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NOTIFICATION OF ACCEPTANCE

Dear Dr. KAMALUL ADHAM CHE RUZLAN,

On behalf of the ACAPI2026 Committee, we are pleased to inform you that your submitted abstract (ACAPI2026: 035-029) entitled "EMERGING TRENDS AND APPLICATIONS OF DRONE TECHNOLOGY IN AGRICULTURE AND PLANTATION MANAGEMENT", has been reviewed and accepted for 1st Asia Conference on Agriculture and Plantation Industry.

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Again, thank you very much for your submission.

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EMERGING TRENDS AND APPLICATIONS OF DRONE TECHNOLOGY IN AGRICULTURE AND PLANTATION MANAGEMENT

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ABSTRACT

This critical narrative review examines whether unmanned aerial vehicle (UAV) sensing, artificial intelligence and spray application improve management decisions and field outcomes in oil palm, paddy, rubber and tropical fruit, with particular attention to Malaysian conditions. Seven purposively selected primary studies were charted by crop, sensor, method, validation design and outcome, then graded against stated evidence criteria. Palm detection had the strongest image-level evidence, with F1-scores near or above 0.90 in two independent studies, although one model differed by eleven percentage points between plantations. Detection accuracy did not establish inventory accuracy. Paddy weed mapping and Ganoderma mapping were validated only within single sites, and lightly infected palms could not be separated from healthy palms. Two studies compared field outcomes with conventional practice. In maize, UAV-derived prescription maps yielded estimated herbicide savings of 14–39.2% without reducing crop biomass. In replanted oil palm, UAV spraying matched pre-planting mist-blower control and used 37% fewer working hours and 91% less water than knapsack spraying, but produced weaker selective grass control. Modelled costs favoured UAV spraying over knapsack spraying from approximately 3,000 ha under the study's assumptions. Durian pollination was evaluated only in simulation. These findings concern a purposive evidence set rather than the whole literature. A sense–interpret–decide–act–verify framework is proposed to connect aerial observations with auditable outcomes. Priorities include cross-site validation, understory weed detection, contract-specific costing and multi-season comparative trials. Practical adoption should therefore distinguish image classification performance from agronomic effectiveness and economic feasibility. Independent ground checks, explicit decision thresholds and comparisons with existing management are needed before promising results can support wider operational deployment. The review distinguishes predictive performance from management effectiveness and identifies the additional validation needed before UAV outputs can support routine operational decisions. Its findings should not be interpreted as a systematic estimate of the effectiveness of technology across the agricultural sector.

Keywords: Field validation; oil palm; precision spraying; unmanned aerial vehicles; weed management

1. INTRODUCTION

1.1 BACKGROUND AND RATIONALE

The practical question behind this review is narrow. When a UAV flies over an oil palm block, a paddy field, a rubber holding or a durian orchard, does the information it returns lead to a better management decision than the one the manager would have made without it, and can that improvement be measured? Published studies answer the first half of the question far more often than the second. Palm-detection models now report F1-scores of 0.90–0.95 on UAV imagery (Lee et al., 2024), and a fully convolutional network has mapped weeds in a rice field with an overall accuracy of 0.935 (Huang et al., 2018). Neither study set out to show what happened to inventory accuracy, weed control or cost once those maps were used on a working farm. This distinction between technical performance and decision value is central: a statistically accurate detection map may still be operationally unsuitable if it arrives too late, misses priority targets or cannot be translated into a cost-effective intervention.

Precision agriculture rests on the observation that crop condition and weed pressure vary within a field, and UAVs suit it because they can be flown when the user chooses, at resolutions satellites rarely match (Velusamy et al., 2022; Guebsi et al., 2024). A successful flight, though, is only the first link in a longer chain. The classification has to be checked against field measurements, the treatment has to be lawful and correctly applied, and the result has to be compared with conventional practice (Anam et al., 2024; Wang et al., 2025). Of the seven primary studies charted in Section 3.2, only two follow that chain as far as a field outcome, one in maize and one in Malaysian oil palm.

