UNIVERSITI TEKNOLOGI MARA

INTEGRATING COMMUNITY PERSPECTIVES AND A DRONE-BASED MACHINE LEARNING FRAMEWORK FOR RISK PROFILING OF POTENTIAL *AEDES* BREEDING SITES

ZULFADLI BIN MAHFODZ

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ZULFADLI BIN MAHFODZ

Thesis submitted in fulfilment
of the requirements for the degree of
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ABSTRACT

Dengue remains a major environmental health challenge in rapidly urbanising environments. This study evaluated the potential of drone technology and Machine Learning (ML) to support community-level dengue prevention in Malaysia. A cross-sectional mixed-methods design was employed, integrating three distinct analytical phases. First, a socio-behavioural assessment combined household surveys ($n = 866$) in urban and rural communities with expert interviews to evaluate public perception and readiness. Second, high-resolution red, green, and blue (RGB) drone imagery was acquired to conduct geospatial and microclimate modelling of the built environment. Finally, these environmental features were integrated into a Machine Learning pipeline to classify potential *Aedes* breeding habitats. Together, these methods form an integrated framework linking community readiness with data-driven spatial risk profiling. Under the first objective (socio-behavioural), urban residents presented higher acceptance of drone-based surveillance (65.4%) than rural residents (38.2%). Privacy concerns were significant (42.7%), particularly in rural areas ($p < 0.001$). Younger adults (18-30 years) were most willing to engage in drone-assisted control and download a surveillance application, whereas older adults favoured traditional training. Across states, a persistent knowledge-practice gap was revealed, with notable urban-rural heterogeneity. Expert interviews highlighted regulatory constraints, privacy, and community engagement as key barriers, with sociopolitical trust acting as a critical mediator. Under the second objective (geospatial), drone-based microclimate modelling revealed that vegetation-shade interactions and housing typology strongly modulate *Aedes* habitat risk. Low-density terrace housing exhibited substantially higher ecological risk scores than high-rise settings, with high-risk zones covering up to 46.5% of terrace areas. Model validation demonstrated high predictive performance ($R^2 = 0.91$), with the top 20% of predicted high-risk pixels successfully accounting for 65% of observed breeding-prone areas. Under the third objective (ML classification), single-site classification of RGB imagery achieved overall accuracies of 70-90% with moderate to strong Kappa coefficients (~0.5-0.9). However, cross-site transferability declined to 40-55% accuracy due to spectral and structural heterogeneity between housing estates. This study proposes an integrated framework that links community readiness, environmental risk profiling, and ML-based habitat classification to support targeted dengue prevention. Ultimately, the findings suggest that when embedded in meaningful community engagement and appropriate governance, drone and ML technologies can significantly enhance the precision and scalability of environmentally oriented dengue surveillance.

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LIST OF ABBREVIATIONS

Abbreviations

Ae.	*Aedes*
ANOVA	Analysis of Variance
BI	Brightness Index
CAAM	Civil Aviation Authority of Malaysia
CERI	Composite Ecological Risk Index
CRI	Composite Risk Index
CV	Cross Validation
DDBIA 1975	Destruction of Disease-Bearing Insects Act 1975 (Act 154)
ESRI	Environmental System Research Institute
ExG	Excess Green Index
GCP	Ground Control Point
GeoTIFF	Geographic Tagged Image File Format
GIS	Geographic Information System
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
GSD	Ground Sampling Distance
HSD	Honestly Significant Difference
ID	Identification
JUPEM	Jabatan Ukur dan Pemetaan Malaysia

KAP	Knowledge, Attitude and Practice
KDE	Kernel Density Estimation
LSM	Larval Source Management
ML	Machine Learning
OA	Overall Accuracy
PA	Producer’s Accurcay
PCIDA 1988	Prevention and Control of Infectios Diseases Act 1988 (Act 342)
PRISMA	Preferred reporting Items for Systematic Reviews and Meta Analyses
RF	Random Forest
RGB	Red, Green, Blue
ROI	Region of Interest
SCP	Semi-automatic Classification Plugin
SPSS	Statistical Package for the Social Science
SWOT	Strengths, Weaknesses, Opportunities, Threats
UA	User’s Accuracy
UAV	Unmanned Aerial Vehicle
COMBI	Communication for Behavioural Impact
VLOS	Visual Line of Sight
WHO	World Health Organization

