarily ground firefighting helicopter
September 5, 2022	Bournemouth, UK	Law Enforcement/First Responders	Bournemouth police pocket seven drones in banned airshow space
September 4, 2022	Zigong, China	Construction	Drone pilot got fined for flying close to the Zigong high-speed railway station
September 2, 2022	Huntington Beach, CA, USA	Private/Non-Corporate	Drone hovers over house, peeps into daughter’s room, mother says
September 2, 2022	Amedi, Iraq	Government/Military	An unidentified drone crashed onto the roof of a house in an apartment complex following several skirmishes between Turkish troops and Kurdistan Worker's Party troops
September 1, 2022	Kinmen Islands, Taiwan	Government/Military	Taiwan Shot Down a Suspicious Drone Flying Over Its Islands Off China’s Coast
August 31, 2022	Kuala Lumpur, Malaysia	Law Enforcement/First Responders	Law Enforcement shot down at least four drones during national day parade venue where numerous dignitaries, including Their Majesties the King and Queen, were gathered
August 29, 2022	Madrid, Spain	Airports	Five flights scheduled to land at Adolfo Suárez-Madrid Barajas airport were diverted and airport operations were disrupted for one hour due to the presence of unauthorized drones
August 28, 2022	Montreal, QC, Canada	Airports	A Cessna pilot reported having to evade a drone near the La Fontaine tunnel
August 27, 2022	Tel Aviv, Israel	Airports	United flight diverted from Tel Aviv landing after small drone enters its path
August 27, 2022	St. John's, NL, Canada	Airports	At 3,200 feet, an Air Canada Airbus reported a drone at the same altitude, just off its left wing
August 25, 2022	Brighton, Ontario, Canada	Prisons	Tobacco, marijuana, shatter, allegedly seized after suspected drone drop at Warkworth Institution
August 24, 2022	Victoria, BC, Canada	Law Enforcement/First Responders	Drone operator risked steep fines for capturing billowing smoke and responders in action during a fire
August 20, 2022	Pitt Meadows, BC, Canada	Airports	A Cessna pilot spotted a drone at approximately 2000 feet in restricted airspace 4NM northeast of Pitt Meadows Airport
August 16, 2022	Kimmen Islands, Taiwan	Government/Military	Troops Throw Rocks At Drone Over Taiwanese Island Close To Chinese Coast
August 14, 2022	McRae-Helena, GA, USA	Prisons	Two people were arrested for using a drone to smuggle contraband into Telfair Prison
August 13, 2022	Spokane, WA, USA	Law Enforcement/First Responders	A burglar used his own drone to attack a police drone in mid-air as it chased him
August 12, 2022	Kolkata, India	Law Enforcement/First Responders	As India prepares to celebrate its 75th Independence Day, two people were arrested for flying drones over the Victoria Memorial
August 4, 2022	Orlando, FL, USA	Airports	High flying drone comes within 8-feet of Delta flight landing at Orlando International Airport
August 2, 2022	Jammu, India	Government/Military	BSF fires on suspected drone at International Border in Jammu
July 30, 2022	Birmingham, UK	Law Enforcement/First Responders	Drone seized in Birmingham after being flown ‘dangerously’ over Commonwealth Games crowds

July 28, 2022	Manjh, India	Government/Military	Amritsar police arrested drug traffickers and seized five kg of heroin drone dropped into the country
July 27, 2022	Ajnala, India	Government/Military	5kg heroin dropped by drone seized near border in Ajnala
July 27, 2022	Haikou, China	Law Enforcement/First Responders	Photographer operating a DJI Mini 2 without permission above the railway line was arrested and fined by the Haikou Railway Police
July 26, 2022	Sagaing, Myanmar	Government/Military	Drones bomb junta troops stationed in Sagaing's Shwebo Township
July 24, 2022	Al-Suqaylabiyah, Syria	Law Enforcement/First Responders	One Killed, Several Injured in Drone Attack on Syria Church Gathering
July 21, 2022	Washington D.C, USA	Airports	DC’s Reagan National Airport briefly halts flights after drone reported in area
July 18, 2022	Israel	Government/Military	A Hezbollah drone breached the Israeli border from Lebanon and was intercepted by the IDF
July 16, 2022	Canada	Prisons	Multiple packages seized following suspected drone drops at Collins Bay Institution
July 16, 2022	Bronx, NY, USA	Stadiums	Drone hovers above Yankee stadium during match against Boston Red Sox
July 16, 2022	Unadilla, GA, USA	Prisons	Arrests made in attempt to smuggle contraband into Dooly State Prison
July 14, 2022	Lawton, OK, USA	Prisons	2 People Arrested in Connection with Drone Drug Smuggling Operation
July 12, 2022	Saint-Jacques, Canada	Airports	Ambulance flight delayed 20 minutes because of drone at Edmundston Airport
July 9, 2022	Dortmund, Germany	Law Enforcement/First Responders	Drones spy on private homes of Borussia Dortmund football stars
July 6, 2022	Aberdeen, UK	Airports	Several sightings of drone flown illegally near city airport
July 3, 2022	Stony Mountain, Canada	Prisons	B.C. men arrested after drone; meth intercepted at Manitoba prison
July 2, 2022	Israel	Energy/Utilities	IDF shoots down 3 Hezbollah drones heading for Karish gas field
July 2, 2022	Popasna, Ukraine	Government/Military	Ukrainian miniature drone destroyed a huge Russian ammunition depot with just one grenade
July 1, 2022	Spangdahlem, Germany	Airports	Drone was operated in no-fly zone near US airbase
June 29, 2022	Rice, Minnesota, USA	Law Enforcement/First Responders	Minnesota sheriff's office locates operator of drone that approached kids, dropped candy
June 27, 2022	Barcelona, Spain	Law Enforcement/First Responders	Mossos report man for flying a drone over Barcelona without permission
June 27, 2022	Srikaranpur, India	Government/Military	Pakistan drone drops heroin in Srikaranpur subdivision of Ganganagar
June 27, 2022	Benton County, MN, USA	Law Enforcement/First Responders	Minnesota officials are investigating after a drone drops a bag of candy near children
June 25, 2022	Mallorca, Spain	Law Enforcement/First Responders	Drone over the "Ballermann": Pilot reported by police
June 25, 2022	Glastonburry, UK	Law Enforcement/First Responders	Glastonbury: Police detect illegal drone flight over festival
June 23, 2022	Sydney, Australia	Hospitality/Real Estate	Drone crash in Sydney hotel injures guest
June 22, 2022	Rostov, Russia	Energy/Utilities	Russian refinery says it was struck by drones from direction of Ukraine
June 20, 2022	Ettumanoor, India	Law Enforcement/First Responders	Man booked for flying drone over Ettumanur temple
June 19, 2022	Amritsar, India	Government/Military	BSF troopers repulse Pak drone spotted in Amritsar
June 19, 2022	North Wales, UK	Private/Non-Corporate	Caution advised after suspicious drone activity over farms in North Wales