1.2 RELEVANCE TO PLANTATION SYSTEMS

Oil palm and rubber pose a problem that open-field crops rarely do. Once their canopies close, a downward-looking camera records fronds and leaves, and the understorey where weeds grow is largely out of view. Paddy has short weed-control windows, so a map delivered after the window has closed is of little use, and durian trees are irregular in shape and spacing (Tang et al., 2025). Methods developed in open fields need testing where they will be used. Consequently, evidence from open-field systems should be treated as transferable hypotheses rather than direct proof of performance under mature tropical plantation canopies.

1.3 KNOWLEDGE GAP, OBJECTIVES AND CONTRIBUTION

Recent reviews cover agricultural UAVs broadly (Guebsi et al., 2024; Wang et al., 2025), AI–IoT–UAV integration (Rashid et al., 2025) and automated weed detection and herbicide application (Ehrampoosh et al., 2025; Saini & Nagesh, 2025; Bhandari & Etienne, 2026). For tropical plantations, three questions remain largely open. How far do reported accuracies hold when a model is moved to another site, season or palm age? Which applications have been carried through to a measured field outcome? Under what arrangement does UAV use make economic sense for estates and smallholders?

The review addresses four research questions: which UAV technologies and methods currently support agricultural decisions, and on what evidence (RQ1); where they create realistic opportunities in oil palm, paddy, rubber and tropical fruit (RQ2); what constraints limit implementation (RQ3); and what research would move them from aerial sensing to verified field action (RQ4). The contribution is a synthesis that separates results measured in the field, results shown only on image datasets, and proposals. As a critical narrative review, it pools no effect sizes and makes no claim to

exhaustive coverage. The unit of comparison is therefore the decision supported and its verification endpoint, rather than the drone platform or algorithm alone.

2. MATERIALS AND METHODS

2.1 LITERATURE SELECTION

This is a purposive narrative review rather than a systematic one. The literature was gathered in October 2026 from scholarly indexes and publisher websites, combining terms for the platform (unmanned aerial vehicle, UAV, drone), the task (weed detection, crop monitoring, tree detection, spraying, water stress) and the setting (oil palm, paddy, rice, rubber, durian, plantation). No reproducible search log, hit counts or deduplication record were kept, so none is reported. Selection was purposive and illustrative, and the absence of a documented search protocol prevents claims of completeness or a reproducible assessment of publication-selection bias.

Recent peer-reviewed reviews (2022–2026) were used to map platforms, sensors and methods. Primary studies were used to test claims, and were included when the crop is grown in the humid tropics or the task transfers directly to one, and when the study reports its sensor, site, reference data and quantitative results. Huang et al. (2018) predates the main window but reports its paddy site, flight parameters and validation split in full. Castaldi et al. (2017) and Che Ruzlan et al. (2025) were included because they measure field outcomes against conventional practice. Che Ruzlan et al. (2025) is the author's own field trial and is charted and graded by the same criteria as the others. Regulatory statements were taken only from the issuing bodies (Civil Aviation Authority of Malaysia [CAAM], n.d.; Food and Agriculture Organization of the United Nations [FAO] & World Health Organization [WHO], 2024). Where full methodological details were unavailable, the review explicitly distinguishes abstract-reported performance from findings verified through accessible study methods; these records should be rechecked against full texts before submission.

2.2 EXTRACTION, EVIDENCE GRADING AND LIMITATIONS

Each primary study was charted on the same fields: study and setting, design and validation, key result and main limitation (Table 1). Field outcomes measured against a conventional comparator carry most weight, followed by image-based results validated on a separate site or date, then results validated on the training site and date, and finally reviews, simulations and proposals. For consistency, the synthesis distinguishes image-level metrics (such as F1-score and overall accuracy), agronomic outcomes (such as weed control and regrowth), operational outcomes (such as labour and water use), and economic projections. These endpoints are not interchangeable.

