Sandpit to Seed (S2S) Fund

Progress Report

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EcoSprAI: Detection, Mapping, and Planning for Smart Spray and Spread

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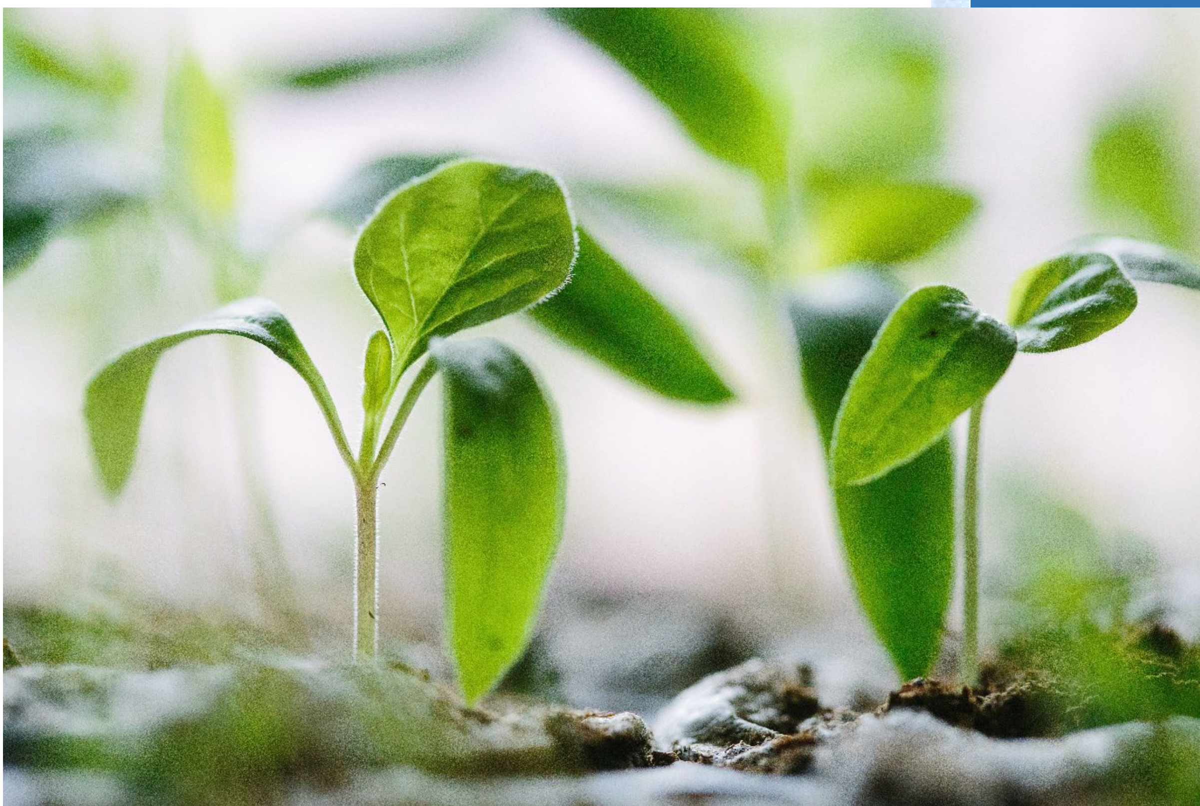

EcoSprAI

Sustainable & Profitable Spraying/Spreading

Executive Summary

Traditional agricultural spraying methods are often inefficient and imprecise, leading to significant chemical waste and environmental harm. Blanket spraying of herbicides, pesticides, and fertilizers causes non-target plants to be affected, contaminates local water sources, and poses risks to human health. Moreover, manual monitoring and spraying methods are labour-intensive, costly, and prone to human error, making them unsustainable for large-scale operations. As global agricultural demands rise, the need for more efficient, cost-effective, and eco-friendly spraying methods becomes crucial.

Towards this end, EcoSprAI is a Software as a Service (SaaS) solution designed to revolutionize agricultural spraying by offering AI-driven image analysis, GIS mapping, and optimized spraying/spreading recommendations. The platform integrates aerial and/or satellite images to detect and map defined weeds like Prickly Acacia, providing tailored spraying recommendations for herbicides, pesticides, and fertilizers. Using AI and GIS mapping, EcoSprAI ensures that only targeted areas are treated with the most suitable chemicals, application methods, and routes, maximizing spraying precision, while cutting down on labour and operational time. EcoSprAI also offers scalability through the integration of satellite and aerial imaging.

From a societal and environmental perspective, EcoSprAI's precision spraying technology brings significant benefits. By reducing chemical usage, it minimizes the exposure of non-target plants, animals, and humans to harmful substances. This not only preserves biodiversity but also lowers the risk of chemical runoff contaminating local water sources. Furthermore, by optimizing spraying techniques, EcoSprAI supports sustainable agricultural practices, reducing the carbon footprint of operations and enhancing overall productivity.

Key technical achievements include the successful development of AI algorithms to detect Prickly Acacia trees in drone and satellite images and the implementation of the *birdview* optimization algorithm for quick and efficient spray/spread planning. In this regard, challenges such as limited drone battery life, line-of-sight regulations, and hawk attacks during drone operations were encountered, prompting a pivot toward satellite and airplane data integration. Accordingly, the key values to stakeholders include:

- Farmers and Landowners: EcoSprAI delivers precise and effective application of chemicals, resulting in reduced chemical use, optimized spraying plans, healthier crop growing, improved yield, and long-term land health.
- Environmental and Regulatory Bodies: EcoSprAI promotes sustainable farming practices, reducing the environmental impact of chemical overuse and runoff. This helps meet regulatory standards and reduces the burden on natural ecosystems.

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1. Project Description

a. Problem

The problem we aim to solve is the inefficiency and imprecision of traditional agricultural spraying methods. Current methods often involve blanket spraying of chemicals, e.g., for weeds, which leads to wasted chemicals. These traditional methods have potential harm to non-target plants, human health, and the environment (through overspray which can be washed in local creeks and estuaries when it rains) [link]. In addition, conventional methods for monitoring and spraying are often manual, therefore highly time-, cost-, and labour-intensive, which is expensive and susceptible to human error.

To have a better understanding of the problem, one might consider the Australian weed spraying market (which we estimate to mostly influence the spraying drones' market) is expected to reach $1 billion by 2030, by offering a superior spray planning and optimisation tool. As our case study, the cost to industry and government through Prickly Acacia control programs alone has been in the $100s of millions over the last few years, and the total cost since it became a severe weed in the 1970s is likely to be in the billions of dollars. Overall, it is beneficial to use cost-effective and more efficient methods for monitoring and quality spraying/spreading.

b. Solution

According to Parven *et al.* [link], traditional herbicide spraying methods often rely on blanket spraying across entire fields using equipment like boom sprayers, aerial spraying via planes or helicopters, or manual backpack sprayers. These approaches apply chemicals uniformly across a landscape without distinguishing between target (e.g., weeds) and non-target plants, leading to inefficiencies. This indiscriminate application results in wasted chemicals, as herbicides are often sprayed in areas without weeds or on resistant species, harming non-target plants, including beneficial crops. Additionally, drift caused by wind and uneven terrain can lead to overspray, contaminating water bodies, affecting nearby ecosystems, and posing health risks to farmworkers and neighbouring populations. The inability to precisely target weeds increases the amount of chemicals used, contributing to environmental pollution and higher operational costs.

This inefficiency demonstrates the need for more advanced, precision-driven methods that can reduce waste, minimize environmental impacts, and improve the overall effectiveness of weed management.

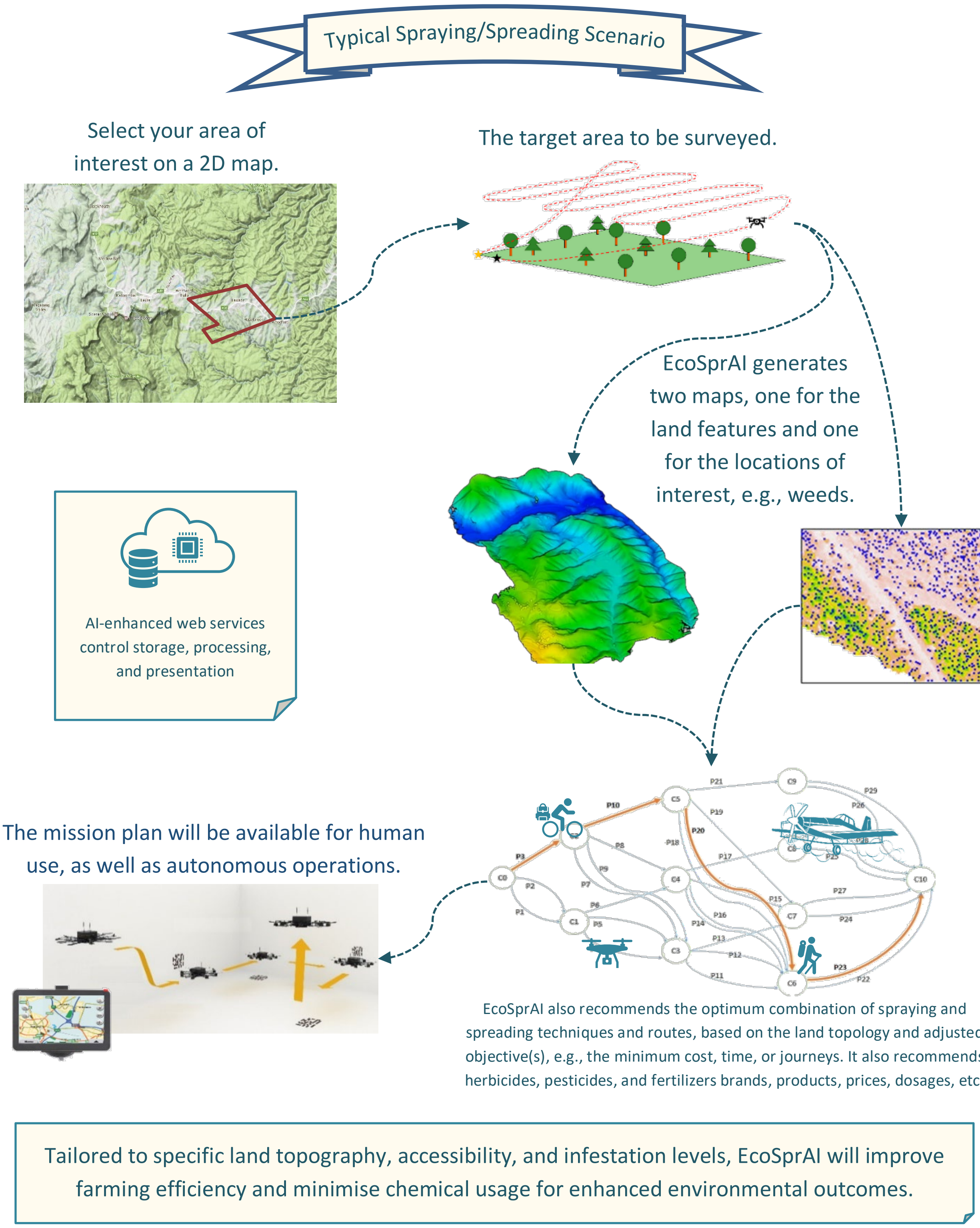


Figure 1: A graphical abstract of the EcoSprAI workflow from 2D land selection to AI-based target detection, and further to optimum spray/spread plan suggestion.