June 13, 2022	Marinka, Ukraine	Government/Military	Mavic 3 drones were used to bomb the Ukrainian front line with makeshift grenade carriers under the drones in paper coffee cups
June 11, 2022	Ritidian, Guam	Government/Military	Air Force security personnel confiscated a drone that entered military airspace near Ritidian Overlook
June 10, 2022	Leicestershire, UK	Law Enforcement/First Responders	Airport disruption after drone sightings near Download Festival
June 10, 2022	Kelowna, BC, Canada	Airports	A drone flew within one kilometre of Kelowna International Airport as aircraft took off below it
June 9, 2022	Jammu, India	Government/Military	BSF troops shoot at Pak drone, force it back
June 8, 2022	Erbil, Iraq	Government/Military	Explosive drone detonates in Iraq's northern city of Erbil
June 8, 2022	Miami, FL, USA	Prisons	Inmates Attempted to Smuggle Contraband Using Drones, Correctional Officer Says
June 7, 2022	Jammu, India	Government/Military	Police fire at drone in Kanachak border
June 6, 2022	Pugachev, Russia	Prisons	Prison officers forcibly landed a contraband-laden quadcopter that was spotted over the Federal Penitentiary Service for the Saratov Region
June 6, 2022	Baghdad, Iraq	Prisons	Iraqi forces down drone over prison in Baghdad
June 6, 2022	Ukraine	Government/Military	Ukraine drone drops grenade in Russian soldiers' trench
June 5, 2022	Kingston, Canada	Prisons	The Correctional Service of Canada has again seized several packages containing contraband dropped by drones at the Collins Bay jail
June 5, 2022	Mallorca, Spain	Law Enforcement/First Responders	Drunk man hovered drone over Mallorca Bay: Pilot threatens beach guests
June 4, 2022	Düsseldorf, Germany	Airports	Drone at Düsseldorf Airport: Airbus 380 must be rerouted to Cologne
June 3, 2022	American Canyon, CA, USA	Law Enforcement/First Responders	California man arrested for dropping illegal fireworks from drone
June 2, 2022	Douglas, Isle of Man, UK	Law Enforcement/First Responders	Police seized a drone within the restricted zone of the TT Course, a street and public rural road circuit used for motorcycle racing
June 1, 2022	Whanganui, New Zealand	Private/Non-Corporate	Girl lucky not to be hurt after drone chased Riding for Disabled Whanganui horses
May 29, 2022	Kathua, India	Law Enforcement/First Responders	Pak drone loaded with magnetic bombs; grenades shot down in J-K's Kathua
May 29, 2022	Berea, OH, USA	Law Enforcement/First Responders	Man injured by falling drone at rib cook-off
May 24, 2022	Parchin, Iran	Government/Military	Drone Targets Iran's Parchin Military Base
May 23, 2022	Venice, Italy	Law Enforcement/First Responders	Drone crashes into Palazzo Ducale
May 19, 2022	Preston, UK	Law Enforcement/First Responders	Rogue drones interfere with firefighters tackling Preston blaze
May 17, 2022	Haifa, Israel	Government/Military	IDF says it downed Hezbollah drone that entered Israeli airspace amid major drill
May 16, 2022	Nuremberg, Germany	Airports	Drone interfers passenger plane at Nuremberg airport
May 15, 2022	London, UK	Energy/Utilities	Drones seized at UK nuclear bases after a 'swarm' and reports of 'red lights'
May 14, 2022	Cerro Pelado, Costa Rica	Law Enforcement/First Responders	Unauthorized Drone Down Firefighting Aircraft
May 14, 2022	Nai Basti, India	Government/Military	J&K Police Recover Drone from Satwari; BSF Continues to Foil Pak's Attempt To Drop Drones
May 14, 2022	Enugu, Nigeria	Private/Non-Coporate	Police Arrest Drone Operator Allegedly Filming, Spying on Church, Cleric's House in Enugu
May 14, 2022	Jordan	Government/Military	Jordanian army downs drone carrying drugs from Syria