Each application in Table 2 is graded against stated criteria. *Established at image level* means the same task is reported by at least two independent primary studies with consistently high accuracy, including results from more than one site. *Emerging* means at least one primary study with field reference data or a measured field outcome, but from a single site or season, or with mixed results against the comparator. *Experimental* means evidence only from simulation or from datasets without field reference. *Not demonstrated* means no primary study in the set addresses the task, and *review evidence only* means the claim rests on reviews or transfer from other crops. No application meets the stricter grade of operationally established, which would require replicated field outcomes against a conventional comparator across sites and seasons.

Studies were charted by a single reviewer and no formal risk-of-bias tool was applied. The seven studies were chosen to compare validation designs and field outcomes in crops relevant to tropical plantations, not to represent the field, so statements that a kind of evidence is absent refer to this set only. Evidence grades reflect the strength of the seven-study sample and are not formal certainty-of-evidence ratings. The inclusion of an author-associated field trial also warrants transparent interpretation, although identical extraction criteria were applied.

Table 1. Evidence extraction matrix for the seven primary studies

Study and setting	Design and validation	Key result	Main limitation
Castaldi et al. (2017); maize, four fields, Italy	UAV maps for patch spraying; patch against uniform spraying	Estimated herbicide saving 14–39.2%; no biomass loss	Temperate crop; saving estimated from untreated area
Huang et al. (2018); rice, one plot, China	RGB at 6 m; FCN; validation tiles from training images	Accuracy 0.935; weed class 0.883	One field and date
Izzuddin et al. (2020); oil palm	Multispectral; OBIA and SVM; disease index ground truth	91.8% accuracy	Light infection not separable
Zheng et al. (2021); oil palm, two sites, Indonesia	RGB; Faster R-CNN; results per site	F1 87.91% and 99.04%	Site gap; abstract only
Lee et al. (2024); oil palm, several regions	RetinaNet; annotated imagery	F1 0.947 and 0.902	Field counts not stated; abstract only
Che Ruzlan et al. (2025); oil palm, Pahang	Field trials: UAV against mist blower and knapsack	Equal pre-planting control; selective control 71.54% against 82.41%; 37% less time	Small trials; modelled costs
Tang et al. (2025); durian, Malaysia	IM-YOLO detection; route planning in simulation	Precision 90.68%; recall 79.92%	No pollination flights

3. RESULTS AND DISCUSSION

3.1 UAV PLATFORMS, SENSORS AND DATA WORKFLOWS

3.1.1 PLATFORMS AND SENSORS

The right platform follows from the decision the imagery must support and from how that decision will be checked. For a stand census over a whole estate, the binding constraints are area per flight and launch space. Fixed-wing and hybrid vertical take-

off and landing (VTOL) aircraft cover long transects on one battery, but a mature planting offers few clearings for launch and recovery, and the census is usable only once automated totals have been compared with ground counts in sample blocks. Confirming a suspected disease cluster is a different decision: area matters less than the ability to hover close to a crown, which favours a multirotor despite its short endurance (Velusamy et al., 2022; Guebsi et al., 2024). Spraying is a third case. In the Pahang replanting trials a multirotor sprayer covered 15 ha per man-day against 1.75 ha with a knapsack, so its value lay in work rate rather than in imaging (Che Ruzlan et al., 2025). Platform selection should additionally account for weather-related downtime, battery turnaround, safe take-off and landing, terrain, and the time required to convert imagery into an actionable map.

Ground sampling distance is the next choice, and it trades directly against area. Separating two grass and sedge species from rice required about 0.3 cm resolution, obtained by flying an RGB camera at 6 m over a 0.54 ha plot (Huang et al., 2018); at that height, estate-scale mapping is impractical. Multispectral cameras give up some resolution for red-edge and near-infrared bands. Indices such as the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Red-Edge index (NDRE) shift with crop stage, exposed soil and calibration, so a low value flags a problem without naming it (Guebsi et al., 2024; Yang et al., 2025). For *Ganoderma*, no single band was adequate (65.5–76.2% accuracy), while green, red and near-infrared combined reached 91.8% (Izzuddin et al., 2020). A project that must grade infection severity therefore needs at least a three-band multispectral sensor, whereas a stand census can rely on RGB. Thermal cameras add water-stress information but drift with wind, humidity and time of day (Ndlovu et al., 2024; Sharma et al., 2025). Sensor selection must be driven by the target variable and an independent ground-reference protocol; higher spectral or spatial resolution does not by itself establish better field decisions. The reported three-band result is study-specific and does not establish a universal minimum sensor specification.