CHAPTER 1
INTRODUCTION

1.1 Research Background

Dengue is currently one of the fastest-growing vector-borne viral diseases globally. Currently, it is classified as endemic in more than 100 countries, mainly in tropical and subtropical regions (Wong *et al.*, 2022). Notably, recent analyses of Global Burden of Disease (GBD) data indicate that between 1990 and 2021, the estimated incidence of dengue rose from approximately 26 million to nearly 59 million cases. This is in addition to dengue-related deaths, which also more than doubled during the same period (Zhang *et al.*, 2025). This expansion is driven by a combination of rapid urbanisation, climate change, population mobility, and insufficient vector control in many settings (Colón-González *et al.*, 2023). Moreover, this disease is transmitted primarily by *Aedes aegypti* and *Aedes albopictus*. These are highly adapted to human environments, breed in artificial containers such as buckets, discarded tyres, roof gutters, and water-storage vessels located near homes (Wong *et al.*, 2022). Likewise, these species exploit microhabitats created by poor solid waste management, intermittent water supply, and unplanned urban development. Building on this, microscale environmental factors, such as shading, vegetation, water accumulation, and housing density, strongly influence the distribution of *Aedes* breeding sites and adult mosquito density (Masrani *et al.*, 2022).

Climate variability and long-term climate change exacerbate the risk of dengue. Projections for Southeast Asia indicate that, under various climate and socio-economic scenarios, dengue incidence and burden are likely to increase in the coming decades without significant improvements in control (Colón-González *et al.*, 2023). As a result, there is a growing emphasis on innovative, environmentally grounded surveillance and control strategies that can complement conventional vector control methods. Malaysia is among the countries most severely affected by dengue in Southeast Asia. Recent analyses of Malaysian surveillance data indicate that more than 600,000 dengue cases and over 1,200 associated deaths were reported between 2015 and 2021. This represents a substantial increase compared with the previous decade (Yenamandra *et al.*, 2024). The majority of cases occur in densely populated urban and peri-urban areas. For example, spatial analyses in Northeast Malaysia have demonstrated apparent clustering of dengue cases in urban areas. This is particularly evident in higher population density, housing concentration, and inadequate environmental sanitation (Masrani *et al.*, 2022).

A recent 10-year mortality analysis reported 1,641 dengue deaths in Malaysia from 2012 to 2021, with peaks corresponding to major national outbreaks (Khaw *et al.*, 2024). These findings emphasise that dengue remains a significant cause of preventable morbidity and mortality, despite long-standing vector control programmes and legislative mechanisms. At the same time, new evidence from an extensive cluster-randomised intervention for dengue epidemiology in Malaysia trial in Kuala Lumpur and Putrajaya suggests that proactive Integrated Vector Management (IVM) should be implemented. It combines larval source management, adult control, and enhanced surveillance and can significantly reduce dengue incidence in urban Malaysia (Saadatian-Elahi *et al.*, 2025). Nevertheless, the success of IVM depends heavily on the timely and accurate identification of productive *Aedes* breeding sites in the urban landscape. Additionally, the spatiotemporal trends in mosquito-borne diseases, along with rapid changes in larval habitats, pose a significant challenge for managing mosquito breeding sites. Note that mosquito breeding site types are typically diverse within highly heterogeneous landscapes comprised of a variety of land cover types. Surveillance is a crucial part of preventing dengue, as it provides the information needed to measure risk and respond to an epidemic. In addition to the rapid detection of human infections and vectors, surveillance activities should ideally include monitoring of environmental and social risk factors.