May 14, 2022	Grünheide, Germany	Airports	Drone interferes approaching plane close to Berlin airport
May 10, 2022	Liverpool, UK	Prisons	HMP Liverpool staff spot drone flying above prison as man arrested nearby
May 9, 2022	Amritsar, India	Government/Military	BSF shoots down drone from Pakistan, recovers 10.6kg of heroin in Amritsar
May 8, 2022	Quebec, Canada	Prisons	Police foiled an attempted drone delivery of drugs to the Quebec City detention Centre
May 7, 2022	Jammu and Kashmir, India	Government/Military	BSF Fires at Pak Drone Near Jammu
May 6, 2022	Berlin, Germany	Airports	Drone sighting causes delays at Berlin airport
May 4, 2022	Glasgow, Scotland, UK	Airports	Flight to Dubai delayed due to drone in Inchinnan area
May 4, 2022	Jammu and Kashmir, India	Government/Military	BSF troops open fire at Pakistani drone near IB in Jammu
April 29, 2022	Dhanoe Kalan, India	Government/Military	BSF shoots down drone in Amritsar sector
April 28, 2022	Rankin County, MS, USA	Prisons	Mississippi man pleads guilty after flying drone with weed, lighters, cell phone to prison
April 28, 2022	Leeds, UK	Airports	Leeds Bradford Airport plane almost collides with drone
April 26, 2022	Golan Heights, Syria	Government/Military	IDF drone crashes in Syria, army says no data leaked
April 23, 2022	Rome, Italy	Law Enforcement/First Responders	Tourists crash drones into Italy landmarks in Rome and Pisa
April 23, 2022	Dorangala, India	Government/Military	Pak drone sighted along Punjab border 165 shots fired
April 20, 2022	Boulder County, CO, USA	Law Enforcement/First Responders	Researchers Drone Crash Caused Fire in Colorado
April 19, 2022	Marseille, France	Law Enforcement/First Responders	Drone pilot arrested for flying drone in restricted area where French President Macron spoke
April 17, 2022	Tarn Taran, India	Law Enforcement/First Responders	Gang using drones for smuggling drugs from Pakistan busted in Tarn Taran; 3 held
April 14, 2022	Minsk, Belarus	Government/Military	Drone Shot Down on Belarusian-Lithuanian Border
April 14, 2022	Singapore	Airports	$51k fine for man who unlawfully operated drone, causing 2 RSAF aircraft to be rerouted
April 13, 2022	Sydney, Australia	Airports	Warning after drones enter Sydney Airport airspace
April 13, 2022	Chennai, India	Law Enforcement/First Responders	Marina police detained and warned two people for flying a drone over a lighthouse in a restricted area.
April 12, 2022	Havelian Village, Pakistan	Prisons	BSF seizes 4-kg heroin dropped via drone in Tarn Taran
April 8, 2022	Riga, Latvia	Government/Military	Latvia's National Armed Forces identified drones that had entered a restricted area of a military facility
April 8, 2022	Poole, UK	Law Enforcement/First Responders	Police drone could have 'seriously injured' people in Poole
April 4, 2022	Prince George, British-Columbia, Canada	Private/Non-Corporate	Prince George RCMP looking into low-flying drone incident
April 2, 2022	Kumbia, Australia	Law Enforcement/First Responders	Drone Mystery in Kumbia
March 31, 2022	Casablanca, Morocco	Stadiums	Drone interrupts training by the DR Congo-team in the lead-up to the 2022 World Cup qualifying play-offs
March 29, 2022	Chennai, India	Law Enforcement/First Responders	A man was arrested for flying a drone over high court
March 28, 2022	Toronto, Ontario, Canada	Airports	Pilot spotted two drones at 3,000 feet
March 27, 2022	Dublin, Ireland	Airports	All flight operations at Dublin Airport stopped for around 20 minutes due to a drone being flown in the area

