CENTRE FOR
INVASIVE SPECIES SOLUTIONS

AUTOMATED THERMAL IMAGERY ANALYSIS PLATFORM FOR MULTIPLE PEST SPECIES

FINAL REPORT FOR PROJECT P01-T-003

AUTHORS

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We are a not-for-profit, member-based organisation formed to address the impact of invasive plants and animals across Australia.

We acknowledge the Traditional Custodians of the lands on which we meet and work and pay our respects to Elders — past, present and emerging.

We acknowledge all Aboriginal and Torres Strait Islander peoples and their continuing connection to country, culture and community.

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Cover image: Thermal imagery of feral pigs. Credit Western Australian Department of Primary Industries and Regional Development.

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FINAL PROJECT REPORT FOR P01-T-003

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EXECUTIVE SUMMARY

Robust and repeatable methods for surveying pest animals are required to measure the impact of control strategies. However, while many organisations undertake control of pests, including governments, contractors, non-government organisations and landholders, very few have the resources or expertise to effectively measure the density of pest animal populations.

The increasing affordability of ‘drones’ and thermal imaging cameras has resulted in many land managers using these tools to survey pest animals; however, a limitation to the use of this technology is people’s ability to robustly analyse the footage generated.

We developed a platform that automatically analyses thermal footage from aerial surveys: ThermEye. ThermEye provides a repeatable, unbiased platform for detecting animals, identifying species and recording their location. It uses a machine-learning framework. The resulting output can then be used to generate robust, accurate density estimates for target pest species.

ThermEye will now allow land managers, who typically lack the resources of a university or government department, to perform robust surveys of vertebrate pests, and therefore measure the efficacy of their control programs. By measuring the impacts of their control programs, land managers can demonstrate success, target their efforts, improve approaches and justify increasing investment.

Importantly, the machine-learning framework that underpins ThermEye allows for its models to be constantly improved and refined, meaning the tool can become more accurate over time, for all users. ThermEye makes it easier for land managers to effectively survey vertebrate pest animals by reducing the barrier to entry and, as such, will result in greater efficacy and transparency of control programs.

INTRODUCTION

LANDSCAPE-SCALE MONITORING IS ESSENTIAL FOR BIOSECURITY AND CONTROL

The widespread adoption of intensive agricultural activities and practices throughout the 20th century has provided abundant opportunities for vertebrate pests, leading to increased human–wildlife conflict worldwide (Witmer 2007). In Australia, many vertebrate pests – such as feral pigs, feral deer, and rabbits – are well established and widely distributed, and effective monitoring programs need to be suitable for deployment at a landscape scale.

If we understand the distribution and density of the target species, it is much easier to implement and assess a targeted management approach, whether we are responding to a disease incursion or performing ongoing control activities.

Commonly used monitoring techniques such as aerial surveys and camera trap arrays can be labour intensive; require substantial investment in equipment and personnel; carry safety risks; and sometimes only generate indices, rather than density estimates.

THERMAL SURVEYS INCREASE DETECTIONS, BUT PROCESSING THE FOOTAGE IS EXPENSIVE

Using thermal sensors to survey wildlife is a rapidly growing field (Garner et al. 1995; Gill et al. 1997; Haroldson et al. 2003; Allison and Destefano 2006; Mccafferty 2007). Thermal sensors have the potential to address common issues associated with traditional survey techniques such as visual acuity and observer fatigue (Fleming and Tracey 2008), especially when attempting to detect cryptic targets or surveying large areas. However, digital footage (thermal or otherwise) generates hours of footage that requires time-consuming and laborious analysis.

There are multiple commercial providers performing thermal surveys of large vertebrates, both pests and native species, throughout Australia. Each provider uses its own analysis approach to score footage, some of which are proprietary, but all require at least one human observer to manually view the footage. In addition, numerous land management organisations use thermal cameras fitted to drones to detect vertebrate pests, but many do not have the resources to analyse this data in a robust way to produce a density estimate. As a result, thermal surveys that aim to monitor vertebrate pests are expensive and highly variable in their quality.

Automated systems for detecting and identifying target objects from thermal imagery have the potential to quickly and accurately analyse large imagery datasets. In the current project, we aimed to develop automated analysis models for thermal imagery that incorporate machine learning to further improve their processing efficiency.

Our objective was to provide an analysis platform that is compatible with all thermal imagery, and equally accessible to all stakeholders and end users. Our aim was that the platform would be capable of using flight-path data and video footage from aerially deployed thermal sensors to identify target heat signatures and map their occurrence.

OBJECTIVES

Our central research questions were:

1. Can automated software improve the speed and accuracy of analysing thermal imagery for the presence of multiple pest species?
2. Can consumer-grade, as well as high-end, thermal sensors provide landscape-scale monitoring of pest species as part of an integrated pest management program?

3. Can a deep-learning computer vision model enhance the accuracy and efficiency of thermal imagery analysis for multiple pest species?

Our project objectives were to:

- demonstrate combined computer vision and geolocation software for detecting target objects from thermal imagery
- develop a deep-machine-learning model for fully autonomous analysis of thermal imagery analysis for monitoring multiple pest animal species at a landscape level
- demonstrate the application of automated thermal imagery analysis for managing multiple pest animal species
- communicate our outcomes and promote end-user uptake of technology.

METHODS

FINDING OUT WHAT USERS NEED

A human-centred design (HCD) process was used to identify and unpack the requirements for an animal-detection solution that fits the needs of users. The methodology is divided into four steps – discover, define, develop and deliver – and focuses on end-user experiences to capture different perspectives on the collection and analysis of video for the detection of vertebrate pests.

DISCOVER

The objective of the discovery phase was to engage with end users from across Australia and understand their perspectives on collecting and analysing video to detect vertebrate pests. Using an online platform to capture insights, 13 representative users from government, universities and industry were interviewed. Users included pest control officers and managers, researchers, drone operators, helicopter pilots and primary producers from across Australia. Each end user explained their existing processes, the strengths of each approach, and opportunities for refinement.

DEFINE

Insights captured in the discovery phase (187 insights) were synthesised to identify the value proposition for potential solutions for detecting animals. We consolidated the strengths and weaknesses, and then mapped each to key themes across the industry (Figure 1).