3.2 APPLICATIONS IN AGRICULTURE AND PLANTATION MANAGEMENT

3.2.1 CROP VIGOUR, STRESS AND DISEASE

Basal stem rot in oil palm shows how far an aerial signal can go, and where it stops. Izzuddin et al. (2020) separated healthy, moderately infected and severely infected palms in UAV multispectral imagery with 91.8% accuracy, using classes from the *Ganoderma* Disease Severity Index. Lightly infected palms, however, could not be distinguished from healthy ones and were left out of the classification. These early-stage palms are the ones a manager most needs to find. On this evidence the imagery can map established infection and direct census teams. It is not yet an early-warning tool.

General vigour mapping meets the same limit. Low NDVI may reflect poor establishment, water stress, nutrient deficiency, disease, weeds or bare soil, and only tissue analysis, water records or laboratory checks can separate them (Guebsi et al., 2024; Anam et al., 2024). No charted study reported disease lead time against a routine census. A UAV map tells people where to look. It is not a diagnosis. A useful field benchmark would report weed-class precision, recall and intersection-over-union on independent fields, together with mapping turnaround time and the effect of false classifications on spray prescriptions.

3.2.2 WEED MAPPING AND PRESCRIPTIONS

Open paddy is the most favourable setting for aerial weed detection, and Huang et al. (2018) show both its promise and the limits of the evidence. Flying an RGB camera at 6 m over a 0.54 ha rice plot in Guangdong, China, they trained a fully convolutional network that reached 0.935 overall accuracy and 0.883 on the weed class, with *Leptochloa chinensis* and *Cyperus iria* mapped against one rice variety at one growth stage. Because the 200 validation tiles were cut from the same 91 images as the training tiles, the 0.935 figure describes how well the network separated weeds in that field on that day, not how it would perform on the next flight.

The Pahang trials add a middle case between open paddy and a closed oil palm canopy. Under 15–16-month-old palms, where the ground was still visible, multispectral imaging tracked the fall in weed cover after spraying, from 100% at treatment to 31.0% at 26 days, yet it could not tell the grass weeds apart from the legume cover crop (Che Ruzlan et al., 2025). That is a classification limit rather than a visibility limit: the weeds were in view, but their signal overlapped with the legumes. In mature plantings the problem changes again, because fronds hide the understorey from a nadir camera, and none of the charted studies tested detection there. Each setting therefore calls for different evidence: cross-field tests in paddy, finer spectral or textural discrimination where cover crops are present, and paired UAV and ground transects in mature blocks, scored against the same field counts.

Errors also cost different things in each setting. A missed grass weed in paddy competes with the crop when control matters most, and a false positive can put herbicide on rice, so studies should report class-level precision and recall with the consequence of each error (Ehrampoosh et al., 2025; Saini & Nagesh, 2025; Bhandari & Etienne, 2026).

A weed map becomes useful only once it is turned into a prescription. Castaldi et al. (2017) did this in four silage maize fields in central Italy, turning multispectral UAV images into prescription maps checked against ground truth. Herbicide savings of 14–39.2% against uniform application were estimated from the untreated area under the patch-spraying design, with no difference in maize biomass in the first season's fields. The UAV supplied the imagery, not the application, and a temperate maize result shows that the map-to-prescription step can save herbicide, not that it will in paddy or oil palm.

3.2.3 UAV SPRAYING

Spray multirotors reach waterlogged paddy and blocks without machine access, but deposition depends on nozzle, droplet size, height, speed, downwash, canopy and weather (Qin & Chen, 2023). Martin et al. (2025) found that wind speed and nozzle choice both altered deposition and drift, so settings must be validated in the field.