March 25, 2022	Jeddah, Saudi Arabia	Energy/Utilities	Houthis rebels attacked oil depot and other facilities with rocket and drone strikes.
February 15, 2022	Valetta, Malta	Government/Military	Drone Spied on Maltese Politicians Home
February 12, 2022	Gobabis, Namibia	Law Enforcement/First Responders	Cops confiscate drone from journalist spying on private elephant farm
February 10, 2022	Kingston, Canada	Prisons	A suspect has been arrested for trying to use a drone to drop 265 grams of cannabis, cellphones, and cellphone accessories into the Collins Bay Institution
February 8, 2022	Amritsar, India	Law Enforcement/First Responders	Punjab: Drone drops bombs in Amritsar, flees to Pakistan after BSF opens fire
February 8, 2022	Fremont, CA, USA	Consumer Products	Disrespectful and dangerous: Tesla employees are harassed by "fan drones"
February 7, 2022	Bishopville, SC, USA	Prisons	20+ People Have Been Arrested Due to Drone-Based Attacks
February 7, 2022	Saskatoon, Canada	Airports	Unauthorized Drone Spotted Near Saskatoon Airport
February 5, 2022	Berkeley, CA, USA	Education	Drones and Falcons Don’t Mix, Recent Incident at UC Berkeley Proves
February 4, 2022	Fort Dix, NJ, USA	Prisons	Two Men Plead Guilty for Their Roles in a Drone Smuggling Operation at the Fort DIX Federal Correctional Facility (Incident Between November 2018 and March 2020)
January 31, 2022	Saladin, Iraq	Government/Military	UAV Crashes Near Speicher Military Base in Saladin
January 30, 2022	Brighton, United Kingdom	Private/Non-Corporate	Drone crashed into Brighton i360 - accident report
January 29, 2022	Gaza	Government/Military	Israeli military forces shot down a Hamas drone
January 29, 2022	Porto, Portugal	Airports	Drone forces flight diversion to Lisbon
January 29, 2022	Marymount, Singapore	Law Enforcement/First Responders	Singapore branch of the China Railway First Group was fined $22,000 for flying a drone in public areas without a permit
January 29, 2022	Shenyang, China	Airports	An Underage Teen Uploaded a Video of His Drone Flying into Shenyang Airport and Being Shot Down on the Runway
January 29, 2022	Marib, Yemen	Education	Houthis fire explosive-laden drone at school in Yemen's Marib
January 29, 2022	USA	Prisons	Inmate Coordinated a Drone Drop of Cannabis Oil and a Cellphone into the Prison Yard
January 29, 2022	Mississauga, Ontario, Canada	Airports	A pilot reported a drone flying 200 feet above his aircraft as he landed at Toronto Pearson International Airport
January 29, 2022	Vancouver, British Columbia, Canada	Airports	A helicopter pilot reported seeing a small red drone flying over Lonsdale Quay at a height of 1700 -1800 feet
January 29, 2022	Amritsar, India	Government/Military	Drone sighted at Indo-Pak border
January 26, 2022	Jabalpur, India	Stadiums	Two hurt as drone falls on them during R-Day event at Jabalpur stadium
January 24, 2022	Amberg, Germany	Law Enforcement/First Responders	Drone confiscated during demonstration in Amberg
January 22, 2022	Brentford, United Kingdom	Stadiums	Premier League game between Brentford, Wolves stopped due to unidentified drone
January 17, 2022	Abu Dhabi, United Arab Emirates	Energy/Utilities	Drone attack in Abu Dhabi claimed by Yemen’s rebels kills 3
January 15, 2022	Stockholm, Sweden	Government/Military	Sweden drones: Sightings reported over royal palace and airports
January 15, 2022	Cincinnati, OH, USA	Stadiums	Illegal Drone Footage of the Cincinnati Bengals Game
January 14, 2022	Forsmark, Sweden	Energy/Utilities	Swedish police hunt for drone seen flying over Forsmark nuclear plant
January 14, 2022	Bermuda	Prisons	Drone Intercepted at Westgate, Man Arrested

January 10, 2022	Tigray, Ethiopia	Government/Military	Ethiopia: 19 people killed in latest drone strikes in Tigray
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8.5 Appendix 5

Drone Specifications adapted from DJI.

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<tr><td>P4 Multispectral</td><td colspan="4">
Figure 6: P4 Multispectral (P4 multispectral, DJI store, 2023)</td></tr>
<tr><td>Cost (AUD)</td><td colspan="4">$9,300 (DJI store, August 24, 2023)</td></tr>
<tr><td colspan="5">Aircraft</td></tr>
<tr><td>Take-off weight</td><td>Max Ascent Speed</td><td>Max Descent Speed</td><td>Max Horizontal Speed</td><td>Max Take-off Altitude</td></tr>
<tr><td>1487 g</td><td>6 m/s</td><td>3 m/s</td><td>31 mph /36 mph</td><td>6000 m</td></tr>
<tr><td>Max Flight Time</td><td>Max Wind Speed Resistance</td><td colspan="2">Global Navigation Satellite System</td><td>Max Flight Distance</td></tr>
<tr><td>27 minutes</td><td>31 mph (50 kph) (P-mode); 36 mph (58 kph) (A-mode)</td><td colspan="2">GPS + BeiDou + Galileo</td><td>2.4 GHz: < 20 dBm (CE / MIC / KCC)
5.8 GHz: < 26 dBm (FCC / SRRC / NCC)</td></tr>
<tr><td colspan="5">Camera</td></tr>
<tr><td>Image Sensor</td><td>Max Image Size</td><td colspan="2">RGB Sensor ISO Range</td><td>Photo Format</td></tr>
<tr><td>Six 1/2.9” CMOS, including one RGB sensor for visible light imaging and five monochrome sensors for multispectral imaging.
Each Sensor: Effective pixels 2.08 MP (2.12 MP in total)</td><td>1600×1300 (4:3.25)</td><td colspan="2">200 - 800</td><td>JPEG (visible light imaging) + TIFF (multispectral imaging)</td></tr>
<tr><td colspan="5">Mapping Functions</td></tr>
<tr><td colspan="2">Ground Sample Distance (GSD)</td><td colspan="3">Rate of Data Collection</td></tr>
<tr><td colspan="2">(H/18.9) cm/pixel, H indicates the aircraft altitude relative to the area mapped (unit: m)</td><td colspan="3">Max operating area of approx. 0.63 km2 for a single flight at an altitude of 180 m, i.e., GSD is approx. 9.52 cm/pixel, with a forward overlap rate of 80% and a side overlap ratio of 60%, during a flight that drains the battery from 100% to 30%.</td></tr>
</table>