Our solution, EcoSprAI, is an AI-enhanced Software as a Service (SaaS) for spraying/spreading recommendation and control. It receives land surveying input images and detects objects/plants, maps the findings, plans an optimum mission, and reports in both human- and machine-readable formats. This will offer farmers efficient and eco-friendly solutions for diverse agricultural spray and spread needs. For example, in a weed spraying application, we detect and map weeds and coverage areas, enabling optimised herbicide spraying plans with recommended herbicide names, fixed/variable rates, and spraying techniques, e.g., spot-, blanket-, or drone-spraying.

As illustrated in *Figure 1*, the main aspects of this solution include:

- Taking input images from drone cameras, satellites, and aerial images.
- The AI backbone will detect and map weeds on interactive GIS maps. In future developments, we can add other plant detection, as well as include customer-tailored features and traits of crops/lands, and/or assess the health of crops.
- Based on the AI detections, EcoSprAI will recommend an herbicide/pesticide/fertilizer in the market, as well as its price, usage recommendations, etc.
- After mapping, EcoSprAI will recommend the optimum spraying/spreading plan, including the spraying techniques and trajectories. Planning is essential to achieve the best outcome in terms of land topology, travelling time, and coverage areas. We aim to cover the largest and/or the highest number of targets, in the shortest possible time, hence, reaching the optimum use of resources.

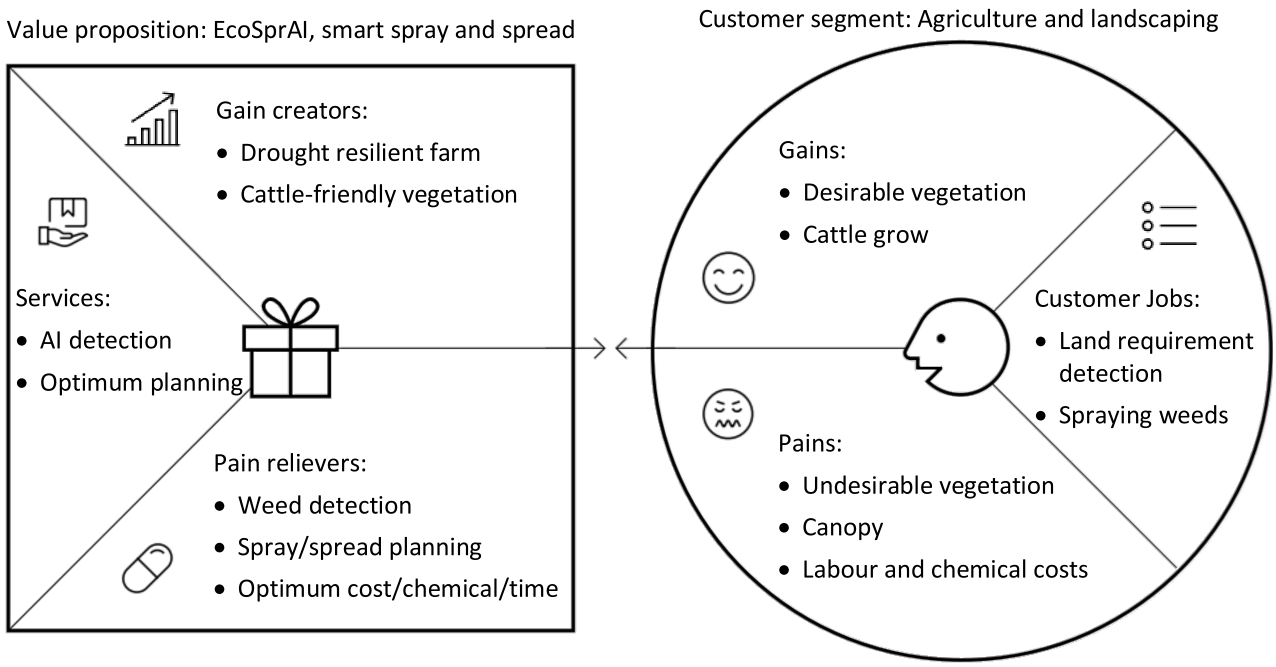


Figure 2: The value proposition canvas for the EcoSprAI services.

c. Problem-Solution Fit

EcoSprAI directly addresses the inefficiencies of traditional agricultural spraying/spreading by leveraging advanced AI and imaging technologies. According to the value proposition canvas in *Figure 2*, current blanket spraying methods waste chemicals by applying them uniformly, regardless of actual weed or pest presence, leading to harmful overspray. By utilizing inputs from drone cameras, satellites, or aerial images, EcoSprAI can precisely detect and map the areas that need treatment, reducing waste, lowering costs, and minimizing environmental impact. This precise targeting prevents chemicals from reaching non-target plants and reduces contamination of local water systems during rainfall.

In addition to precise detection, EcoSprAI's AI backbone offers recommendations on herbicides, pesticides, or fertilizers. These recommendations are tailored to specific conditions on the ground, ensuring that users not only apply chemicals in the right place but also use the right products.

EcoSprAI also optimizes spraying and spreading operations by providing an efficient application plan. It considers factors like land topology and coverage area, recommending the most effective techniques and trajectories for drones or machinery. This minimizes labour and fuel costs by reducing unnecessary passes over the field, shortening operation times, and achieving better results with fewer resources. Through this integrated approach, EcoSprAI offers a comprehensive solution that addresses both the environmental and economic inefficiencies of traditional spraying methods.

2. Current Landscape

a. Potential Market

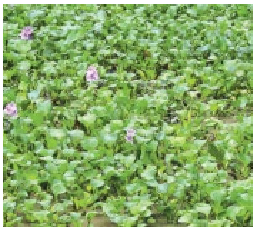
Farmers and agribusinesses can benefit from more precise and efficient spraying plans that can reduce costs and minimise environmental impacts. Despite our initial focus on the prickly acacia infestation in North Queensland cattle farms, there are other application areas in fruit, grain, cane, and vegetable farms, as well as land/pasture restoration projects and pest control.

If we narrow our focus on weed problems in the North Queensland area only, there is a huge market for EcoSprAI in the sense of weed detection, mapping, and planning. A shortlist of these weed problems is presented in *Table 1*. According to the State of Queensland, Department of Agriculture and Fisheries, some of these weeds are recognised as a Weed of National Significance.

Based on our market analysis, the main customers of our spray planning service are landowners with widespread weed/pest/disease spraying problems. Lands with high infestations are more likely to use traditional spraying techniques. EcoSprAI can dramatically reduce the complexity, cost, and environmental impacts of land management projects in (A) wide areas with irregularly distributed weeds/pests/disease, and (B) wide and inaccessible ponds, lakes, stream banks, and wetlands. This is also reflected in our potential customers, which are listed in the following subsections.

Table 1: A shortlist of weed problems in North Queensland area (taken from https://www.publications.qld.gov.au/dataset/invasive-plant-weed) that can be addressed by EcoSprAI

Weed Name	Description
Hymenachne 	Hymenachne was introduced to Australia from South America to provide ponded pasture for cattle. It has become an unwanted pest of stream banks, wetlands, and irrigation ditches in coastal and central areas of Queensland, invading low-lying sugarcane, fish habitats and natural wetlands with high conservation value. Hymenachne can increase flooding by reducing the flow capacity of the drainage networks. Hymenachne infestations are a physical barrier for aquatic and semi-aquatic animals, restricting their territorial movements and breeding activities. Hymenachne has been recognised as a Weed of National Significance.
Lantana 	Lantana covers more than 5 million ha of subcoastal New South Wales to Far North Queensland. Fruit-eating birds and mammals spread lantana. It forms dense thickets that can smother and destroy native vegetation and are impenetrable to animals, people, and vehicles. Research indicates more than 1400 native species are negatively affected by lantana invasion, including endangered and threatened species. As lantana is a woody shrub that has thin, combustible canes, its presence can also create hotter bushfires, altering native vegetation communities and pastures.
Rat's Tail Grasses 	Rat's tail grasses are invasive grasses that can reduce pasture productivity, out-compete desirable pasture grasses and cause significant degradation of natural areas. These species were originally introduced and trialled as pasture grasses and for soil conservation and have been unintentionally spread from these initial introductions and other accidental introductions. They have low palatability when mature, are difficult to control and can quickly dominate a pasture, especially following drought, overgrazing or soil disturbance. They can affect cattle health and productivity reducing weight gain and growth rates and weaning percentages and weights.
Salvinia 	Salvinia Molesta (a native of Brazil) affects water quality and availability by creating a haven for mosquitoes. Heavy weed cover also prevents the exchange of air that normally occurs on an open-water surface. High rates of transpiration through the leaves during summer can cause up to four times more water to be lost than is normally lost through water surface evaporation. Under flood conditions, rafts of weed material build up at fences and bridges that, in turn, collect other floating debris. The combined weight may cause these structures to collapse. Water flow to irrigation equipment is reduced due to the restrictive action of the roots. Salvinia is listed as a Weed of National Significance.