The Pahang trials are the only study in the charted set to set UAV spraying against conventional application in oil palm, and they covered two contrasting tasks (Che Ruzlan et al., 2025). On 10 ha of replanting land at Mengkarak, Bera, a UAV applying 40 L ha⁻¹ gave the same pre-planting control of a mixed broadleaf and grass flora as a mist blower at 50 L ha⁻¹, both reaching 100% two weeks after treatment. On 2 ha of 15–16-month-old palms with a legume cover crop, where only the grasses were targeted, the knapsack sprayer at 450 L ha⁻¹ gave higher control at every assessment, 82.41% against 71.54% at four weeks, and regrowth by twelve weeks was greater after the UAV. The operational figures pointed the other way. The UAV needed three workers instead of six, 5 h instead of 8 h, 91% less water and covered 15 ha per man-day, and labour cost fell from MYR 43.00 to MYR 8.33 per hectare. Economic

evaluation should include equipment depreciation, maintenance, battery replacement, transport, mobilisation, insurance, compliance, operator training, weather downtime, reapplication and quality assurance, rather than labour cost alone.

The trial does not settle why selective control fell short. Separate droplet tests recorded 69–424 droplets cm^{-2} at 0.25 MPa and 64–241 at 0.15 MPa, above the 40 droplets cm^{-2} the authors treat as the minimum for effective control, but those tests measured deposition per square centimetre, not the dose retained by grasses beneath the legume layer. Whether the much smaller carrier volume, interception by the cover crop or drift reduced that dose remains a research question. Until it is answered, a lower spray volume cannot be read as an equivalent dose. The product must also be registered for the crop, target and application method, under FAO and WHO (2024) safeguards and the separate CAAM approval route described in Section 3.4.3.

3.2.4 PALM COUNTING, INVENTORY AND YIELD

Palm detection has the strongest image-level evidence in the charted set, which makes it a useful test of what an F1-score can and cannot tell an estate manager. Lee et al. (2024) report F1-scores of 0.947 and 0.902 for single- and dual-species detection with a modified RetinaNet, with their largest gains on young palms that blend into the background. Those scores were computed against annotated imagery. Whether the full study also checked counts on the ground could not be established from the abstract, and that is the step an estate needs, because a model can score well overall while still missing young palms in particular blocks, where replanting and supply decisions are made. Before automated counts replace manual census, a block-level audit should compare automated and manual counts by age class and report the count error per block.

Zheng et al. (2021) show how much the site matters. Applying a modified Faster R-CNN to UAV imagery of 363,877 palms at two Indonesian sites, they reported overall detection F1-scores of 87.91% at one site and 99.04% at the other, an eleven-point difference for the same model. The defensible estate practice is to treat automated counts as a draft inventory and audit a sample of blocks on the ground, stratified by age class and terrain, before the counts replace manual census. Yield prediction is harder still (Wang et al., 2025), and no charted study predicted oil palm yield against harvest records.

3.2.5 PADDY, RUBBER AND TROPICAL FRUIT

In paddy, beyond the weed-mapping evidence above, the constraints are short flight windows, herbicide label conditions and drift towards neighbouring fields, and the control efficacy of spray drones against a ground-applied comparator in Malaysian paddy was not established in the charted studies. In rubber the evidence is thinner still. Stand inventory, gap detection and terrain mapping transfer from general UAV mapping, but no primary rubber study met the selection criteria.

Durian shows how far some applications remain from operation. Tang et al. (2025) trained a flower-detection model (IM-YOLO, based on YOLOv8) on 7,250 images of four cultivars from a Malaysian orchard, reporting 90.68% precision and 79.92% recall, and planned pollination routes of 5.43 km against 9.66 km for a standard travelling-salesman solution. Routing was tested only in simulation, and no pollination flights, fruit set or yield were measured. The work is a credible proof of concept whose claimed labour and yield benefits await field trials.

Each application pays by a different route, and Table 2 grades them using the criteria in Section 2.2.