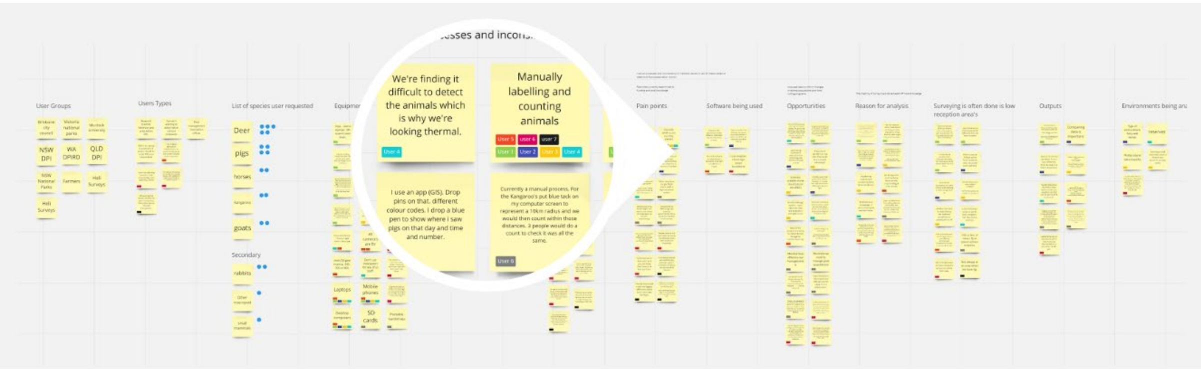

Figure 1. Insights, strengths and weaknesses of existing methods were synthesised using an online platform.

DEVELOP AND DELIVER

The develop and deliver phase used the key themes identified in the define phase to develop a set of key insights to inform the requirements for developing an improved animal-detection solution. Across the user interviews, we consolidated the 187 insights into 13 key insights (Table 1). We then prioritised them with the project team to deliver the requirements of a solution that would fit the needs of users. An ideation session was then undertaken with the project team to generate conceptual ideas on how a solution would best work and inform the design and development of the platform.

Using the insights and concept ideas generated by the project team, a design of the platform was created. The design focused on delivering:

1. an artificial intelligence (AI) model to automate the detection of vertebrate pests (addressing *insights 1,3,4,6,12*)
2. a tool to simplify and standardise the approach and process for analysing video footage (addressing *insights 2,3,4,7,8,9,10,11*).

Table 1. Key insights gained from the human-centred design process

	Insight description	Findings
1.	Deer and pigs are the most requested animals.	The solution should first focus on accuracy for detecting deer and pigs.
2.	Common technologies are used by all users: a. DJI drones are used by all users interviewed. b. FLIR thermal sensors are the most common. c. Users all have multiple batteries.	There may be potential to streamline solutions using DJI tools making it easier for users.
3.	Users of the solution may range from scientists, PhD students, farmers and pest management officers.	The solution must take into account all user types and their capabilities, with a design focused on ease of use to ensure adoption is successful.
4.	Inconsistent methods and manual processing of footage result in: a. loss of productivity b. difficulty determining accurate control measures c. difficulties in showing return on investment.	The solution must attempt to use standardised processing methods and providing outputs fit for users.
5.	There is a need for real-time labelling of targets while in the field, and for analysing large files taken from large areas, with the ability to compare results over 6–12-month intervals to determine the success of control measures.	The solution should take into account the identified use cases (Appendix 2) when designing how the system needs to work.
6.	Where to survey is primarily determined through local landholder knowledge.	Data collected from the solution should be combined with local knowledge to ensure effective control measures.
7.	The reason for analysis is primarily around pest management.	The solution should still consider possibilities that functionality may extend into other areas (e.g. flora/weeds); however, this would be outside the scope of this project.
8.	Users prefer raw data outputs for easier integration into their existing work and applications.	The solution should display results and output raw formats to fit into users' workflows.
9.	It is very common for surveying to be completed in areas of little or no data/cellular reception.	The solution must take into consideration no data/cellular reception at the time footage is collected.
10.	Parameters used to collect footage can vary.	A user guide for best practices will need to form part of the solution to ensure consistency and accuracy.
11.	Different approaches are being used to store footage and results (e.g. portable hard drives, paper notes, Excel documents, etc.).	The solution should standardise the way analysed data is stored and used.
12.	The biggest opportunities are likely to be in the effectiveness of management and justification of costs.	The output of the solution should deliver data insights that can easily be used for better effectiveness of management and justification of costs.
13.	Areas being surveyed are often high-density vegetation areas.	This highlights the need of people using thermal to be able to see through dense vegetation for accurate detection.

AERIAL IMAGERY WAS USED TO TRAIN THE ALGORITHM

To provide the training data required for the development of the automated detection algorithm, thermal footage of vertebrate pest species was gathered from across Australia, including from the south-west and mid-west of Western Australia, south-east Queensland, and New South Wales.

After extracting frames from the videos, each one is then tagged (the target animal is identified on the image, and the species is identified; Figure 2). This library of known images provides the training database which the model uses to learn to identify animals and distinguish species.

To ensure the model is trained on realistic data, training libraries must be extensive (Table 2), including data from a range of environments and conditions, as well as variable image quality (i.e. images with part of the animal obscured by vegetation, and imagery from variable sensor quality).