Weed Name	Description
Water Hyacinth 	Originally introduced to Australia as an aquatic ornamental plant, water hyacinth has become a major pest of rivers and dams. Not only does it destroy native habitats, but it also seriously depletes water bodies of oxygen, increases water loss, and provides a breeding ground for mosquitoes. Rampant growth of water hyacinth can destroy native wetlands and waterways, killing native fish and other wildlife. Propagation can be so rapid that an infestation may double in size every week under ideal conditions.
Pond Apple 	Pond apple is a major environmental weed of the Wet Tropics bioregion of Far North Queensland and a Weed of National Significance. This small to medium size tree forms dense stands, particularly in swamp areas. Pond apple invades fresh, brackish, and saltwater areas and its thickets can replace whole ecosystems. Its seed is primarily dispersed by water, especially during floods. Disturbed flood-prone ecosystems are most at risk from pond apple invasion, particularly mangroves, melaleuca woodlands, riparian areas, drainage lines, coastal dunes, and islands. Pond apple currently covers around 2000 ha of the Wet Tropics bioregion in Queensland. Unlike many weeds, pond apple has an alarming ability to invade undisturbed areas. Pond apple is also a pioneering plant and will opportunistically invade areas after disturbances such as cyclones and floods.
Prickly Acacia 	Prickly acacia was introduced into Queensland for shade and fodder. Prickly acacia infestations favour bore drains and water courses where trees spread out onto adjacent grassland. Trees along bore drains use valuable water, make maintenance of bore drains more costly, and provide seed to further increase the spread of prickly acacia. As a tree increases in size, it outcompetes pasture for water. Thorny thickets interfere with mustering, movement of stock and access to water. Prickly acacia is a threat to biodiversity through the transformation of natural grasslands into thorny scrub and woodlands. Prickly acacia also causes soil degradation by facilitating erosion. Prickly acacia has been recognised in Australia as a Weed of National Significance.
Similar prickly bushes are often present in the same area. So, land managers should identify them before considering control measures.	 Mesquite  Parkinsonia  Mimosa Bush

Desert Channel Queensland

Desert Channels Queensland (DCQ) is a community-based natural resource management body working to ensure a sustainable social, economic, and environmental future for the Queensland section of the Lake Eyre Basin. It is about 10 years since they started their Prickly Acacia eradication work across western Queensland. They used drones and other imaging technologies to develop machine-learning models for Prickly Acacia detection.

Reef Catchments

Reef Catchments are the Natural Resource Management (NRM) group for the Mackay Whitsunday Isaac region. They work on long-term solutions to sustain, protect, and improve their region's natural resources and environment.

They are currently dealing with pond pasture wetlands that are infested with various weed types. They are hoping that EcoSprAI will help them optimize their tactics through mapping, planning, and spraying diverse weed types. Some of the weeds in their list of priorities include Hymenachne, Lantana, Rat's Tail Grasses, Salvinia, and Water Hyacinth, which are previously studied in *Table 1*.

Mackay Regional Pest Management Group

The Mackay Regional Pest Management Group (MRPMG) is a voluntary unincorporated advisory group and stakeholder network. The MRPMG was established in 2002 and consists of representatives from local and state government departments, community groups, and industry bodies whose core business involves pest management.

b. Competitors

According to our market analyses, there is no other company that offers optimum spray planning. However, there are many spraying companies that might use the outcome of our planning software to efficiently conduct their tasks. Two of these companies are Travearth and Innoflight. We have discussed with both collaboration ideas around our tool helping their chemical spraying capacity.

There are some other companies like Pasture.io, Robotic Systems, PrismaTech, SpectroAI, etc. offer AI-enhanced land mapping and high-tech solutions by drones. However, to the best of our knowledge, there is no automated mapping and planning solution in the market. In other words, none of these competitors currently offer spray planning and optimisation as offered by EcoSprAI.

Uniqueness of Solution

EcoSprAI provides significant advantages over existing products on the market for

- Using advanced computer vision and AI technologies to detect field requirements,
- Optimally planning the spraying and spreading strategies based on the land topology, and
- Recommending chemicals, rates, and mixtures, based on the automatically detected weeds/pest/problem.

3. Team Members

a. Dr Mohammad Jahanbakht

Dr Jahanbakht is the main software and AI engineer to manage the PoC development and integrate all the required components of it. He is an experienced software engineer with an excellent background in using machine/deep learning technologies, edge processing on embedded systems, software development in web-based platforms, etc. He currently manages collecting data, designing, and training all AI models, developing optimization algorithms, and drafting this report.

b. Dr Alzayat Saleh

Dr Saleh has a strong background in deep learning and computer vision. He is currently a postdoctoral research fellow in deep learning for agriculture at James Cook University. He offered general advice on AI design.

c. A/Prof Nathan Waltham

A/Prof Waltham acted as an advisor to the team and project. He contributed his 25 year's field experience and management skills in environmental science, as JCU–TropWATER's in-kind support. Besides, his involvement was not for future interest, which means, he will not have a share from the project's IP, etc.

d. A/Prof Mostafa Rahimiazghadi

A/Prof Azghadi acted as an advisor to the team and project. He offered his knowledge of AI and its applications in agriculture, as JCU's in-kind support. Besides, the initial weed mapping tool was conceptualised by him.

4. Technical Discussions

a. Objectives

Detecting Prickly Acacia weed trees in aerial images is set as our case study. The study area is a 25 km² land inside the Olga Downs cattle farm[1] as shown in *Figure 3*. The project started by flying a DJI Phantom 4 RTK drone over an infested area. Despite constant hawk attacks, the pilot (i.e., Mohammad) managed to fly four times and successfully surveyed a 0.28 km² area (see *Figure 4*). Covering the entire 25 km² could take weeks to complete. Having said that, our small-scale drone survey provided enough data for training an AI model.

[1] 632 Olga Downs Road, Richmond QLD 4822, Australia

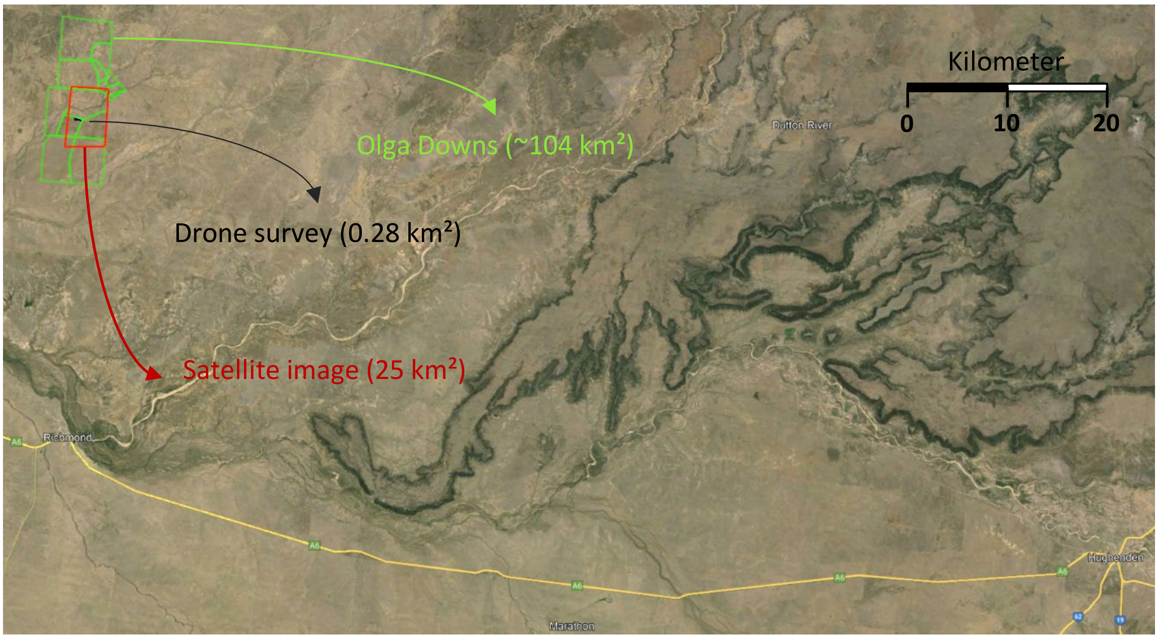


Figure 3: The Olga Downs cattle farm is located ~26 km north of Richmond.

It is worth noting that drone flying in the presence of aggressive birds was not easy. To address this problem, Mohammad proposes an alternative solution to use high-resolution satellite imagery. This idea is further investigated in upcoming sections, and it will be shown how satellite remote sensing can be employed for large weeds like Prickly Acacia.

b. Drone and Satellite Datasets

As shown in *Figure 4*, the dataset collection task has started by planning four drone flies over infested land. During these flies, 280 images are captured, which will be used to train a drone-AI model.

According to *Figure 5*, the average area of the trees in this dataset is 9.8 m^2, with 8.7 m^2 Standard Deviation (STD). In other words, Prickly Acacia trees have an average diameter of 3.5 m, while 68.3% of them have a diameter between 1.2- and 4.9-meter. It is worth noting that all diameter values in this report are calculated based on the rough assumption that Prickly Acacia trees look circular in aerial views. So, the diameter would be equal to $2 \times \sqrt{area / \pi}$.

As stated before, drone surveying of the entire land is not an easy task and can take up to weeks to accomplish. This is for (I) the limited drone battery life, (II) government rules for a constant line-of-sight between drone and pilot, and (III) the presence of aggressive birds like hawks.