<table>
<tr><td colspan="5">2020</td></tr>
<tr><td>DJI Mini 2</td><td colspan="4">
Figure 6: DJI Mini 2 (DJI Mini 2, DJI store, 2023)</td></tr>
<tr><td>Cost (AUD)</td><td colspan="4">$749 (DJI store, August 24, 2023)</td></tr>
<tr><td colspan="5">Aircraft</td></tr>
<tr><td>Takeoff weight</td><td>Max Ascent Speed</td><td>Max Descent Speed</td><td>Max Horizontal Speed</td><td>Max Takeoff Altitude</td></tr>
<tr><td>242 g</td><td>5 m/s</td><td>3.5 m/s</td><td>16 m/s</td><td>4000 m</td></tr>
<tr><td>Max Flight Time</td><td>Max Wind Speed Resistance</td><td colspan="2">Global Navigation Satellite System</td><td>Max Flight Distance</td></tr>
<tr><td>31 minutes</td><td>10.7 m/s</td><td colspan="2">GPS + GLONASS + Galileo</td><td>16 km</td></tr>
<tr><td colspan="5">Camera</td></tr>
<tr><td>Image Sensor</td><td>Max Image Size</td><td colspan="2">Video Resolution</td><td>Photo Format</td></tr>
<tr><td>1/2.3-inch CMOS, Effective Pixels: 12 MP</td><td>4:3: 4000×3000
16:9: 4000×2250</td><td colspan="2">4K: 3840×2160@24/25/30 fps</td><td>JPEG/DNG (RAW)</td></tr>
<tr><td colspan="5">Sensing</td></tr>
<tr><td colspan="2">Sensing Type</td><td colspan="3">Max Transmission Distance (free of interference)</td></tr>
<tr><td colspan="2">Downward vision system</td><td colspan="3">10 km</td></tr>
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<table>
<tr><td colspan="5">2021</td></tr>
<tr><td>DJI Mini SE</td><td colspan="4">
Figure 5: DJI Mini SE (DJI Mini SE, DJI store, 2023)</td></tr>
<tr><td>Cost (AUD)</td><td colspan="4">$459 (DJI store, August 24, 2023)</td></tr>
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<tr><td>Takeoff weight</td><td>Max Ascent Speed</td><td>Max Descent Speed</td><td>Max Horizontal Speed</td><td>Max Takeoff Altitude</td></tr>
<tr><td>242 g</td><td>4 m/s</td><td>3 m/s</td><td>13 m/s</td><td>3000 m</td></tr>
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Max Flight Time	Max Wind Speed Resistance	Global Navigation Satellite System	Max Flight Distance
30 minutes	10.7 m/s	GPS + GLONASS	11KM
Camera			
Image Sensor	**Max Image Size**	**Video Resolution**	**Photo Format**
1/2.3-inch CMOS, Effective Pixels: **12 MP**	4:3: 4000×3000 16:9: 4000×2250	2.7K: 2720×1530@24/25/30 fps FHD: 1920×1080@24/25/30/48/50/60 fps	JPEG
Sensing			

Sensing Type	Max Transmission Distance (free of interference)
Downward vision system	4 KM

2021	
DJI Mini 3 pro	 Figure 6: DJI Mini 3 pro (DJI Mini 3 pro, DJI store, 2023)
Cost (AUD)	$1,119 (DJI store, August 24, 2023)

Aircraft				
Takeoff weight	**Max Ascent Speed**	**Max Descent Speed**	**Max Horizontal Speed**	**Max Takeoff Altitude**
249 g With intelligent battery weight about 290 g	5 m/s	5 m/s	16 m/s	4000 m

Max Flight Time	Max Wind Speed Resistance	Global Navigation Satellite System	Max Flight Distance
34 minutes (with Intelligent Flight Battery) 47 minutes (with Intelligent Flight Battery Plus)	10.7 m/s	GPS + Galileo + BeiDou	18 km (w Intel Flight Battery and measured while flying at 43.2 kph in windless conditions) 25 km (with Intelligent Flight Battery Plus* and measured while flying at 43.2 kph in windless conditions)
Camera			
Image Sensor	**Max Image Size**	**Video Resolution**	**Photo Format**