Table 2. The size of the dataset used to train the final version of the model

Species	Number of frames
Pig (*Sus scrofa*)	8,500
Kangaroos (*Macropus fuliginosus* and *Osphranter robustus*)	7,000
Deer (*Cervus elephas* and *Dama dama*)	3,000

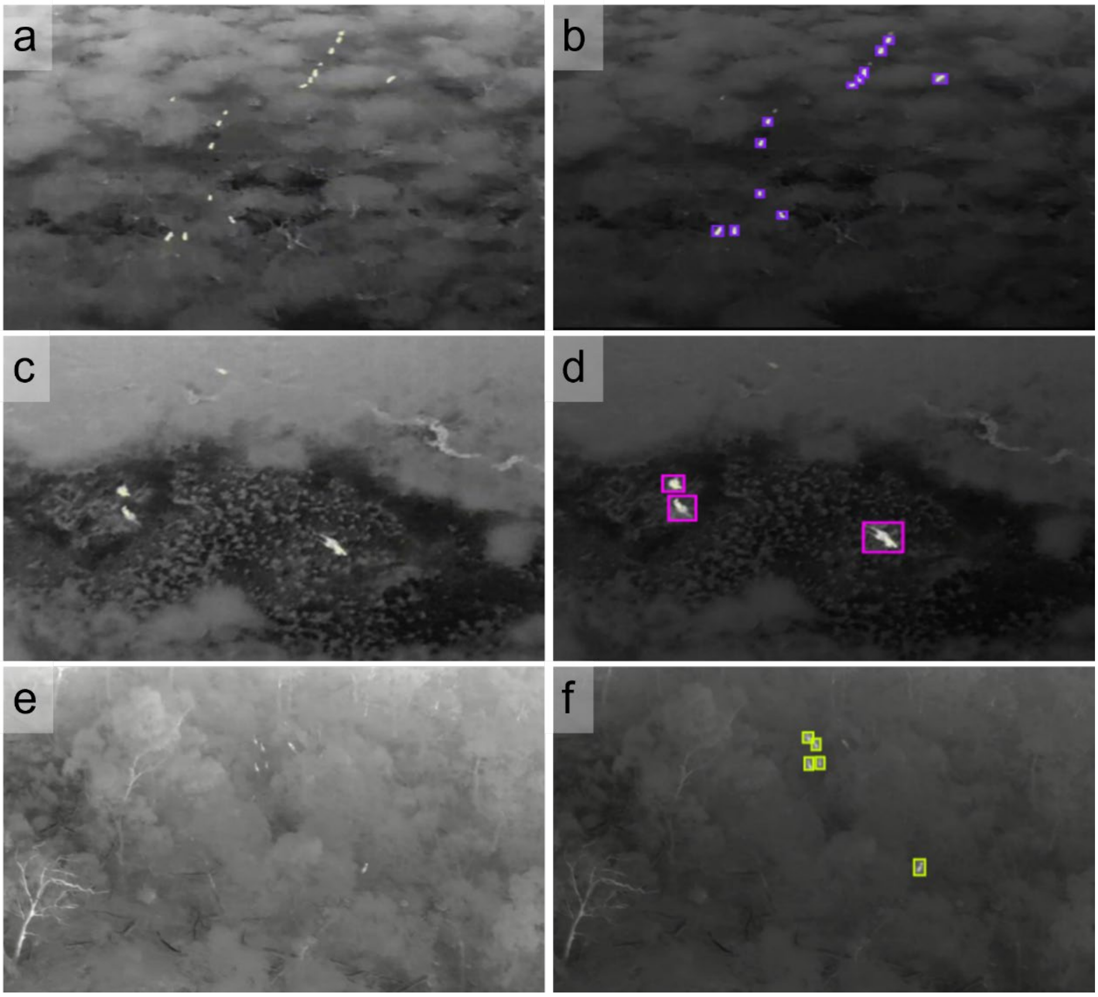

Figure 2. Example of tagged images (right column) used to train the model, with untagged images for comparison (left column). The final version of the model was trained to detect pigs (a, b), kangaroos, (c, d), and deer (e, f).

INTRODUCING THERMEYE

ThermEye is the automated analysis platform built as a result of this work.

ThermEye accepts video from helicopter surveys and footage from remotely piloted aircraft ('drones'). The platform requires the flight log and video file to be uploaded (Figure 3), and the UTC start time of the video, with an offset for conversion to local time.

To reduce processing time, ThermEye splits videos into non-overlapping still frames, which are then analysed as images.