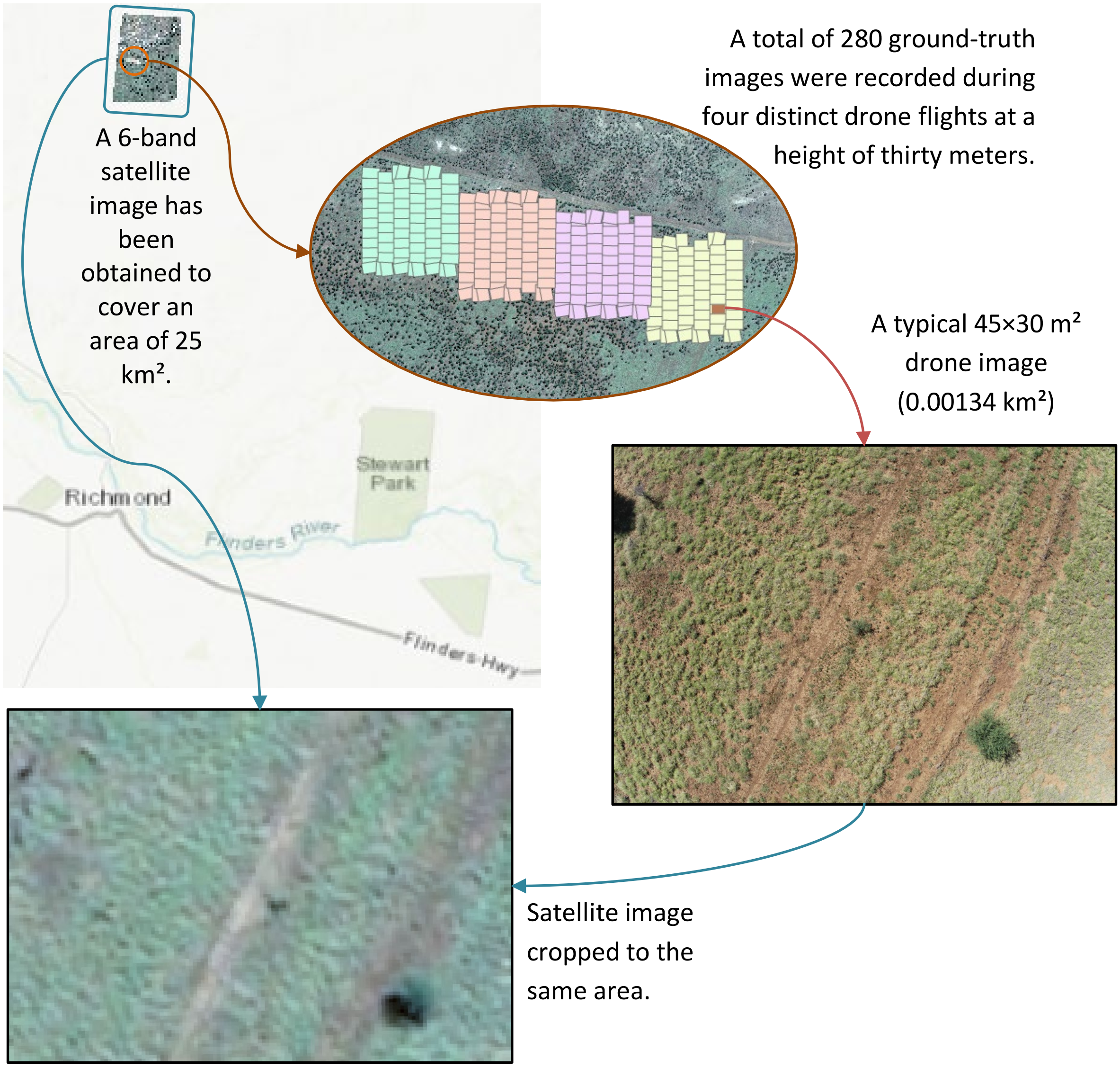


Figure 4: Comparing a 6-band satellite data coverage and its quality with a 3-band (RGB) drone data[2]

To address this problem, we took a novel approach of using satellite images in conjunction with drone images to detect Prickly Acacias. This is also shown in *Figure 4*. To elaborate, we ordered a 6-band satellite image with a 30-cm resolution to cover our study area.

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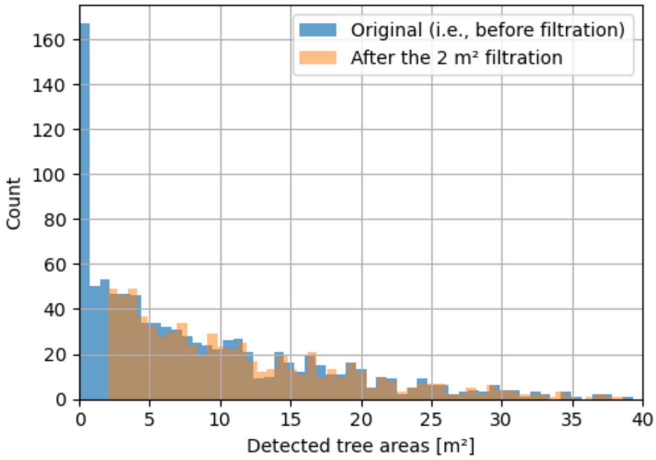
[2] Image number **100_0003_0056** under the **14_50-Hay_Paddock** folder.



Statistics	Original		After filtration	
	Area [m^2]	Diameter [m]	Area [m^2]	Diameter [m]
Min	0.0	0.0	2.0	1.6
Max	59.4	8.7	59.4	8.7
Average	9.8	3.5	11.7	3.9
STD	8.7	–	8.4	–

Figure 5: Histogram of the Prickly Acacia tree area, as seen in aerial views, as well as the tree area statistics. Wide areas are a result of multiple trees that are densely attached. Later we will put a minimum threshold (i.e., two m^2) on this area to filter noise from the AI detections.

Then, by using the existing drone images, we have annotated/labelled the Prickly Acacia trees in the remotely sensed satellite data. These annotations will be used later for satellite-AI model training. Using this novel technique,

- It would cost around AU$600 to acquire 25 km^2 satellite imagery.
- Weather would not be an issue, as the satellite data can be selected from non-cloudy days.
- Having the images in hand, we can study hundreds of hectares in a few hours.
- There would be no need for fieldwork and the high-risk drone flies.

c. Airplane setup and dataset

This is a placeholder for our airplane survey experiment and its dataset explanation.

d. Drone-AI Evaluation

The first AI is designed for drone images. A typical output of this drone-AI is illustrated in *Figure 6*.

From a technical perspective, the scenarios of tree existence and no tree existence are respectively called positive and negative situations. So, true positive and true negative are both good, meaning that our AI has correctly detected tree presence and tree absence. Similarly, false positives and false negatives are not good, as they mean our AI model has reported a non-existing tree or missed reporting an existing one.

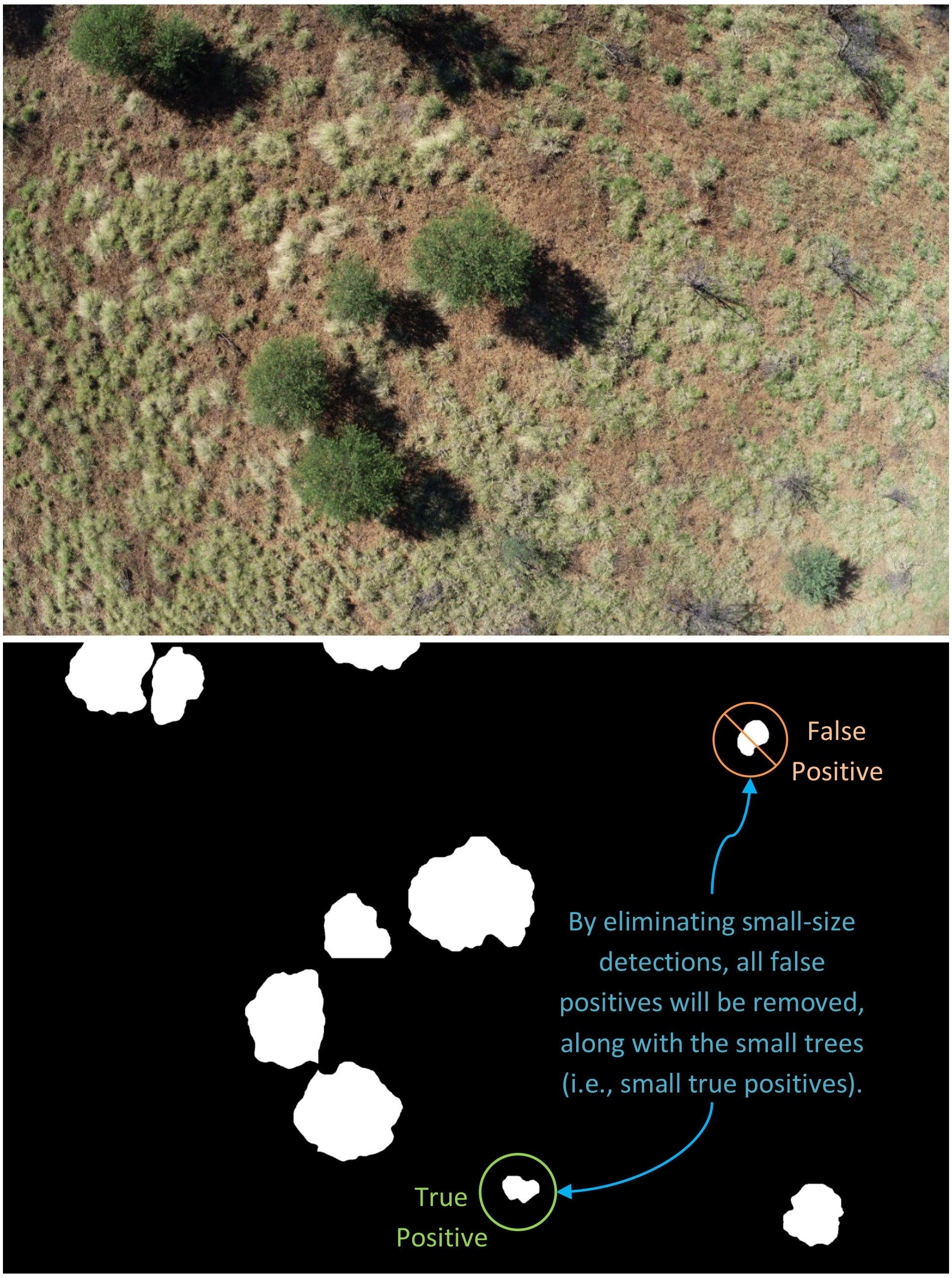


Figure 6: The inference result of our Drone-AI with many true detections and a small false positive[3]

As graphically illustrated in *Figure 6*, our drone-AI does a good job of detecting big trees with its good true positive performance. However, when it comes to smaller trees, it shows false positive detection of trees (that do not really exist). To avoid this problem, we should limit the detection size

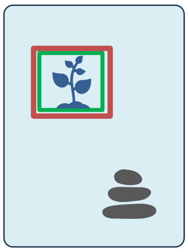
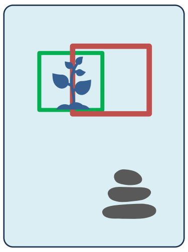
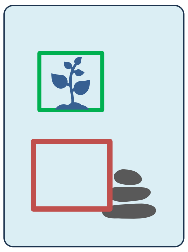
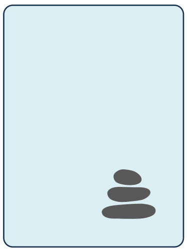
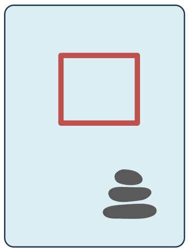
[3] Image number **100_0004_0069** under the **15_39-Hay_Paddock** folder.

to broad/wide trees only.

For numerical evaluation of true/false positives/negatives, the Intersection over Union (IoU) metric is used. IoU measures the localisation accuracy of an object detection model. It calculates the amount of overlap between the predicted bounding box and the ground truth bounding box. As shown in the following equation, this is calculated by dividing the intersection of the two boxes' areas by their combined areas. This is better illustrated in *Table 2*.