Mosquito control strategies vary at the individual, community, and regional levels for different environments (Joshi & Miller, 2021). Traditional surveillance approaches, such as house-to-house larval surveys and complaint-driven inspections, are labour-intensive and time-consuming. However, it may miss cryptic or inaccessible containers, particularly in high-rise flats and complex built-up environments. It also lacks community participation and is susceptible to insecticide resistance in mosquitoes (Selvarajoo *et al.*, 2022). Therefore, a need for tools that can rapidly scan urban neighbourhoods and prioritise high-risk micro-environments for targeted intervention. Following this, behavioural factors remain central to dengue prevention since *Aedes* mosquitoes breed predominantly in manufactured containers. Numerous Knowledge, Attitude, and Practice (KAP) studies in Malaysia and the wider region have reported that while general awareness of dengue is often high, there are persistent gaps in risk perception, preventive behaviour, and sustained community engagement. For instance, a cross-sectional study in a Malaysian dengue hotspot discovered that although most respondents recognised dengue as serious, only a subset consistently implemented source-reduction practices. Still, dengue seroprevalence in the community remained high (Selvarajoo *et al.*, 2020). Similar patterns have been observed among university students and other groups in Malaysia, where knowledge does not always translate into effective routine practices (Khan *et al.*, 2024). Recent global and regional systematic reviews confirm that, across many countries, dengue-related KAP is suboptimal and heterogeneous, even in hyper-endemic settings (Crowley *et al.*, 2025). Importantly, these reviews emphasise the need to understand local perceptions, misinformation, trust in authorities, and barriers to effective environmental management when designing more effective interventions.

In this context, the perspectives of technical experts, such as entomologists, public health officers, and local council staff, are crucial for implementation. They are responsible for operationalising policies, translating surveillance data into action, and communicating risk to the public. Nonetheless, studies on vector-control professionals have noted challenges, including fragmented responsibilities, limited resources, difficulties sustaining community participation, and the need to integrate new technologies into existing systems (Mechan *et al.*, 2023; Saadatian-Elahi *et al.*, 2025). Relatively few Malaysian studies have jointly explored public perceptions and KAP, together with expert perceptions, regarding innovative tools such as drones. Thus, understanding both perspectives is essential for designing feasible, acceptable, and ethically sound drone-based surveillance strategies. In line with this, Unmanned Aerial Vehicles (UAVs), commonly known as drones, have attracted increasing attention as a tool for vector surveillance and control. Rapid technological advancements, driven by commercial demand and open market competition, have transformed drones from mere hobbies into potentially useful tools that can streamline surveillance activities and enhance mosquito control programmes. Over the past decade, high-resolution drone imagery and multispectral sensors have been used to detect malaria vector larval habitats, water bodies, and other environmental risk factors with high accuracy (Carrasco-Escobar *et al.*, 2019). A recent systematic review of UAV use for vector-borne disease control concludes that drones can enhance spatial coverage, provide access to difficult terrain, and generate detailed orthomosaics and vegetation indices useful for targeting interventions (Mechan *et al.*, 2023).

For dengue, drone-based studies are still emerging, yet promising. Bravo *et al.* (2021) developed methods to automatically detect potential mosquito breeding sites from UAV-acquired aerial images in urban environments. This demonstrates that high-resolution images can support semi-automated identification of containers and problem areas. Similarly, Yu *et al.* (2024) utilised drone images and deep learning models to identify mosquito breeding sites, indicating exemplary performance in distinguishing high-risk structures based on roof, vegetation, and water-holding features. Studies on community engagement and acceptability of UAV-based dengue management in Malaysia and other countries have noted that communities are generally supportive. This is provided that privacy, safety, and perceived benefits are addressed transparently (Annan *et al.*, 2022). Furthermore, advances in Machine Learning (ML) and remote sensing have transformed land-cover and risk mapping. On a similar note, Random Forest (RF) algorithms have become one of the most widely used classifiers for land cover mapping using satellite and UAV imagery, often outperforming or matching Support Vector Machines (SVMs) in accuracy and robustness (Dabija *et al.*, 2021; Tan *et al.*, 2024). Optimisation studies suggest that, with appropriate parameter tuning and data inputs, RF can achieve high Overall Accuracy (OA) in land-cover and land-use classification across urban and rural landscapes (Sun & Ongsomwang, 2023; Sabaghy *et al.*, 2025).