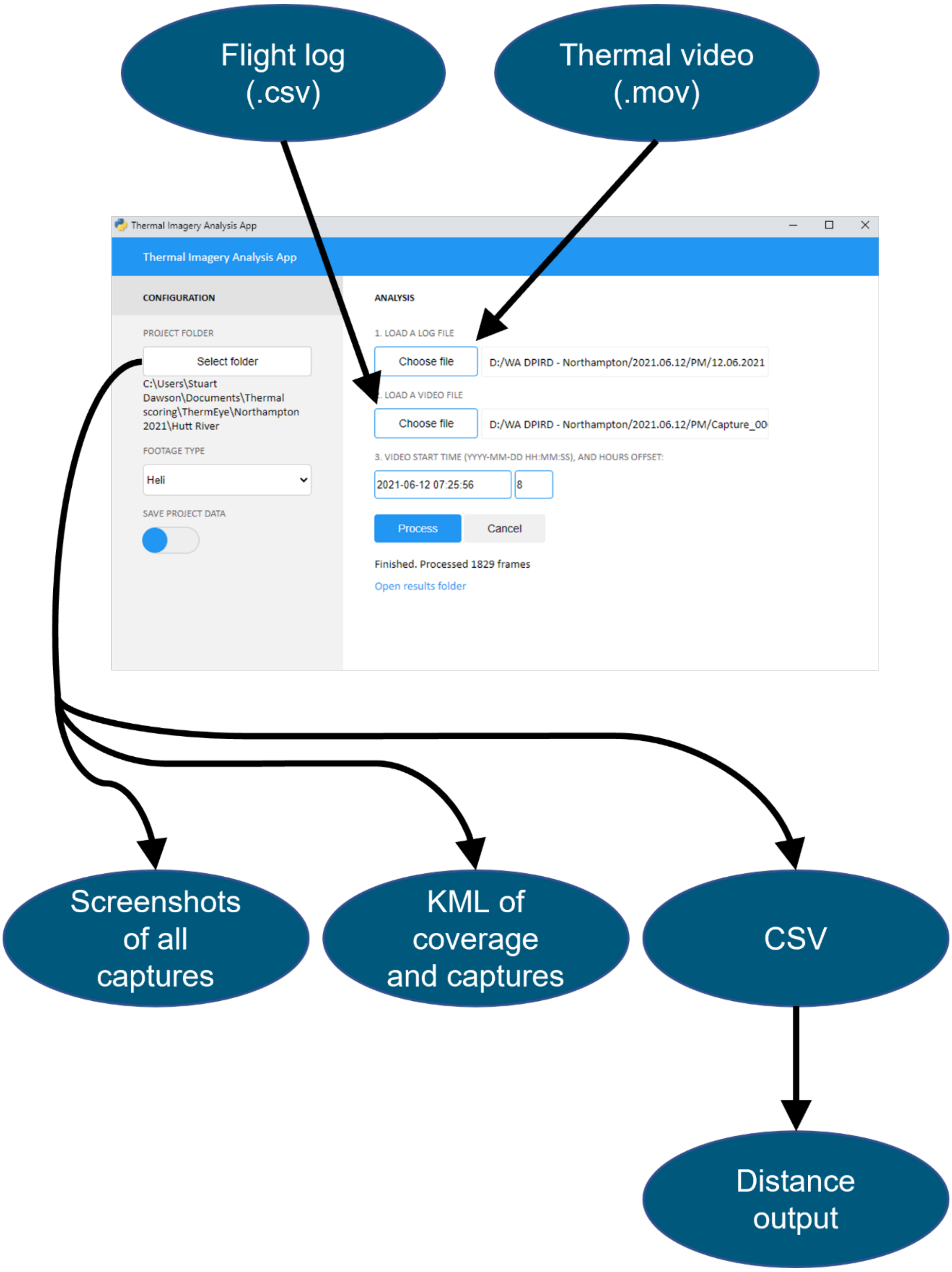

Figure 3. How ThermEye processes and analyses images

After analysis is complete, the platform produces:

- a folder containing all the analysed images
- a folder containing screenshots of all identified target species
- a .kml (a file format used to display geographic data in a map browser such as Google Earth) plotting the footprint of all non-overlapping frames
- a .kml of all identified target species (Figure 4)
- two .csv files, one containing the details of each capture, including location, confidence, and species; and another .csv designed to be imported directly into the package *distance* in R.

Figure 4. An example of the two .kml outputs from the ThermEye, showing (a) the survey coverage and detections, with (b) a measure of confidence

RESULTS: THERMEYE IS FASTER THAN HUMAN OBSERVERS BUT FAILS TO DETECT SOME ANIMALS

A key component in developing any survey tool is validation: comparing the new approach to alternative, pre-existing approaches. Validating new tools is critical to understanding if the new approach improves on previous methods, or how it can be compared. This is particularly important when an automated approach is being developed to replace a human observer method.

ThermEye was able to analyse thermal footage at a rate of approximately 0.11 minutes of analysis per minute of footage, compared to traditional human scoring, which takes approximately two minutes of analysis per minute of footage (Figure 5).

ThermEye analysis is 12.5 times faster than human analysis – it reduces analysis time to eight per cent of the current requirement.

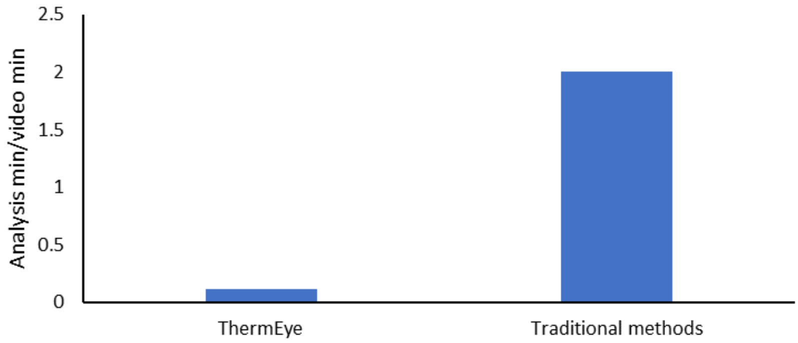

Figure 5. Average analysis time required to process two thermal survey videos

In a comparison across two aerial surveys, we compared the number of feral pigs and kangaroos detected by an expert observer, a novice observer and ThermEye.

In Survey 1, the total **feral pig** observations of the novice observer were 98% of the expert observer recorded; however, ThermEye recorded six per cent of the expert's observerations (Figure 6). Similarly, in Survey 2, while the novice observer recorded 59% of the total records of the expert observer, ThermEye recorded only three per cent.

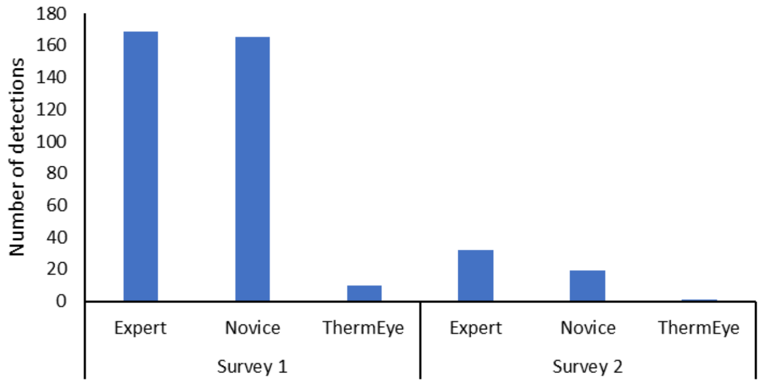

Figure 6. The total number of detections of feral pigs from two thermal survey videos

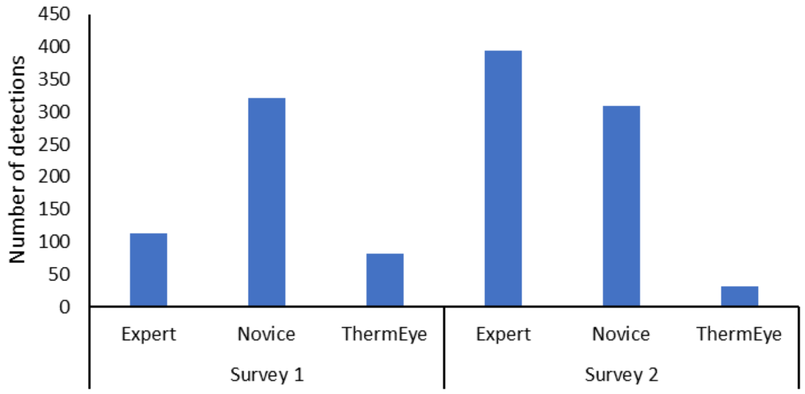

Figure 7. The total number of detections of kangaroos from two thermal survey videos

Similar to feral pigs, ThermEye detected fewer **kangaroos** than both the expert and novice observer in both surveys (Figure 7). There was greater variation between human observers when recording kangaroos than feral pigs.