Table 2. Evidence grade of UAV applications and the verification still required

Application	Evidence grade and basis	Verification needed
Oil palm: palm detection	Established at image level (Zheng et al., 2021; Lee et al., 2024)	Ground-audited counts across estates
Oil palm: Ganoderma mapping	Emerging; moderate and severe infection only (Izzuddin et al., 2020)	Early detection; lead time over census
Oil palm: UAV spraying	Emerging; one trial, mixed results (Che Ruzlan et al., 2025)	Multi-site, multi-season trials
Oil palm: understorey weeds	Not demonstrated	Paired aerial and ground surveys
Paddy: weed mapping	Emerging; one field and date (Huang et al., 2018)	Cross-field and cross-season tests
Paddy: spraying	Review evidence only (Qin & Chen, 2023)	Efficacy and drift against ground spraying
Maize: patch-spraying maps	Emerging; estimated saving (Castaldi et al., 2017)	Transfer to tropical crops
Rubber: inventory	Review evidence only (Guebsi et al., 2024)	Rubber-specific validation
Durian: pollination	Experimental; simulation only (Tang et al., 2025)	Field flights and fruit set

3.3 EMERGING TECHNOLOGICAL TRENDS

3.3.1 ARTIFICIAL INTELLIGENCE AND VALIDATION

Detection architectures for UAV imagery now include YOLO-family detectors, RetinaNet, Faster R-CNN, U-Net and transformer models (Saini & Nagesh, 2025; Bhandari & Etienne, 2026). Both the site and the architecture affect results. Lee et al. (2024) report gains of 1.5–6.3% for their model over competing detectors on the same data, and Zheng et al. (2021) report an eleven-point gap between two sites for a single model. These are different comparisons, made on different datasets under different evaluation conditions, so they cannot show which factor matters more; that would need one study varying architecture and site together on a common protocol.

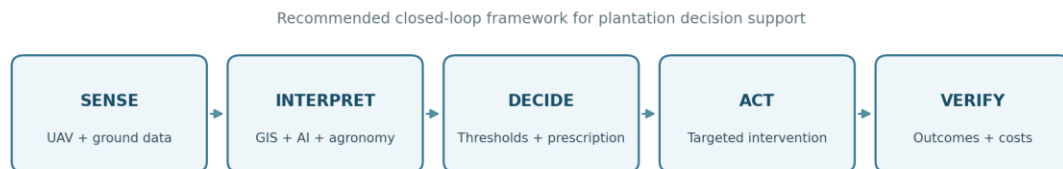
Validation design is the larger weakness. In Huang et al. (2018), the 892 training tiles and 200 validation tiles were all cut from the same 91 images of one field. Because the tiles share a field, a date and lighting, spatial dependence may weaken the independence of the validation, and the reported accuracy cannot establish performance on other fields or dates. How large any resulting optimism is was not measured. Benchmarks for tropical crops should hold out whole sites or dates; transfer learning reduces the annotation burden but does not remove domain shift between crops, soils, cameras and lighting.

3.3.2 CLOSED-LOOP SPRAYING AND THE PROPOSED FRAMEWORK

Proposals for UAV weed control usually describe an automated pipeline in which aerial images are classified, converted to georeferenced spray zones and passed to a sprayer, with follow-up imaging to check the result (Ehrampoosh et al., 2025). Rashid et al. (2025) add ground sensors and onboard processing to shorten the delay between flight and treatment, while noting connectivity, interoperability and cost barriers. The framework in Figure 1 does not claim that such a loop already works in plantations. It is a way of recording, for any UAV programme, who made each decision and what evidence supported it.

Two features separate it from the automated pipeline. The decide step belongs to an agronomist, who applies action thresholds, the product label and CAAM conditions before a map becomes a spray instruction, and records the reason. The verify step compares the outcome with conventional practice, not only with the map. Set against these five stages, the Pahang trials covered act and verify fully, since drone and conventional treatments were applied to replicated plots and scored for control and regrowth over twelve weeks. Sensing was partial, because imaging tracked weed cover but could not separate weeds from legumes, and interpret and decide were not tested, because plots were treated as whole units rather than from a weed map (Che Ruzlan et al., 2025). The verify step is where that trial proved its worth: judged against the knapsack, the drone's selective control fell short despite strong operational figures. The weakest links in the current evidence are therefore the middle stages, interpreting imagery and turning it into an accountable decision.