Despite these advances, very few studies have adopted an integrated approach that combines nationwide surveys of public perceptions and KAP related to dengue. This includes drone-based surveillance with expert interviews on the real-world feasibility and governance of UAV applications. In addition, the integration of drone-derived orthomosaics, vegetation indices, shade analysis, and RF classification within mixed-methods environmental health research remains limited. Correspondingly, this study aims to address this gap by focusing on the urban area of Shah Alam, Selangor, while drawing on stakeholders across Malaysia. This novel approach will provide high-quality evidence for a new outcome in dengue prevention and control in Malaysia.

1.2 Problem Statement

Worldwide, an estimated 390 million human dengue infections and 96 million symptomatic cases occur every year. The global incidence of dengue has increased dramatically over the last three decades and is expected to continue rising in Asia, sub-

Saharan Africa, and Latin America. Approximately half of the world's population is now at risk (Wong *et al.*, 2022). More than 100 nations in the Americas, Africa, Southeast Asia, Eastern Mediterranean, and Western Pacific regions of the World Health Organisation (WHO) are currently endemic. The Americas, Western Pacific, and Southeast Asian Regions (SEAR) are the most severely affected, accounting for 70% of the global disease burden (Prajapati *et al.*, 2022). In 2020, there were 90,304 lab-confirmed cases of dengue in Malaysia and 145 deaths. However, there is no specific treatment for dengue fever. In limited clinical trials, the live attenuated dengue vaccine is efficacious, covers serotype 4, and is safe in persons previously infected with dengue. For example, Dengvaxia was provisionally registered in Malaysia in 2016 for a two-year post-registration study. Nonetheless, Malaysia decided not to renew the registration of Dengvaxia after examining the risks associated with the vaccine. Despite promising test results for several vaccines, Malaysia has not yet authorised their use (Tay *et al.*, 2022). Thus, vector control and surveillance remain the only dengue prevention or management measures in many areas.

Dengue continues to impose a substantial health and economic burden in Malaysia, particularly in urban areas where *Aedes* mosquitoes are prevalent. Conventional surveillance and vector-control activities still rely heavily on case notification, premise inspections, and reactive fogging, which are labour-intensive and often limited in spatial and temporal coverage. Meanwhile, rapid urbanisation has produced complex residential environments, such as high-rise flats and dense terrace housing, where microhabitats favourable to *Aedes* mosquitoes can develop and change rapidly. Recurrent outbreaks, despite ongoing vector control, suggest that existing strategies, such as routine larval surveys, fogging, community campaigns, and enforcement, have not been fully effective in reducing transmission sustainably (Yenamandra *et al.*, 2024; Khaw *et al.*, 2024). In this regard, there is growing interest in using drones and high-resolution environmental data to support more proactive and spatially targeted dengue control. Still, the extent to which such technologies are technically feasible, environmentally informative, and socially acceptable in the Malaysian urban areas remains insufficiently understood. From a social and governance perspective, current evidence on KAP regarding dengue prevention in Malaysia highlights persistent gaps between awareness and sustained preventive behaviour. This includes varying levels of trust in public health interventions.