Currently, ThermEye is not detecting target species with enough reliability to be acceptable. However, re-training and updating the model underlying the program is a simple process. Developing a usable and reliable interface and analysis process is the primary foundational step, and refinement of the model can follow easily from here.

RESULTS

THERMEYE WILL MAKE AERIAL THERMAL SURVEYS MORE AFFORDABLE

Automated analysis of digital footage can reduce the time required for analysis; reduce human observer bias and fatigue; and standardise analysis approaches across surveys, regions and years. Automated analysis will therefore make these surveys more efficient and robust, leading to more affordable surveys.

As of November 2022, the ThermEye detection model is still being refined and developed, and has not been used in an operational survey. As such, there have been no changes yet to on-ground management.

Likely implications when it is used on-ground are:

- increased use of thermal surveys to monitor vertebrate pests
- improved robustness of thermal surveys conducted by non-commercial providers
- standardised analysis methods across surveys, regions, organisations and years
- better ability to measure the density of pest populations
- greater ability to measure the effect of pest control operations
- greater leverage of thermal data collected from a variety of sources.

AUTOMATION INCREASES EFFICIENCY, BUT AERIAL SURVEYS ARE STILL EXPENSIVE

Analysis of thermal footage is a key component of thermal surveys; however, it represents a small component of the cost of such surveys.

All thermal surveys require the use of a thermal-sensing camera, which may cost anywhere from $15,000 for small drone-mounted models, to over $100,000 for custom-built helicopter-mounted models. Secondly, an aerial platform must be used: either a drone, of which a suitable model may cost $10,000 to purchase; or a helicopter, which may cost $2,500 per hour. Finally, licensed pilots are required for both drone and helicopter surveys, and camera operators are also required in helicopter surveys. As a result, aerial thermal surveys are expensive. For example, a recent survey in WA cost approximately $4,500 per hour, or $78 per km flown.

Analysis of thermal imagery by a human observer ranges in cost from $60–150 per hour of footage, depending on the personnel used. As such, while automation of the analysis of footage will reduce analysis time in surveys, it is unlikely to represent a dramatic reduction in the cost of those surveys.

MACHINE LEARNING ALLOWS ANALYSIS TO IMPROVE AS MORE DATA IS ANALYSED

Machine learning, the process by which an algorithm is improved over time based on continuous feedback and training, provides a significant opportunity for the automation of analysis. As such, the model underlying ThermEye can be periodically re-trained. This represents an underlying strength of using machine-learning approaches: they can be continually refined and improved.

DISCUSSION

THE NEXT STEPS ARE TRAINING, SUPPORT AND EXTENSION

TRAINING THE MODEL

Currently, ThermEye is performing poorly compared to human observers. This is an indication of the comparatively small amount of data the model has been trained on and exposed to. As such, the model requires additional training data and validation. Gaining additional training data to increase the robustness of the model will improve its performance.

COMMERCIALISING THERMEYE

For a platform such as ThermEye to be accessible to all users and to be refined over time, it will require continual support. This includes an organisation to host the software, address faults and collect additional training data to re-train the underlying model. Commercialising ThermEye will provide the financial backing for this support to occur. Currently, a trademark application has been accepted for the ThermEye name and is currently in the waiting period prior to registration.

EXTENDING THERMEYE TO REAL-TIME ANALYSIS

When conducting aerial-shooting operations, detecting targets is a key component of effective control.

The model underlying ThermEye that allows identification of target pest species could be deployed during aerial-shooting operations, providing real-time and accurate identification of targets. This will provide initial identification of species to shooters/observers; allow shooters to quickly prioritise and engage targets; and where necessary, re-acquire targets following engagement.

The rollout of ThermEye into a real-time analysis format has received significant in-principle support from potential end users during stakeholder engagement activities. Importantly, however, extending ThermEye to real-time video analysis is likely to require significant development of a fundamentally different architecture.

WHAT HAVE WE LEARNED?

THE PLATFORM IS AS IMPORTANT AS THE DETECTION MODEL

Training a model to identify target pests is very achievable; however, the platform that supports the model – allowing users to upload footage and receive results logically and efficiently – is just as important. The human-centred design approach used in this project informed the well-targeted design of ThermEye, resulting in a platform that is logical and accessible, and produces outputs (such as .kml files of survey coverage and screenshots of identified targets) that allow users to feel confident in the results.

HUMANS SEE MOVEMENT; MACHINES SEE SHAPES

ThermEye breaks video footage into non-overlapping images and then identifies targets from these images. In comparison, when analysing thermal footage, human observers rely on both the detection of the ‘hot body’, but also the movement patterns and behaviour of the target object, to identify the species. Using the current approach, it is not possible to directly analyse video footage, which would allow assessment of animal behaviour and movement. This represents a key difference between the two approaches, and is likely the cause of observed differences in results.

AERIAL THERMAL SURVEY DESIGN IS STILL KEY

While refinement is an important component of continual development of monitoring techniques, a robust and repeatable survey design is still a fundamental requirement. Aerial thermal surveys to monitor pests must be carefully designed to be able to calculate the desired metric. This planning process must take into account logistical constraints, biological factors and the requirements of the statistical test used, all processes that cannot be automated.