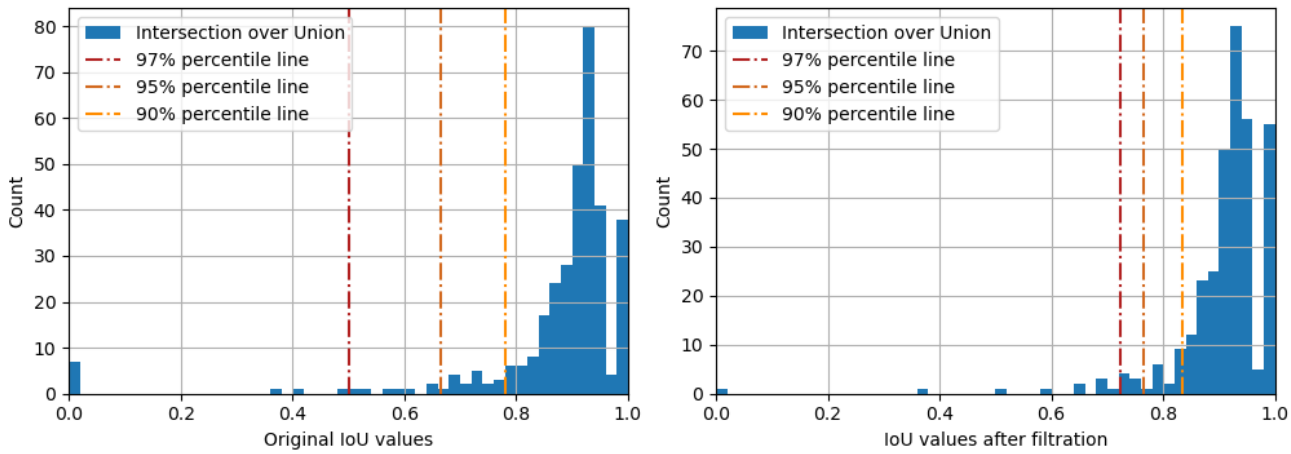
$$Intersection\ over\ Union = \frac{|\,Truth \cap Prediction\,|}{|\,Truth \cup Prediction\,|}$$

Table 2: The IoU value in some typical AI detections with and without target object presence. ☐ and ☐ respectively represent ground truth and AI detection.

When Target Plant Is Present			When Target Plant Is Absent	
Image 01	Image 02	Image 03	Image 04	Image 05
				
$IoU \cong 1$	$IoU \cong 0.5$	$IoU = 0$	$IoU = 1$	$IoU = 0$

A histogram plot of the IoU results of our drone-AI is plotted in *Figure 7a*. By looking at the far-left end of this plot, a column of near-to-zero IoU values is visible. These small IoUs are mostly correlated to false detections (a.k.a., output noise). To eliminate this noise, we put a threshold on the minimum AI detection area. This was previously studied in *Figure 5*, and two m^2 was selected as the lower band of our filtration process.

After applying this threshold, the average IoU has improved from 0.88 to 0.91. This is better illustrated in *Figure 7b*, where the vertical percentile lines are shifted right, towards better IoU values.



(a) Average: 0.88 (b) Average: 0.91

Figure 7: The IoU histogram of our drone-AI outputs (a) before and (b) after applying the two m^2 area threshold filter.

e. Satellite-AI Evaluation

The second AI is designed for satellite images. This AI is trained with ground-truth images that are already taken by drone. All detected ~83,500 Prickly Acacia trees in our 25 km^2 study area are shown in *Figure 8*. If we combine the results from this figure with the average tree area in *Figure 5*, we can conclude that the minimum canopy area (at noon) equals ~0.8 km^2.

$$Minimum\ canopy\ area\ (at\ noon) = 83{,}518 \times 9.8\ m^2 = 818{,}476.4\ m^2$$

To better understand the performance of our satellite-AI, two comparisons are made with our previous drone-AI model. These evaluations are shown in *Figure 9* and *Figure 10*. As expected and according to these figures, satellite-AI fails to detect very small trees, but performs well in detecting bigger ones.

Furthermore, the Olga Downs's landowner has raised an important concern about keeping native trees. To analyse the performance of satellite-AI on this matter, we zoomed in on a couple of regions inside our study area. As can be seen in *Figure 11*, satellite-AI does a great job of excluding native trees around the creeks, while broadly identifying sparse Prickly Acacia trees.

It is worth noting that the satellite-AI was not the case at the time of data collection. So, no evaluation data is collected for the satellite-AI validation.

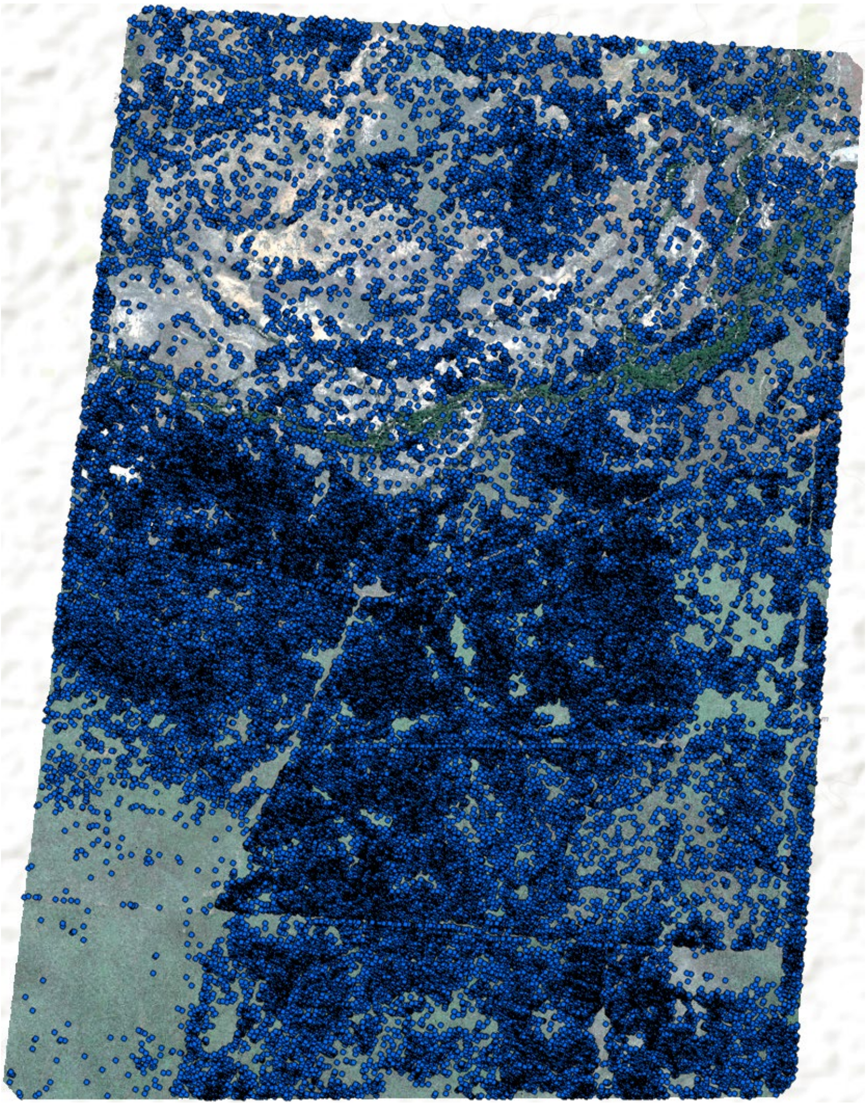
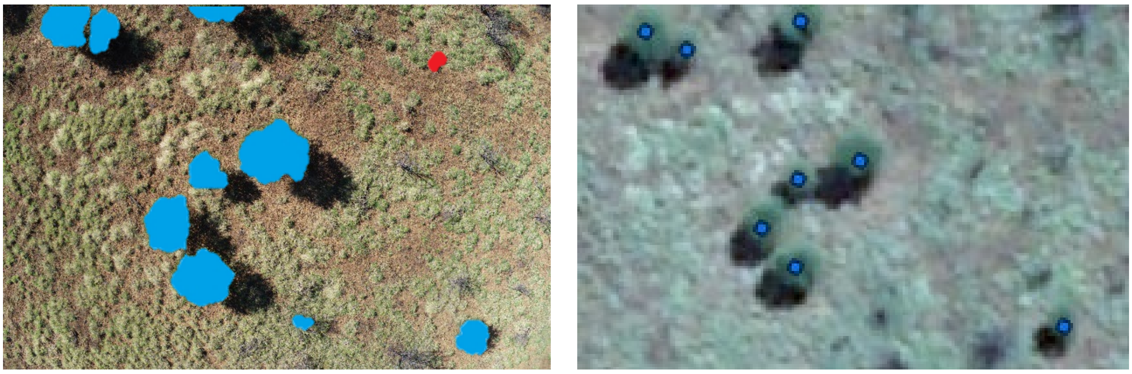


Figure 8: All 83,518 Prickly Acacia trees that are detected by our proposed Satellite-AI are highlighted with blue dots (●).

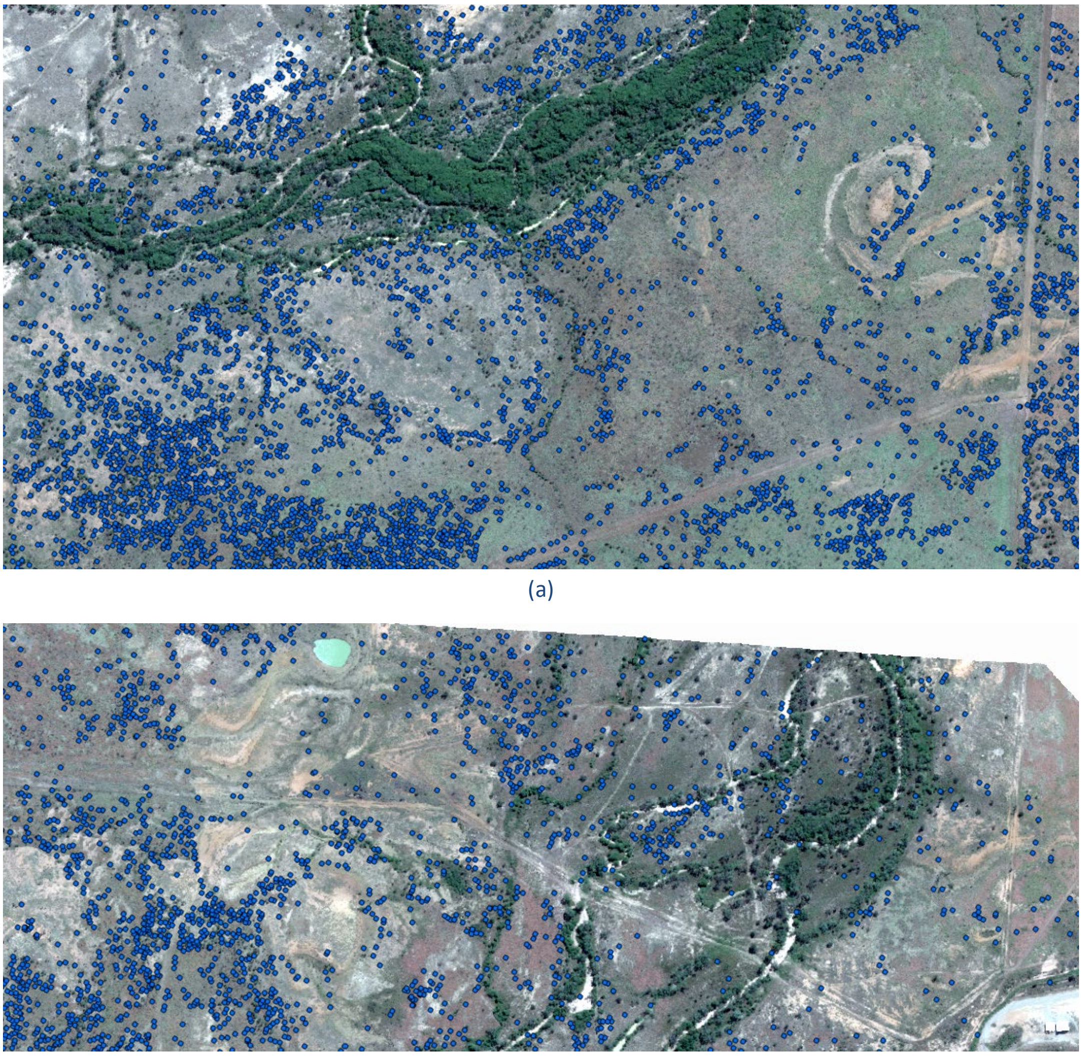
(a) (b)