At the local level, two interrelated problems are apparent. Firstly, an incomplete understanding of behavioural and perception factors across communities and experts. While numerous KAP studies have been conducted, very few have systematically examined perceptions of using drones for dengue surveillance across Malaysian states. Moreover, there is limited evidence on how Malaysians perceive the benefits, risks, privacy issues, and acceptability of drones in their neighbourhoods, as well as how these perceptions differ between the public and experts in the Ministry of Health (MOH) (Annan *et al.*, 2022). Without this understanding, policymakers may face resistance or ethical concerns when deploying UAVs for public-health purposes. Secondly, limited spatially detailed information on microenvironmental risk factors for *Aedes* breeding in dense urban housing. Additionally, there is significantly less empirical work using drones to characterise land-cover patterns, vegetation, and shade as environmental proxies for mosquito breeding risk at the scale of residential blocks or neighbourhoods. In particular, there is a lack of detailed studies that utilise drone-derived orthomosaics and Geographic Information System (GIS) to quantify how vegetation-shade interactions differ between common urban housing typologies, such as flats and terrace houses in Malaysia. There is also minimal information on how these patterns might signal areas of higher or lower environmental risk for *Aedes* breeding. Note that existing risk maps usually rely on aggregated epidemiological data or coarse land-use categories, which are insufficient to guide fine-scale interventions within specific urban areas (Masrani *et al.*, 2022).

Furthermore, ML approaches, particularly RF classification in Quantum Geographic Information System (QGIS), have not yet been widely applied to classify urban land covers and potential breeding sites using high-resolution drone imagery in Malaysia. Other studies indicate that RF can effectively classify built-up areas, vegetation, bare ground, and water bodies from optical and multispectral imagery (Sun & Ongsomwang, 2023; Sabaghy et al., 2025). Nevertheless, their application to *Aedes* breeding site profiling in Malaysian urban contexts remains sparse. At the same time, there is little evidence on whether an open-source workflow that combines vegetation-shade indices, QGIS, and RF can produce land-cover maps of sufficient accuracy and practicality to guide local dengue surveillance and control activities. Consequently, the absence of empirically tested, operationally defined workflows constrains local authorities' ability to make informed decisions about investing in and integrating drone-based tools. Accordingly, this study has addressed these constraints by developing an integrated evidence base that simultaneously (i) captures community and expert perceptions of drone-based dengue surveillance at national and institutional levels, (ii) characterises fine-scale vegetation, shade, and land-cover patterns in real urban areas using drone and GIS tools, and (iii) evaluates the performance of RF-based land-cover classification for delineating land-cover-defined mosquito breeding sites in a Malaysian urban context. In essence, by integrating social, environmental, and ML perspectives into a coherent framework, the study provides a structured basis for assessing the use of drones for dengue surveillance and control.

1.3 Hypothesis

i) Higher dengue-related knowledge, more positive attitudes, and better preventive practices among community respondents are associated with greater acceptance of drone-based dengue surveillance.
ii) Drone-based imaging is a viable method for mapping and risk characterising in potential breeding sites of the *Aedes* mosquito.
iii) An ML algorithm trained on drone-derived spectral data can achieve high OA in land-cover classification across the study areas.

1.4 Research Objectives

The primary objective of this study is to evaluate the effectiveness of drone imagery and ML techniques for identifying potential mosquito breeding sites. The specific objectives below outline the key aims required to achieve this goal:

a) To identify the perception, specific needs, preferences, and challenges of households and experts in utilising drone technology for dengue prevention strategies.
    i) To identify sociodemographic determinants of public perception and engagement in drone-assisted dengue surveillance.
    ii) To identify sociodemographic determinants of willingness to adopt surveillance technology and mosquito control training for dengue.
    iii) To evaluate community knowledge and practices on mosquito control at the state-level and urban-rural areas for sustainable dengue.
    iv) To determine expert perspectives on drone-based surveillance of

mosquito breeding sites.

b) To evaluate the effectiveness of drone-based imaging in profiling potential breeding sites of the *Aedes* mosquito.
   i) To determine vegetation-shade interactions for *Aedes* habitat risk in urban areas using drone-based geospatial modelling
   ii) To evaluate vegetation-shade interactions and housing typology using drone-based microclimate modelling and a Composite Risk Index (CRI)

c) To evaluate the accuracy of the ML algorithm in classifying land cover types associated with potential mosquito breeding sites.