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*Note: bold references indicate project outputs. Other CISS and IA CRC publications are marked with an **

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APPENDICES

APPENDIX 1. *REMOTE SENSING* JOURNAL PAPER: 'AUTOMATED DETECTION OF ANIMALS IN LOW-RESOLUTION AIRBORNE THERMAL IMAGERY'

See: Ulhaq A, Adams P, Cox TE, Khan A, Low T and Manoranjan P (2021) 'Automated Detection of Animals in Low-Resolution Airborne Thermal Imagery', *Remote Sensing*, 13(16):3276.

remote sensing

MDPI

Article

Automated Detection of Animals in Low-Resolution Airborne Thermal Imagery

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Abstract: Detecting animals to estimate abundance can be difficult, particularly when the habitat is dense or the target animals are fossorial. The recent surge in the use of thermal imagers in ecology and their use in animal detections can increase the accuracy of population estimates and improve the subsequent implementation of management programs. However, the use of thermal imagers results in many hours of captured flight videos which require manual review for confirmation of species detection and identification. Therefore, the perceived cost and efficiency trade-off often restricts the use of these systems. Additionally, for many off-the-shelf systems, the exported imagery can be quite low resolution (<9 Hz), increasing the difficulty of using automated detections algorithms to streamline the review process. This paper presents an animal species detection system that utilises the cost-effectiveness of these lower resolution thermal imagers while harnessing the power of transfer learning and an enhanced small object detection algorithm. We have proposed a distant object detection algorithm named Distant-YOLO (D-YOLO) that utilises YOLO (You Only Look Once) and improves its training and structure for the automated detection of target objects in thermal imagery. We trained our system on thermal imaging data of rabbits, their active warrens, feral pigs, and kangaroos collected by thermal imaging researchers in New South Wales and Western Australia. This work will enhance the visual analysis of animal species while performing well on low, medium and high-resolution thermal imagery.

Keywords: invasive species; thermal imaging; habitat identification; deep learning; drone

check for updates

Citation: Ulhaq, A.; Adams, P.; Cox, T.E.; Khan, A.; Low, T.; Paul, M. Automated Detection of Animals in Low-Resolution Airborne Thermal Imagery. *Remote Sens.* **2021**, *13*, 3276. https://doi.org/10.3390/rs13163276

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APPENDIX 2. END-USER SURVEY RESULTS

Insights

Insight 1

Deer & pigs are the most requested Animals

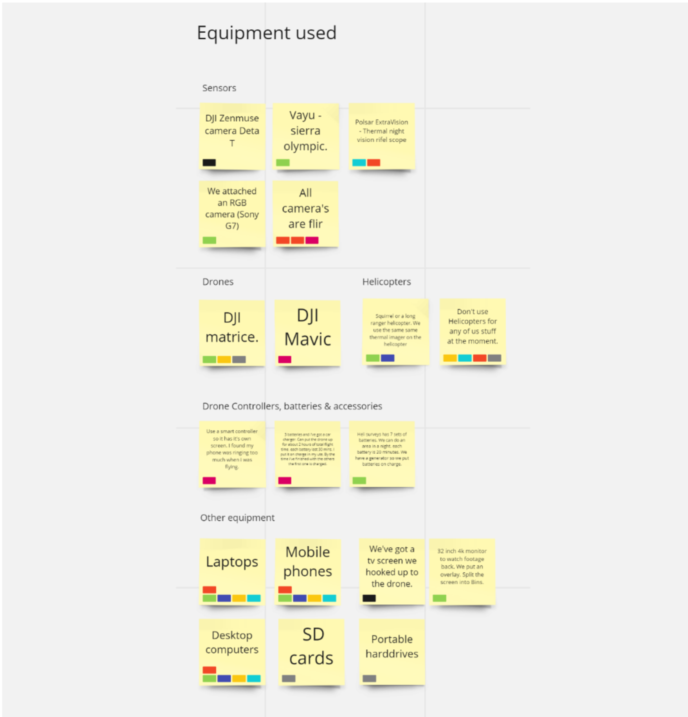
The solution should focus on accuracy for detecting deer and pigs and then….

Insights

Insight 2

- **Drones used are all DJI**
- **Flir thermal sensors are most common**
- **Users all have multiple batteries**

There may be potential to streamline solution using DJI tools making it easier for users.

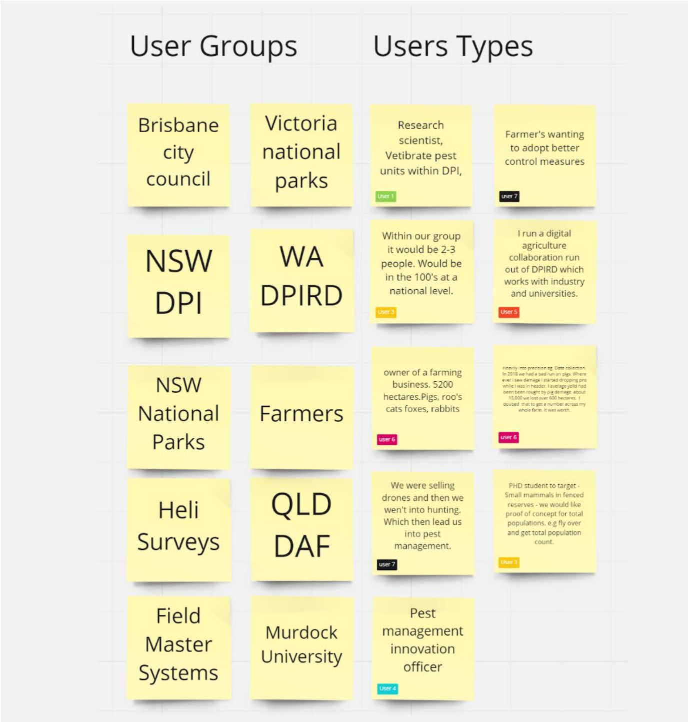


Insights

Insight 3

Users of the solution may range from Scientists, PHD students, farmers and pest management officers

The solution must take into account all users types and their capabilities to design an easy to use system to ensure adoption is successful