Figure 1. Proposed sense–interpret–decide–act–verify framework for UAV-based farm decisions



3.4 CHALLENGES AND LIMITATIONS

3.4.1 TECHNICAL, ENVIRONMENTAL AND HUMAN BARRIERS

Flight time per battery, payload and processing capacity limit how much ground one crew can cover, and afternoon convective rain and gusty wind regularly close spray windows. Skills limit the system as much as hardware, since a programme needs a pilot, an image analyst and an agronomist. On the research side, only two of the seven charted studies compared a management outcome with conventional practice.

3.4.2 ECONOMIC AND ORGANISATIONAL BARRIERS

Table 3 sets out where each cost usually falls under three arrangements: owning and operating aircraft, buying mapping or spraying as a service, or sharing equipment and trained staff through a cooperative or estate cluster. The only cost analysis in the charted set comes from the Pahang trial (Che Ruzlan et al., 2025). Its model, built on 2022 prices and two spraying rounds a year, found UAV spraying 58% more expensive than knapsack spraying at 1,000 ha and 12% more expensive at 2,000 ha, with savings appearing from approximately 3,000 ha (4%) under the study's assumptions and reaching 28% at 15,000 ha. Against a mist blower, the UAV was cheaper only at 15,000

ha (5%). These are projections from trials of 10 ha and 2 ha, not measured estate accounts, but they show how strongly the comparison depends on the conventional method chosen and the area served. A contract-based comparison should report the actual area treated annually, service availability during narrow spray windows, mobilisation fees and responsibility for unsuccessful applications. The break-even area reported for an ownership model should not be generalised to outsourced services.

Two propositions follow, both to be tested rather than assumed. Ownership turns most costs into fixed costs, so cost per hectare should fall as utilisation rises, but whether a farm reaches that utilisation depends on task frequency, service availability and quality-control needs, not on farm size alone. Service provision converts costs into a per-hectare charge but leaves the farmer with quality checks and scheduling risk. The allocations in Table 3 describe typical arrangements; real service agreements and liability provisions may move any of these costs and should replace the table when actual options are compared.

Table 3. Allocation of UAV costs and risks under three arrangements

Cost or risk	Ownership	Outsourced service	Shared
Aircraft and batteries	Owner	Provider (in fee)	Members
Insurance and CAAM approvals	Owner	Provider, per contract	Cooperative
Pilot training	Owner's staff	Provider	Shared operators
Interpretation and ground checks	Owner	Farmer, unless contracted	Members or extension
Aircraft not available when needed	Lower; breakdown and weather remain	Mostly farmer	Members compete
Failed flights and rework	Owner	Per contract	Shared

3.4.3 REGULATORY, PESTICIDE AND SAFETY CONSIDERATIONS

In Malaysia, agricultural UAS operations that dispense payloads are regulated under Civil Aviation Directive (CAD) 6011 Part (II) and require an Unmanned Aerial Work Certificate (UAWC); the standard Authorisation to Fly excludes spraying and dispensing (CAAM, n.d.). CAAM's published requirements were consulted in October 2026, and because directives are revised, the version in force should be confirmed before each spraying campaign. Registration and label conditions for the pesticide are a separate obligation from aviation approval, and FAO and WHO (2024) set out measures to limit operator exposure and off-target movement.

3.4.4 CLAIMED SUSTAINABILITY BENEFITS

Measured and projected benefits need to be kept apart. In the Pahang trials, water use, crew size and working time were measured and fell sharply. The cost advantage over knapsack spraying from approximately 3,000 ha is a projection under the study's assumptions, and the weaker selective control and greater regrowth after UAV application, also measured, could mean an extra spray round that erodes part of the

saving (Che Ruzlan et al., 2025). A fast sprayer or an accurate map changes little if the estate cannot schedule labour to act on it, so environmental claims should be judged over the whole workflow and against the management it replaces.