1/1.3-inch CMOS, Effective Pixels: **48 MP**	4:3: 8064×6048 (48 MP) 4032×3024 (12 MP) 16:9: 4032×2268 (12 MP)	4K: 3840×2160@24/25/30/48/50/60 fps	JPEG/DNG (RAW)

Sensing	
Sensing Type	**Max Transmission Distance (free of interference)**
Forward, backward, and downward vision system	12 km

2022	
DJI Mavic 3	 Figure 6: DJI Mavic 3 (DJI Mavic 3 - DJI store, 2023)
Cost (AUD)	$2,899 (DJI store, August 24, 2023)

Aircraft				
Takeoff weight	**Max Ascent Speed**	**Max Descent Speed**	**Max Horizontal Speed**	**Max Takeoff Altitude**
895 g	8 m/s	6 m/s	21 m/s	6000 m

Max Flight Time	**Max Wind Speed Resistance**	**Global Navigation Satellite System**	**Max Flight Distance**
46 minutes	12 m/s	GPS + Galileo + BeiDou	16 Km

Camera			
Image Sensor	**Max Image Size**	**Video Resolution**	**Photo Format**
Hasselblad Camera: 4/3 CMOS, Effective Pixels: 20 MP Tele Camera: 1/2-inch CMOS, Effective Pixels: 12 MP	Hasselblad Camera: 5280×3956 Tele Camera: 4000×3000	Hasselblad Camera: 5.1K: 5120×2700@24/25/30/48/50 fps Tele Camera: 4K: 3840×2160@25/30/50 fps	JPEG/DNG (RAW)

Sensing	
Sensing Type	**Max Transmission Distance (free of interference)**
Omnidirectional binocular vision system, supplemented with an infrared sensor at the bottom of the aircraft	12 km

2022	
Phantom 4 Pro V2.0	 Figure 6: Phantom 4 Pro V2.0 (Phantom 4 Pro, 2023)

Cost (AUD)	$2,399 (DJI store, August 24, 2023)

Aircraft				
Takeoff weight	**Max Ascent Speed**	**Max Descent Speed**	**Max Horizontal Speed**	**Max Takeoff Altitude**
1375 g	6 m/s	4 m/s	45 mph	6000 m

Max Flight Time	Max Wind Speed Resistance	Global Navigation Satellite System	Max Flight Distance
30 minutes	10 m/s	GPS/GLONASS	2.400-2.483 GHz, 5.725-5.850 GHz (Unobstructed, free of interference))

Camera			
Image Sensor	**Max Image Size**	**Video Resolution**	**Photo Format**
1-inch CMOS Effective pixels: 20M	3:2 Aspect Ratio: 5472×3648 4:3 Aspect Ratio: 4864×3648 16:9 Aspect Ratio: 5472×3078	4K: 3840×2160 24/25/30p @100Mbps	JPEG, DNG (RAW), JPEG + DNG

Sensing /Sensor		
Sensing Type/ Vision System	**Infrared Sensing System**	
Forward Vision System Backward Vision System Downward Vision System	Obstacle Sensory Range	0.6-23 feet (0.2-7 m)
	Measuring Frequency	10 Hz

2022	
DJI Mavic 3 Multispectral M3M	 Figure 6: DJI Mavic 3 Multispectral M3M (DJI Mavic 3 Multispectral, 2023)
Cost (AUD)	$7,919 (DJI store, August 24, 2023)

Aircraft				
Takeoff weight	**Max Ascent Speed**	**Max Descent Speed**	**Max Horizontal Speed**	**Max Takeoff Altitude**
951 g	6 m/s (Normal Mode) 8 m/s (Sport Mode)	6 m/s (Normal Mode) 6 m/s (Sport Mode)	15 m/s	6000 m

Max Flight Time	Max Wind Speed Resistance	Global Navigation Satellite System	Max Flight Distance
43 minutes	12 m/s	GPS + Galileo + BeiDou	32 Km

RGB Camera			
Image Sensor	**Max Image Size**	**Video Resolution**	**Photo Format**

4/3 CMOS Effective Pixels: 20 MP	5280×3956	4K: 3840×2160@30fps FHD: 1920×1080@30fps 4K: 3840×2160@25/30/50 fps	JPEG/DNG (RAW)
Multispectral Camera			
Image Sensor	**Multispectral Camera Band**	**Video Resolution**	**Photo Format**
1/2.8-inch CMOS, effective pixels: 5 MP	Green (G): 560 ± 16 nm; Red (R): 650 ± 16 nm; Red Edge (RE): 730 ± 16 nm; Near infrared (NIR): 860 ± 26 nm;	FHD: 1920 x 1080@30fps Video content: NDVI/GNDVI/NDRE	TIFF

Sensing System	**Antennas**
Omnidirectional binocular vision system, supplemented with an infrared sensor at the bottom of the aircraft	4 antennas, 2 transmitting and 4 receiving