Insights

Insight 4

Inconsistent methods & manual processing of footage

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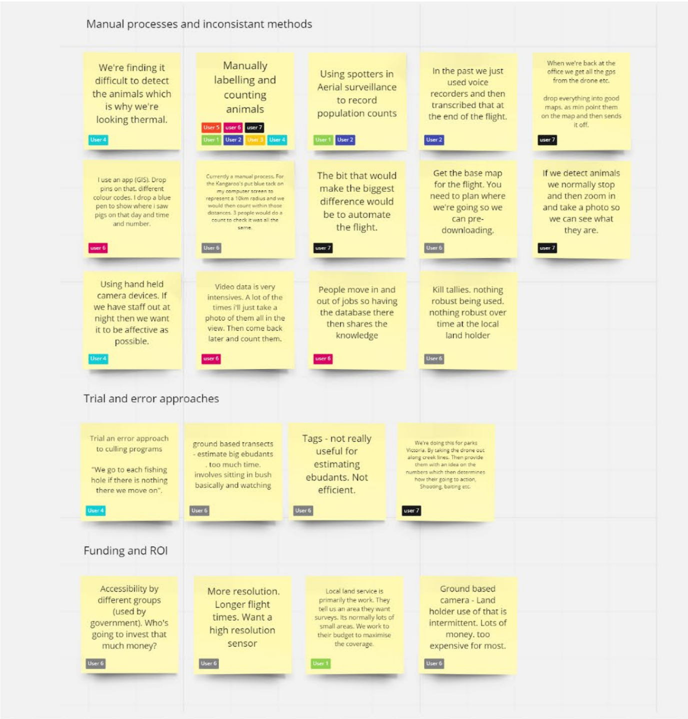
- Loss in productivity
- Difficulty determining accurate control measures
- Difficulties in showing ROI



Insights

Insight 5

A need for real-time labeling of targets while in the field

A need for analysing large files taken from large areas, with the ability to compare results over 6-12 month intervals to determine success of control measures.

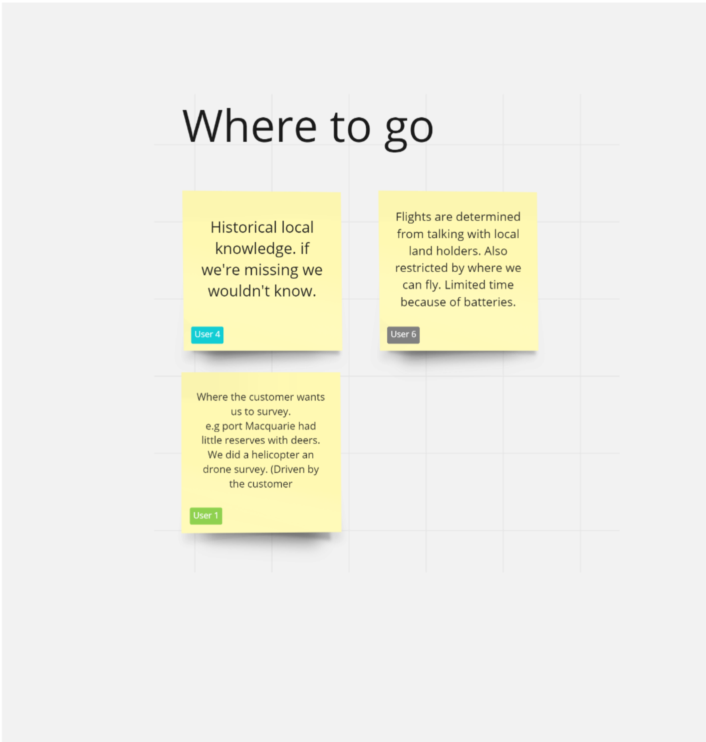
The solution should take into account the use cases above when designing how the system needs to work.

Insights

Insight 6

Where to survey is primarily determined through local land holder knowledge

Data collected from the solution should be combined with local knowledge to ensure effective control measures



Insights

Insight 7

The reason for analysis is primarily around pest management.

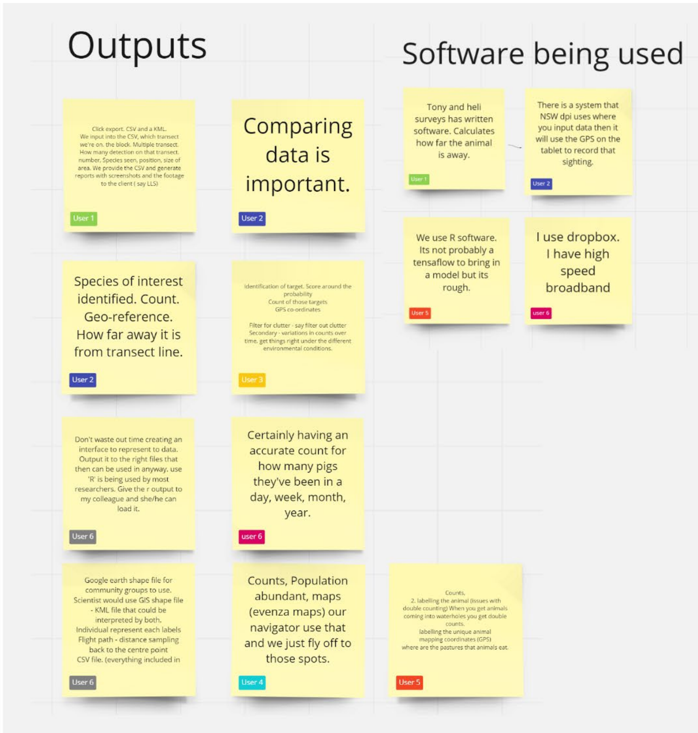
The solution should still consider possibilities that functionality may extend into other areas e.g plants HOWEVER this would be outside the scope of this project

Insights

Insight 8

Users prefer raw data outputs for easier integration into their existing work and applications

The solution should display results and output raw formats to fit into users workflow.