3.5 FUTURE RESEARCH DIRECTIONS

3.5.1 RESEARCH QUESTIONS ARISING FROM THE BARRIERS

Each barrier translates into a research question with a design that can test it (Table 4). Two designs are especially relevant to perennial tropical plantations: paired aerial and ground surveys of understorey weeds beneath closed canopies, and repeated flights matched to *Ganoderma* census records to measure how much earlier, if at all, aerial data flag infection. Both need to run over several seasons and report outcomes such as count error, detection rate, lead time, cost per hectare and active ingredient used.

Table 4. Research questions and validation designs arising from the barriers

Barrier	Research question	Validation design
Cross-site transfer	Does palm detection hold on estates with other ages and terrain?	Ground-audited counts on independent estates
Understorey occlusion	How much understorey weed cover can aerial imagery detect?	Paired UAV and ground transects
Early disease detection	Can UAV data flag <i>Ganoderma</i> before routine census?	Repeated flights matched to census
Spray efficacy and drift	Does UAV selective control match ground spraying?	Multi-site field trials
Cost of adoption	At what utilisation does ownership beat a service?	Estate and provider cost records
Long-term impact	Do UAV programmes change yield, input use or cost?	Multi-season comparative trials

3.5.2 A STAGED PATHWAY APPLIED TO WEED MANAGEMENT IN PADDY

Five stages are proposed before large-scale investment, each with a test that decides whether the work moves on. For UAV-assisted weed control in paddy, define fixes the decision and records the farm's existing spraying programme for a season as the baseline. Validate tests the weed model on fields and dates it was not trained on; Huang et al. (2018) would not yet pass. Integrate turns maps into prescriptions within the control window, since a late map is useless however accurate. Trial compares blanket, ground-targeted and UAV-targeted programmes in one season on control, regrowth, active ingredient, crop injury and cost per hectare, as the Pahang trial did in oil palm (Che Ruzlan et al., 2025). Scale then tests repeatability, training and the service model. Progression between stages should be conditional on prespecified acceptance criteria, including independent-site predictive performance, timely prescription delivery, satisfactory control without unacceptable crop injury, and total cost per hectare relative to the existing practice.

4. CONCLUSION

Within the seven primary studies charted, the evidence supports a narrower conclusion than the breadth of UAV applications suggests. Image-based palm detection is the most mature plantation application (Zheng et al., 2021; Lee et al., 2024), yet one model's score differed by eleven points between two sites, and detection still has to be translated into ground-checked inventory accuracy. Paddy weed mapping and *Ganoderma* mapping are emerging but untested beyond single sites. UAV spraying in oil palm is also emerging: equal control before planting, weaker selective grass control than knapsack spraying, large savings in water and working time, and modelled costs favouring the UAV only from approximately 3,000 ha under the study's assumptions (Che Ruzlan et al., 2025). Robotic durian pollination remains experimental, and understorey weed detection beneath mature palms has not been demonstrated.

On RQ1 and RQ2, the technologies with practical value now are RGB and multispectral mapping for inventory and scouting, with the clearest case in palm detection for oil palm inventory, subject to ground audit; UAV spraying offers operational gains in oil palm but not yet equal selective control. On RQ3, the binding constraint is the scarcity of validation on independent sites and of comparisons with conventional practice, compounded by canopy occlusion, the separate approval route for spraying under CAD 6011 Part (II) and contract-dependent economics. On RQ4, the priorities are those in Table 4, designed through the framework in Figure 1 so that a UAV's contribution is measured rather than assumed. These conclusions rest on seven purposively selected studies, one of them the author's own, and do not establish that other outcome studies are absent from the wider literature.

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Use of generative AI: During preparation and revision of this manuscript, the author used two AI-based tools. Consensus (consensus.app), an AI-powered academic search engine, was used to identify and retrieve published studies and their abstracts. Claude (Anthropic) was used to check references against bibliographic records, extract study

details from the cited publications, and edit the language and structure of the text. All sources identified through these tools were checked against publisher or bibliographic records before inclusion. The author reviewed and revised all output and takes full responsibility for the content of the publication.

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