Figure 9: Using the sample image in *Figure 4* to compare (a) drone-AI result with (b) satellite-AI result. Drone-AI has correctly detected the small tree in the middle of the image, but it was too small to be picked by satellite-AI.



(a) (b)

Figure 10: Using the sample image in *Figure 6* to compare (a) drone-AI result with (b) satellite-AI result. The satellite-AI does not have a false positive detection on top-right (as drone-AI has). However, it has a false negative for not detecting the small Prickly Acacia in bottom-middle.



(a)

(b)

Figure 11: A closer look at two random areas with dirt roads, ponds, native trees, and buildings.

f. The Optimum Plan

In this section, we develop an algorithm to take the exact geolocation of trees from the AI models and then recommend the optimum travelling plan to go from the first tree to the last. This plan can be optimized for eliminating the weed in the shortest time, distance, cost, etc. This is a well-known problem in academia, known as the *travel salesman problem*.

Our travel salesman optimization process starts by dividing the area into arbitrary-shaped zones. As shown in *Figure 12*, the zones must be carefully selected to enclose weeds based on their land feature or proximity. Each zone in a given problem will be treated independently. Generally speaking, it is not recommended to enclose the whole problem area as one single zone. This will not only cause a longer processing time but also contradict the assumption of land feature diversity.

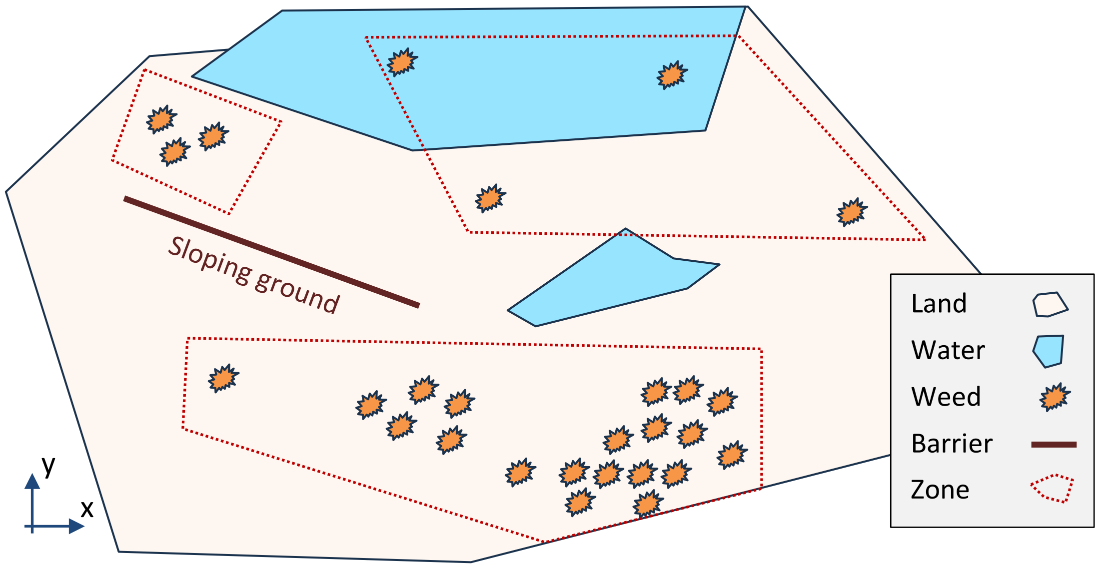


Figure 12: A typical weed-infested area with limiting land features like lakes and sloping grounds.

After zoning the area, we must define our optimization variables. A shortlist of optimization parameters that are used in this study is brought to you in *Table 3*. These variables are categorized under chemical, sprayer/spreader equipment, carrier utility, and contract terms.

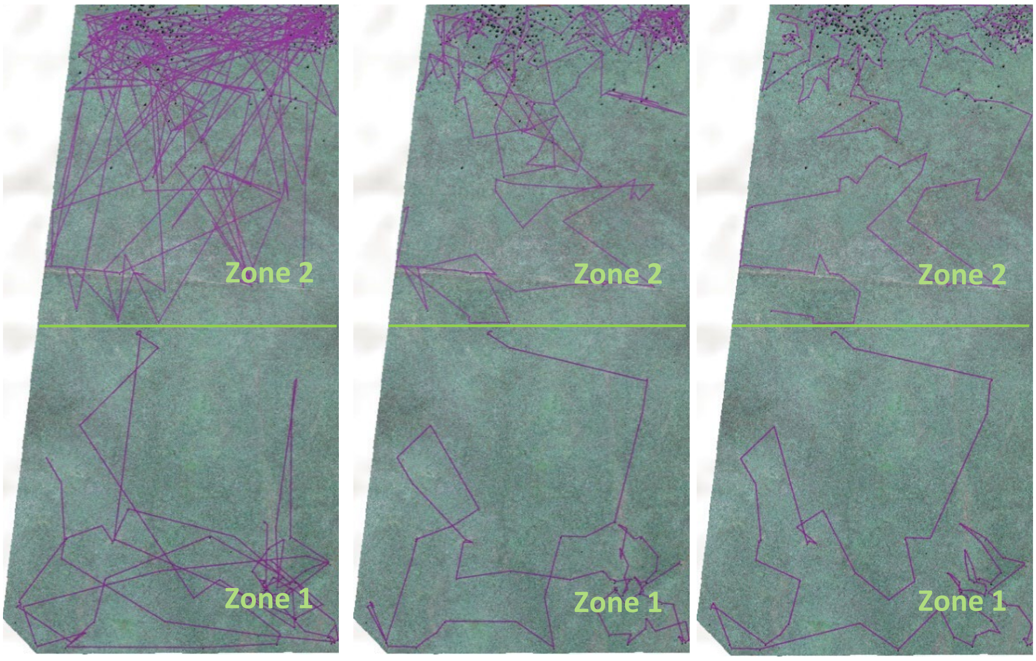
Before presenting our solution to the travel salesman problem, it is worth noting that the existing optimization algorithms like the Genetic Algorithm (GA) fall short in our application. To elaborate, the number of target trees in every zone of our problem is far more than the maximum those algorithms can efficiently manage.

Table 3: A shortlist of major optimization variables that are used in this study.

Category	Variable Name	Description
Chemical	spread_or_spray	Is it meant to be sprayed or spread?
	cost_per_volume	The chemical cost per litre
	volume_per_tree	The effective volume to be applied per tree
Sprayer/Spreader	tank_volume	The maximum volume of the Sprayer/Spreader tank
	weight_after_filling	The gross weight of the Sprayer/Spreader (including the full tank)
	time_per_tree	The average time of Spraying/Spreading spent on one tree
	refill_time	The average time to refill the Sprayer/Spreader tank
Carrier	Category	What/who is carrying the Sprayer/Spreader? It can be labour, vehicle, tractor, drone, airplane, etc.
	average_speed	The average speed to travel from one tree to another
	inter_zones_relocation_time	The time required to travel from one zone to another, and to settle in the new zone
	max_payload_weight	Maximum payload weight that can be carried
	power_source_type	The power source type depends on the carrier category, and it can be food for labour, petrol/diesel for vehicle, electricity for drone, etc.
	power_consumption_per_meter	Average power consumption per meter
	power_cost_per_consumption_unit	Power cost per litre for petrol, per kilowatt for electricity, etc.
	power_storage_capacity	The maximum storage capacity for the previously indicated power source type
	power_storage_refill_time	The average time required to refill/recharge the power storage
Contract	travel_to_farm_cost_daily	How much are we responsible to pay daily for labour travelling to farm?
	travel_to_farm_cost_one_off	One-off payment to labour(s) to travel to the farm and starting the project
	daily_workhours	The number hours and minutes in a workday
	hourly_rate	The agreed labours' hourly rate in dollars
	daily_extras	The other daily costs, including admin, insurance, superannuation, etc.

To address this issue, we firstly improved the traditional GA by proposing a mating mechanism. Current GA models for the travel salesman problem do not have a mating step, and they solely rely on the mutation. As can be seen in *Figure 13*, the improved GA achieves a better loss than the traditional GA. Loss value is simply the travel distance in kilometres, plus a penalty term for every steep path. Even after improving GA, the resulting loss was not acceptable. Besides, the processing time of the improved GA is more than 24 hours in the case of Zone 2 with only 254 target trees.

Both the unsatisfying loss value and the long optimization times of the GA models have forced us to design our new optimization algorithm, called *birdview*. According to *Figure 13*, this new algorithm has not only achieved acceptable loss values but also gained these achievements in the order of a few seconds! The better routing performance of our proposed birdview model is visually perceivable in *Figure 13*, especially in the dense weed areas.



	Zone 1	Zone 2
Number of Trees	85	254
Traditional GA		
Duration	0.9 hour	4.3 hour
Loss	12289.0	50728.5
New improved GA		
Duration	3.4 hour	27.8 hour
Loss	6445.7	19042.5
New proposed birdview		
Duration	0.3 sec	2.6 sec
Loss	6202.2	10039.2

(a) Traditional GA (b) New improved GA (c) New proposed birdview

Figure 13: Comparing the performance of (a) the traditional genetic algorithm, (b) proposed new genetic algorithm, and (c) the proposed birdview algorithm. The comparison is made in the first two zones of our project, and the results are showing an impressive performance increase from both genetic models to the new birdview model.