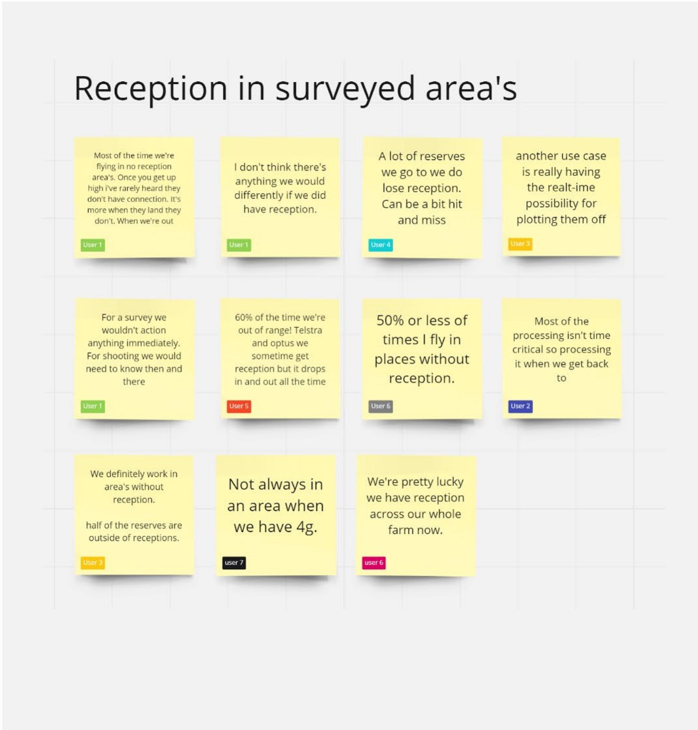


Insights

Insight 9

It is very common for surveying to be completed in areas of little of no reception

The solution must take into consideration no reception at time footage is collected

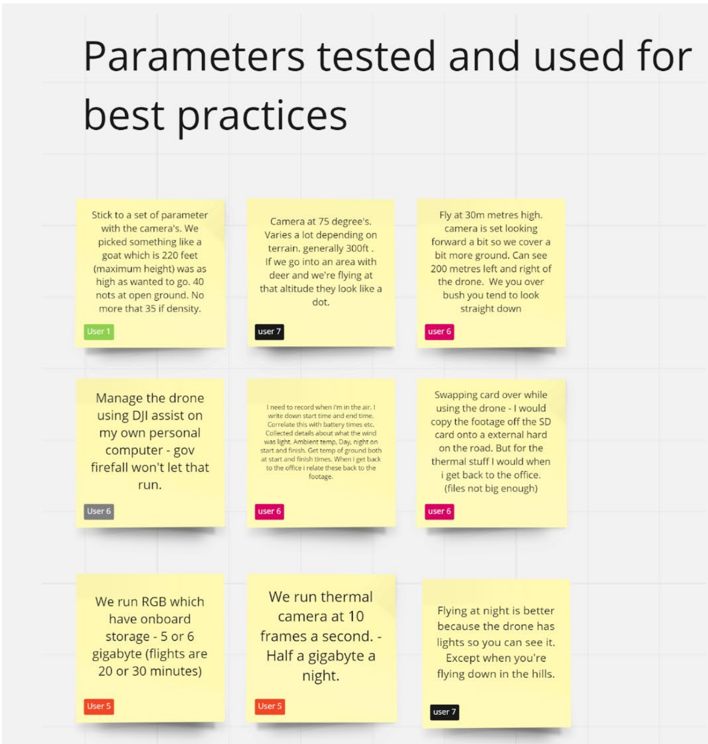


Insights

Insight 10

Parameters used to collect footage can vary.

A user guide for best practices will need to form part of the solution to insure consistency and accuracy



Insights

Insight 11

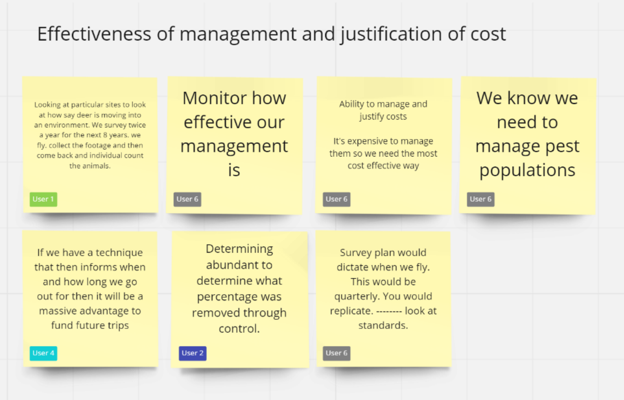
Different approaches are being used to store footage and results. E.g portable hard-drives, paper notes, excel documents etc

The solution must take into consideration how users add footage, receive results and

Insights

Insight 12

The biggest opportunities are seen in the effectiveness of management and justification of costs

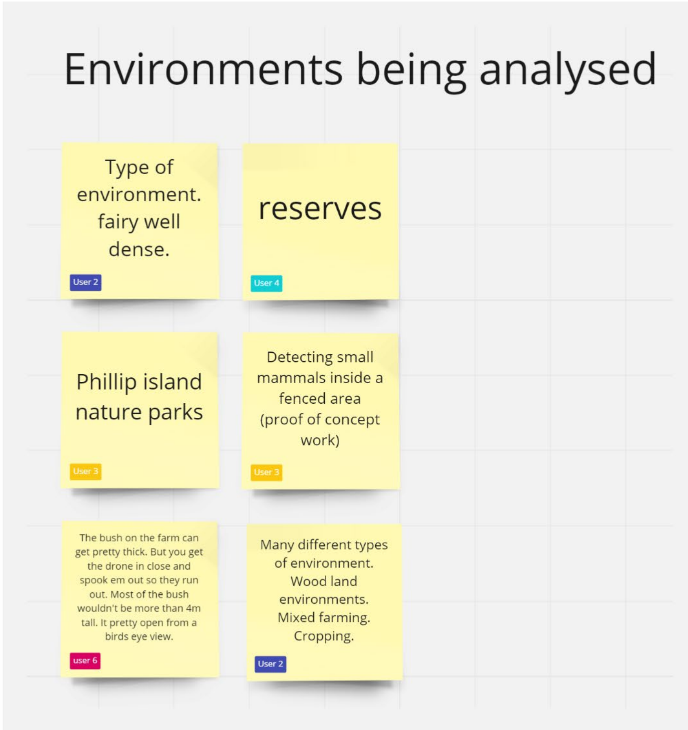


Insights

Insight 13

Area's being surveyed are often high density

Highlights the need around using thermal to see through dense vegetations for accurate detection



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