2023	
DJI Mini 3	 Figure 6: DJI Mini 3 (DJI Mini 3, 2023)
Cost (AUD)	$829 (DJI store, August 24, 2023)

Aircraft				
Takeoff weight	**Max Ascent Speed**	**Max Descent Speed**	**Max Horizontal Speed**	**Max Takeoff Altitude**
249 g With intelligent battery weight about 290 g	5 m/s	3.5 m/s	16 m/s	4000 m

Max Flight Time	**Max Wind Speed Resistance**	**Global Navigation Satellite System**	**Max Flight Distance**
38 minutes (with Intelligent Flight Battery) 51 minutes (with Intelligent Flight Battery Plus*)	10.7 m/s	GPS + GLONASS + Galileo	18 km (with Intelligent Flight Battery and measured while flying at 43.2 kph in windless conditions) 25 km (with Intelligent Flight Battery Plus* and measured while flying at 43.2 kph in windless conditions)
Camera			
Image Sensor	**Max Image Size**	**Video Resolution**	**Photo Format**

1/1.3-inch CMOS, Effective Pixels: 12 MP	4000×3000	4K: 3840×2160@24/25/30 fps	JPEG/DNG (RAW)
Sensing			
Sensing Type/Vision system		**Max Transmission Distance (free of interference)**	
Downward vision system		10 km	

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8.6 Appendix 6

Summary of Drone Models and associated variations

	2019	2020	2021		2022	2022	2022	2023
Model	P4 Multispectral	DJI Mini 2	DJI Mini SE	DJI Mini 3 pro	DJI Mavic 3	Phantom 4 Pro V2.0	DJI Mavic 3 Multispectral M3M	DJI Mini 3
Cost (AUD)	$9,300	$749	$459	$1,119	$2,899	$2,399	$7,919	$829
Max Horizontal Speed	36 mph	36 mph	30 mph	36 mph	47 mph	45 mph	34 mph	36 mph
Max Flight Distance	2.4 GHz: < 20 dBm (CE / MIC / KCC) 5.8 GHz: < 26 dBm (FCC / SRRC / NCC)	16 km	11 km	18 km- 25 km	16 KM	2.400-2.483 GHz, 5.725-5.850 GHz (Unobstructed, free of interference))	32 km	18 -25 KM
Battery	27 minutes	31 minutes	30 minutes	34 minutes 47 min w/ Intelligent flight battery Plus	46 minutes	30 minutes	43 minutes	38 minutes 51 minutes w/ intelligent flight battery Plus
Camera Sensor	Six 1/2.9” CMOS, Inc. RGB sensor for visible light imaging + 5 monochrome sensors for multispectral imaging. Each Sensor 2.08 MP	1/2.3-inch CMOS, Effective Pixels: 12 MP	1/2.3-inch CMOS, Effective Pixels: 12 MP	1/1.3-inch CMOS, Effective Pixels: **48 MP**	Hasselblad Camera: 4/3 CMOS, Effective Pixels: 20 MP Tele Camera: 1/2-inch CMOS, Effective Pixels: 12 MP	1-inch CMOS Effective pixels: 20M	1/2.8-inch CMOS, effective pixels: 5 MP RGB Camera 4/3 CMOS Effective Pixels: 20 MP	1/1.3-inch CMOS, Effective Pixels: 12 MP
Weight	1487 g	242 g	242 g	249g or 290 g W/intel battery	895 g	1375 g	951 g	249 g
Global Navigation Satellite System	GPS + BeiDou + Galileo	GPS + GLONASS + Galileo	GPS + GLONASS	GPS + Galileo + BeiDou	GPS + Galileo + BeiDou	GPS/GLONASS	GPS + Galileo + BeiDou	GPS + GLONASS + Galileo
Sensing Type	Ground Sample Distance (GSD)	Downward vision system	Downward vision system	Forward, backward, and downward vision system	Omnidirectional binocular vision system, supplemented with an infrared sensor at the bottom of the aircraft	Forward Vision System Backward Vision System Downward Vision System	Omnidirectional binocular vision system, supplemented with infrared sensor at bottom of aircraft	Downward vision system

8.7 Appendix 7

Risk Register with entropy / decay column

This risk register lists known technology issues and suggests a probability and impact assessment based on analysis of the literature. The table includes a column showing the movement (increasing or decreasing) of entropy and the presence of decay.