We divided our study area into thirty-five rectangular zones, which are uniformly distributed in seven rows and five columns. This is better shown in *Figure 14*. It is worth reminding that the area zoning is an arbitrary process, and our model works with any zone shape or size.

After dividing the study area into zones, our birdview optimization model has ran over each zone independently to find the best route. These optimum routes are also presented in *Figure 14*, and available as binary files to be used by machines and humans.

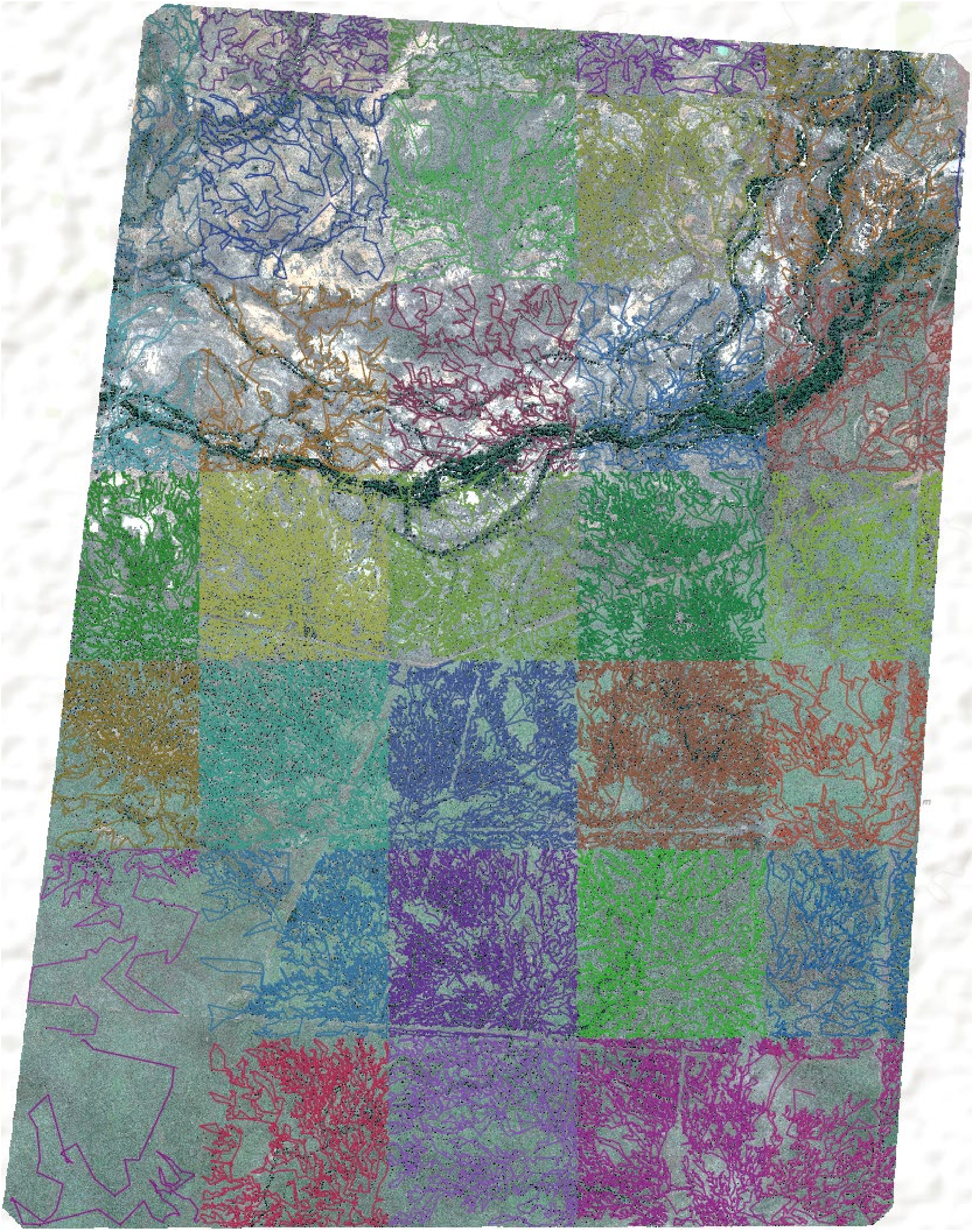


Figure 14: The study area is divided into 5×7 uniform rectangular zones. The proposed birdview optimization algorithm is then employed in each zone (independently) to suggest the optimum spraying plan.

Optimum routes in *Figure 14* are topography-aware, as the optimization model receives a penalty for going over a maximum acceptable climbing angle. This climbing angle itself depends on the carrier type in *Table 3*. For instance, there is no climbing angle limit for drones, but it is limited to 30° for Toyota Hilux.

To be able to evaluate the optimum budget, two scenarios are defined in *Table 4*. Scenario A uses a Toyota Hilux with an embedded Rondini SP500 spreader. The variable names in this table are previously defined in *Table 3*. The second scenario B uses a DJI Agras T50 drone. Both scenarios follow the zones and optimum routes in *Figure 14* to spread GP Regain 200 tebuthiuron granules.

Table 4: Defining the optimization parameters of two asymptotic scenarios. The first scenario A is defined for spreading herbicide pallets using a Toyota Hilux, while the second scenario B is defined for spreading the same pallets with a drone.

Category	Variable Name	Scenario A (car)	Scenario B (drone)
Chemical	spread_or_spray	Spreading (GP Regain 200)	
	cost_per_volume	$9.4 (link)	
	volume_per_tree	3.75 mL (link)	
Sprayer/ Spreader	tank_volume	345 L (Rondini SP500 Steel)	74 L (Agras T50 Spreader)
	weight_after_filling	198 kg	35.6 kg
	time_per_tree	5 sec	3 sec
	refill_time	10 minutes	10 minutes
Carrier	Category	Car – Toyota Hilux 2014	Drone – DJI AGRAS T50
	average_speed	2.8 m/sec	10 m/s
	inter_zones_relocation_time	45 minutes	45 minutes
	max_payload_weight	920 kg	50 kg
	power_source_type	Diesel	Battery
	power_consumption_per_meter	12 L per 100 km	4.2 mAh
	power_cost_per_consumption_unit	$1.82	$0.043 (inverter's petrol)
	power_storage_capacity	70 L	25 Ah
	power_storage_refill_time	15 minutes	10 minutes
Contract	Category	C-class Car Driver	Drone Pilot
	travel_to_farm_cost_daily	$0	$0
	travel_to_farm_cost_one_off	$200	$400
	daily_workhours	8 hours	8 hours
	hourly_rate	$30	$40
	daily_extras	$100	$100

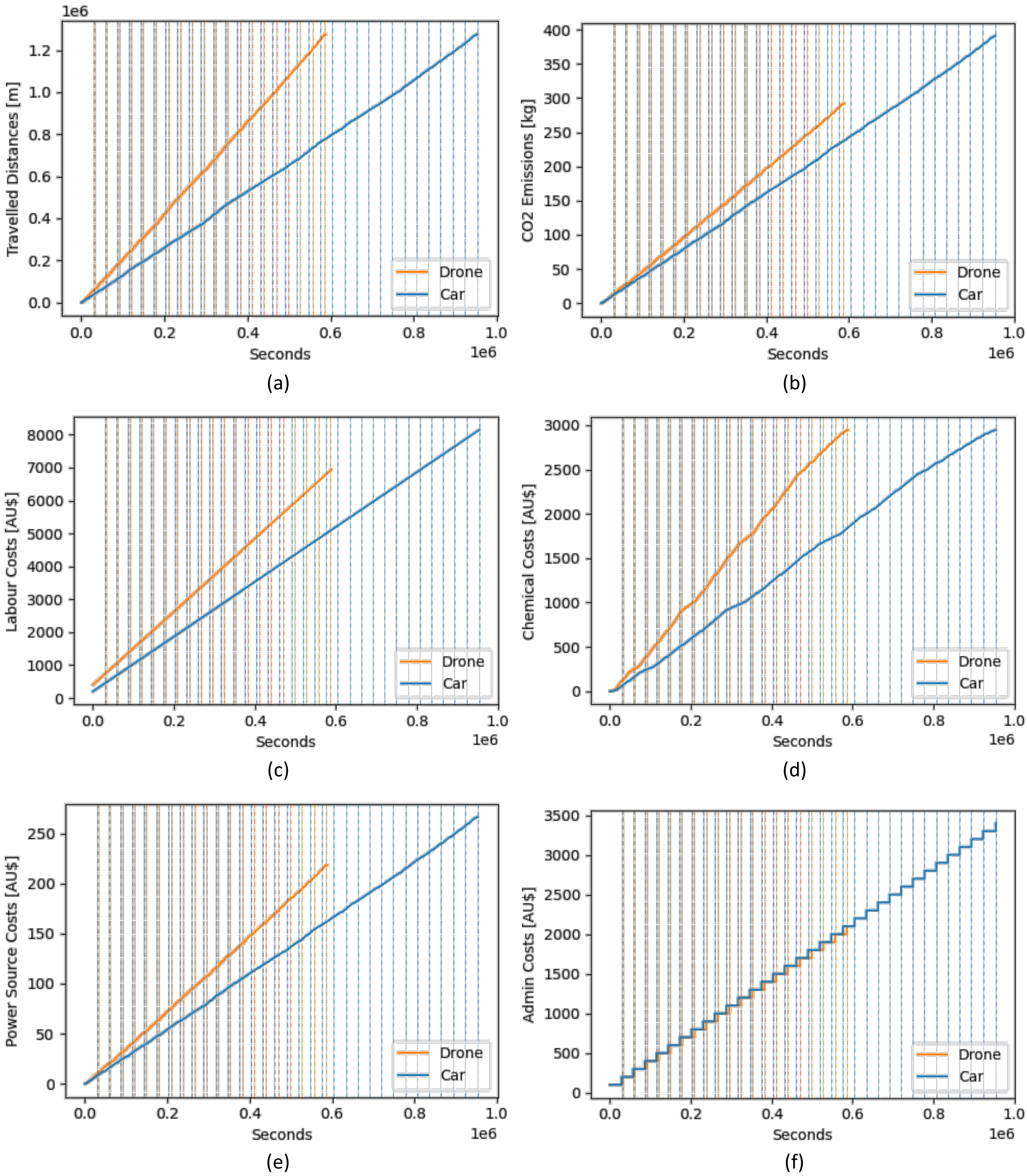


Figure 15: Cumulative increase in the (a) travelled distances, (b) CO_2 emissions, (c) labour costs, (d) chemical costs, (e) power/fuel costs, and (f) admin costs are compared between the two scenarios in *Table 4* (i.e., car for scenario A and drone for scenario B). The vertical lines in these figures represent the day change.

The calculated budgets for scenarios A and B from *Table 4* are presented in *Figure 15* and *Table 5*. These budgets include labour, chemical, petrol, and admin costs, as well as the travelling distance and CO_2 emission. The vertical lines in *Figure 15* indicate the end of the day, and they are not necessarily coinciding between drone and car scenarios. The reason is the daily mission might end earlier than 8-hour daily worktime if the next task might not finish in time. For example, changing the zone takes 45 minutes, and if we have only 15 minutes left from the daytime, this task will be left for another day.

According to both *Figure 15* and *Table 5*, our drone scenario B can finish in 21 days with ~AU$12,200 compared to the car scenario B in 34 days and ~AU$14,800. Travel distance is theoretically the same between both scenarios, we know that cars cannot always travel in direct line. So, we expect higher practical values in any car-involved application. The correct way to compensate for the difference between theoretical and practical traveling distance values is to decrease the average_speed and increase the power_consumption_per_meter. This compensation is not carried out in our *Figure 15* and *Table 5*, as it needs to be trialled to get accurate results.

Another inaccurate assumption in *Figure 15* and *Table 5* is the fact that drones are more accurate on the chemical spread. So, assuming equal volume_per_tree values for scenarios A and B in *Table 4* cannot be realistic. Having said that, we did not change this value, as it needs to be trialled.

Table 5: The overall travelling time and distance, along with the emitted CO_2 and project costs are compared between the two scenarios in *Table 4*.

Parameter	Scenario A (car)	Scenario B (drone)
Number of workdays	34	21
Travelled distance	1,275.4 km	1,275.4 km
CO_2 emission	390.79 kg	292.22 kg
Total cost	$14,759.3	$12,208.2
• Labour cost	$8,148.9	$6,945.8
• Chemical cost	$2,943.9	$2,943.9
• Power/fuel cost	$266.4	$218.5
• admin cost	$3,400.0	$2,100.0

5. Potential EcoSprAI SaaS Model

A schematic view of the EcoSprAI's web interface (from user login to optimum plan downloading) is shown in *Figure 16*. This is the potential SaaS model of EcoSprAI, where the income venues are marked by $ signs. To elaborate, EcoSprAI can make revenue from land/aerial surveying, data storage on the cloud, target plant detection by advanced AI models, and optimum plan suggestions.

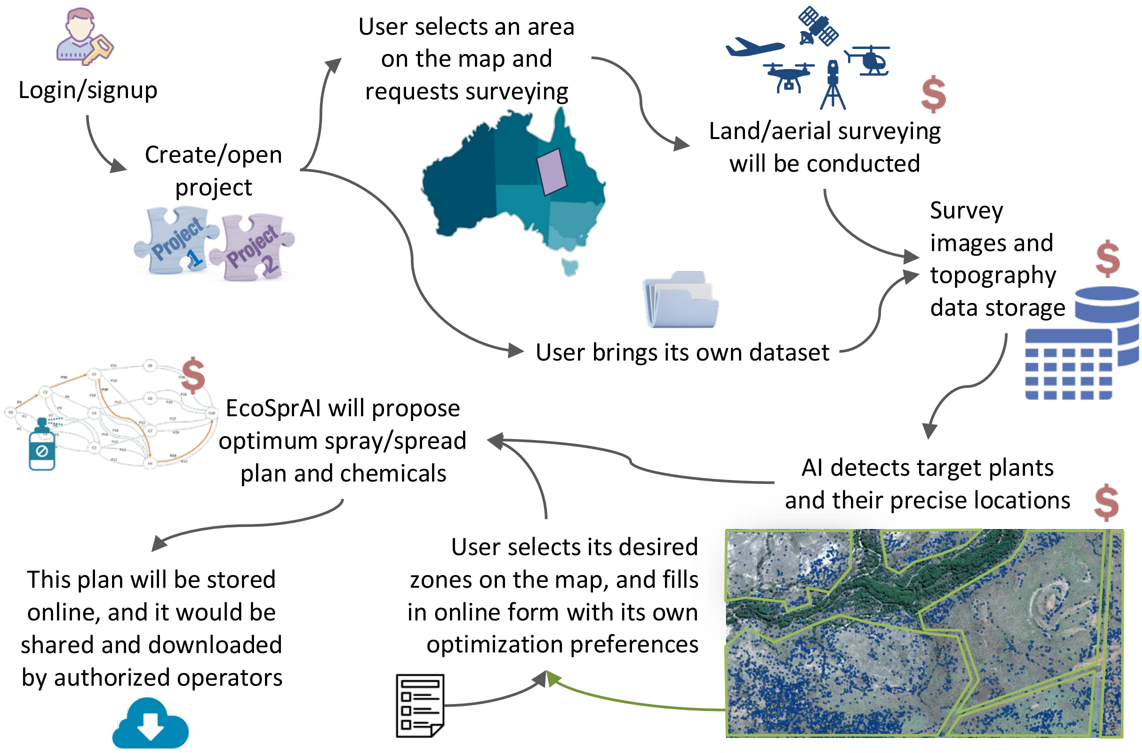


Figure 16: Schematic of the EcoSprAI's web interface from login to data download. The **$** icons indicate potential revenues.

6. Conclusion and Achievements

The inefficiencies and environmental impact of traditional agricultural spraying/spreading methods present a significant challenge in modern farming. The blanket spraying of chemicals not only leads to waste but also harms non-target plants, poses health risks, and contributes to environmental degradation. The excessive costs, labour intensity, and susceptibility to human error further compound these issues. To address these problems, EcoSprAI offers a comprehensive, AI-driven solution for precision agriculture, optimizing the application of herbicides, pesticides, and fertilizers.

Our approach integrates aerial imagery (from drones, satellites, airplane, etc.) with advanced AI algorithms to detect, map, and target weed infestations, such as the Prickly Acacia, as our case study.

Our designed drone-AI model can take high-resolution drone images and accurately detect big and medium-sized trees with an impressive IoU performance of 0.91. As a further step, we have innovatively used our drone dataset as the ground-truth for our second AI model training, i.e., the satellite-AI. The large-scale satellite data along with our satellite-AI enhances detection speed, while overcoming drone's practical limitations, such as flight restrictions, battery life, and natural situations. Using our satellite-AI, we have successfully automated the identification of over 83,500 weed trees in a 25 km^2 area.

Both drone- and satellite-AI models have a sensitivity variable. Using this variable, one can easily adjust the level of object detection. To elaborate, Drone-AI's sensitivity variable refers to the object area and it is set to 0.0 in *Figure 6* and *Figure 7a*, and is set to 2.0 in *Figure 7b*. This means that every detected object that has an area greater than the set threshold will be reported. Increasing this value will automatically filter out the small objects and only report those bigger than the threshold. On the other hand, the sensitivity of the satellite-AI refers to the detection probability, and it is currently set to 0.3 in *Figure 8*, etc. Reducing this number will include more objects, which might increase the chance of mis-reporting native trees as Prickly Acacia.

EcoSprAI's unique value lies not only in its AI-based detection capabilities but also in its recommendation and optimization engine. The platform suggests the most effective chemicals, provides usage guidelines, and generates optimal spraying and spreading plans based on factors like land topology and coverage. Our innovatively proposed birdview optimization algorithm efficiently solves the complex travel salesman problem, minimizing travel distance, time, and costs, as demonstrated by the routing results in our study. In a typical case study, we analysed a drone-based spreading scenario, and we showed that it reduced the time required by more than 38% and the cost by more than 18%, making it a highly competitive alternative to traditional vehicle-based spreading.

By accepting a wide range of adjustable parameters, our optimization algorithm can recommend optimum time, travel distance, cost, etc. for any combination of

- Chemicals (spraying and spreading herbicides, pesticides, fertilizers, etc.),
- Carriers (drone spot, drone blanket, plane blanket, vehicle, motorcycle, tractor, etc.), and
- Contracts (labour, commuting, admin, etc.).

EcoSprAI, as a high-tech incorporation of AI, GIS mapping, and advanced topography-aware optimization techniques, enables farmers to significantly reduce chemical usage, lower costs, and minimize environmental and health risks.

7. Further Works

There are several promising directions for the future development of EcoSprAI. First, based on our learning, large landowners and managers with persistent weed issues are the most likely to benefit from and regularly utilize our services. As a result, our marketing efforts should focus on identifying and targeting this specific customer base to build long-term relationships.

In terms of technology, one exciting proposal is to integrate Augmented Reality (AR) with All-Terrain Vehicles (ATVs) to create a remotely operated spraying/spreading system. This innovative idea, as proposed by Mohammad and depicted in *Figure 17*, would reduce operational costs by eliminating the need for a physical driver in the field, allowing for remote control and real-time weed targeting.

Another benefit is that the human operator can confirm the AI detection in-place, avoiding AI false-positive and false-negative detections. However, the risk of regulatory challenges with AR-controlled vehicles needs to be addressed.

Figure 17: It is proposed to use remotely operated ATV machines for weed spraying/spreading. The driver will remotely control the vehicle through the internet, using augmented reality accessories.

While our current work has taken steps toward using satellite imagery as an alternative to drones for land surveying, this approach requires further validation. Collecting additional field data will be essential to rigorously evaluate the performance of our satellite-AI model.

Figure 18: Existing well-maintained planes can be used for land surveying in larger farms.

Furthermore, the use of airplanes offers another opportunity for expanding EcoSprAI's capabilities. This method, also proposed by Mohammad, holds immense potential for large-scale monitoring. Given the limited time remaining in the current project, we might be able to collect data, but the design and testing of airplane-AI model will be deferred to future phases. Regarding the airplane data collection, the farm owner (i.e., Peter Harrington) has had a squadron of airplanes in his backyard. A couple of his airplanes are shown in *Figure 18*. He expressed his interest in helping with aerial land imaging, as a substitute for drone surveying. JCU's TropWATER has valuable experience with airplane surveying of the Great Barrier Reef. The same technology can be employed on land, using one of Harrington's planes. By using this technology,

- We can survey wide areas in a few minutes (compared to multiple weeks with a drone),
- We do not need to be worried about the birds,
- We can employ a better camera with higher resolution (as we are not limited to the drone's battery), and
- In this specific case, for example, we do not need to pay the airplane costs (as Harrington's in-kind support). This can apply to other big cattle farms, as they usually have their own planes.