Technology Issue	Challenge	Probability (P)	Impact (I)	Entropy and Decay ↓↑	Risk Score P x I
Lidar	Lack of Clarity in Recognising Objects / Livestock	4	3	Decreasing- many research are being conducted in this field.	12
3G/4G	Lack of Mobile Signal Access in Remote & Rural areas	3	4	Decreasing – better Coverage Telstra / Optus Others Software defined networks (eg Starlink)	12
Storms	Inability to Fly Drones in Bad Weather	4	4	Increasing (Climate Change)	16
Cloud Cover	Clarity of image	3	3	Decreasing- some drone has semi-auto pilot, which can direct the drone to original take off position	9
LoRaWAN	Problem if not Line of Sight and Low Bandwidth	4	3	Decreasing – LoRaWAN technology increasingly used and connected with adjoining areas / farms	12
Cost on Fixed Wing Drones	Very Large Expense	4	4	Increasing	16
Cost on Large Payload +25Kg Multirotors e.g. Octa	Large Expense + Training + Hardware + Software	4	4	Increasing – High End Drone expenses above $100,000	16
Cost of Small Multirotors (DJI Phantom / Mavic or similar	Very inexpensive – BUT - No Payload Limited camera and sensor capabilities	4	2	Decreasing – Very cheap entry – but unable to assist large scale broadacre operations	8
Smart Battery Technology	Expensive	3	3	Decreasing – cost of Batteries slowly decreasing	9
Cost of Thermal Camera	Expensive	3	3	Increasing- as they used unique and distinct metal to for manufacture	9
RGB	Limited in the task that can be performed	3	3	Decreasing- camera can be modified to capture additional feature like infra -red	9
Rules and Regulations	Too complex, people do what they want on their own land	5	4	Increasing – Rules and differences are increasing with different local and bespoke rules and regs.	20
Rainy day	Cannot fly drone	1	5	Increasing (Climate change)	5
Sunny day	Affect the image clarity	2	3	Decreasing- image can be modify with appropriate software	6
Access to electricity	Outage	1	5	Depend on locations	10
Equipment defect	Damaged drone	1	5	Decreasing- drone come with warranty	1
Flight flying planning	Wrong coordinates entered -poor data collection	2	4	Decreasing- many UAV are using google map as their base platform	8
Drone Crash	Software failure	2	5	Decreasing- more drones are getting automated	10
Drone loss in Wheat field	Lack of Visual Recognition	3	3	Steady – wheat fields less likely to suffer fatal crash	9
Pilot Error	Accidental press the wrong button	1	5	Decreasing	5
Drone loss of signal	Drone can loss signal	2	5	Intermittent depending on access and topography	10

Bird attack	attacking drone	2	5	Increasing- specially in hill area	10
Animal Impact	Animal welfare Animal stress	2	3	Decreasing, as some drones are being designed to be silent	6
Obstacle	Trees, Electric poles	1	3	Decreasing- some drones have collision detection system	3
Wind impact on UAV	Air -Turbulence	2	3	Decreasing- some drone design has higher wind resistance	6
Wind impact on UAV-Spraying	Chemical can be blow away	2	5	Increasing -due to climate change	10
Flight altitude impact on image	Flying to distance from the target can affect image clarity	2	4	Decreasing- image can be modify with appropriate software	8
Flight altitude on Crop spraying	Affect the droplet rates	3	4	Decreasing- researcher are working on automate drone which are pre-plan	12
Multispectral camera	hyperspectral which captures in 100s	3	2	Increasing- due to the complexity of some crops or farms	6
Multispectral Image process method	Required to apply more complex pre-processing method	4	4	Increasing- as image processing in precision farming is new	16
Thermal image	Hard to interpret/analysis	2	3	Decreasing-slowly algorithm are being train for image processing	6
Lidar bad weather	Poor performance	2	5	Increasing reliance on Lidar	10
Lidar on Harsh environment	Lidar cannot reach dense area	4	3	Deceasing – as yet poor recognition	12
Amount of space on the Drone	Cannot install many sensor	2	3	Decreasing- some companies giving more room to fit additional gadgets	6
Camera calibration	Inaccurate data being captured Image overlapping	3	4	Increasing- as size and weight of new sensors keep changing	12
Payload	Limited weight for take-off and landing	2	4	Increasing- some sensors can be heavy	12
Farming application complexity	Need to use a range of application sometime	3	3	Increasing- precision farming is new, and application are still being develop or in trail / testing phase	6
Flight Range Sml Multi-rotors Phantom / Mavic	Limited to distance drone can travel	3	3	Decreasing- new design are constantly improve drone range	6
Drone repair	Replacing defect or broken parts	3	3	Decreasing- lot for drone spart are available	9
Farmer engagement	Willing to adopt drone technology in precision farming	3	5	Increasing- with the license, rule and skills required to operate some drone	15
No framework for standard planned flight	No standard or guideline for drone can be used for what purpose	3	3	Increasing- commercial UAV are becoming affordable and their usage in agriculture will increase o	9
Lack of software available	Lack free open-source software available for image processing	4	4	Increasing- there are many areas in agriculture where drone experimental has not be yet conducted.it will take time to develop accurate Algorithm	16
Image overlapping	UAV capture both overlapping image	4	2	Decreasing- this can be addressed photogrammetry technique	8
Machine learning	Lack of algorithms detection of disease	4	2	Decreasing- algorithm are getting train to detect new disease	8
Machine learning Skill & equipment	Better computers Extra software computer skills	4	4	Increasing- for advance image processing, ML is normal use	16
Multispectral camera availability	A variation of Multispectral to reduce payload	3	2	Decreasing- some drone designs are coming with in-build multispectral camera	6
Lack of Research Knowledge in agriculture	Research needs to have knowledge of farming	2	3	Decreasing – much research exists with agricultural companies to address precision farming issue	6
Drone Parts	Lack of Parts	4	3	Increasing – post Covid limits	12
3rd Party Data	Shared data	3	4	Increasing – Predatory tactics	12
Privacy Laws	New Drone Laws	3	3	Increasing – focus on surveillance Laws	9