1.5 Research Question

The following research questions define the scope of this study. These specific research questions facilitate data collection and analysis, thereby enhancing the research process and yielding significant results.

a) What are the perceptions, specific needs, preferences, and challenges of local households and experts regarding the utilisation of drone technology for dengue prevention strategies across varying sociodemographic and urban-rural contexts?
b) How effective is drone-based imaging in profiling potential *Aedes* mosquito breeding sites based on micro-environmental features, specifically vegetation-shade interactions and housing typologies?
c) How accurately can a Machine Learning (ML) algorithm, using drone-derived RGB imagery, classify land-cover types associated with potential mosquito breeding sites in an urban setting?

1.6 Scope of Study

This study assesses the field effectiveness of drones in identifying potential *Aedes* mosquito breeding sites through a mixed-methods design structured into three bounded phases.

The first phase focused on understanding the community perspective of dengue and drone-based surveillance. A validated questionnaire adapted from Annan *et al.* (2022) was used to assess KAP and perceptions regarding dengue and the use of drones among residents across all states in Malaysia. The survey was administered online and via a hybrid approach to capture a wide range of sociodemographic and regional backgrounds. In parallel, semi-structured interviews were conducted with purposively selected experts and institutional stakeholders from the MOH and local councils who were directly involved in dengue surveillance and control. The semi-structured interviews focused on perceived feasibility, operational barriers, ethical and policy considerations, and the potential added value of drone-based dengue surveillance. This stage was cross-sectional and aimed to provide a national-level picture of community and expert perceptions.

In comparison, the second phase concentrated on environmental characterisation using GIS, with a specific emphasis on vegetation-shade interactions derived from drone imagery. Geographically, this component was restricted to Seksyen 24, Shah Alam, as a representative of an urban area in Selangor with documented dengue cases. Within this locality, four residential study sites, two flat housing areas, and two terrace housing areas were selected for detailed mapping to allow comparisons between different residential typologies. Following this, high-resolution orthomosaics generated from drone flights were processed in QGIS to derive land-cover layers, vegetation indices, and indicators related to shade. The purpose of this stage was to describe how vegetation, shade, and land-cover patterns interacted in these urban micro-environments and how they might be related to potential mosquito breeding risk.

The last phase, focused on the ML component, specifically on applying an RF classifier to the drone-derived datasets. Within this scope, RF was employed to classify land-cover types. As such, RF was selected for its documented robustness, relative interpretability, and firm performance in remote-sensing image classification. Building on this, the model was developed, tuned, and validated using spectral and environmental features extracted from the orthomosaics. Subsequently, accuracy assessment was conducted within a QGIS-based workflow. This stage concentrated on evaluating whether RF could provide sufficiently accurate and operationally useful land-cover classification for this specific urban context.

1.7 Limitation

This study is subject to several methodological constraints. First, the cross-sectional design of the survey and expert interviews captures data at a single point in time, precluding the assessment of temporal changes or causal relationships. Additionally, self-reported survey responses are subject to social desirability bias, and the online distribution method likely over-represented younger, urban, and digitally literate populations. Second, the geospatial and Machine Learning (ML) components were geographically restricted to four specific residential typologies in Seksyen 24, Shah Alam, meaning the observed vegetation-shade patterns and Random Forest (RF) model accuracy may require recalibration before application to other Malaysian urban contexts. Finally, environmental indicators (vegetation, shade, and land-cover) were utilised as proxies for potential *Aedes* breeding risk, without direct entomological or virological validation, which may lead to under or overestimation of actual vector density.

1.8 Conclusion

Dengue remains a significant public health challenge in Malaysia. This is particularly true in areas experiencing rapid urbanisation, increasingly complex urban form, and evolving climatic conditions. Such areas have continued to sustain a high level of transmission despite long-standing control efforts. Additionally, the limited integration of environmental structural data and emerging technologies, such as drones, into routine surveillance activities, together with uncertainties regarding community acceptability and institutional readiness, emphasise the need for more integrated, operationally grounded approaches to surveillance and vector management. In this context, the present study brings together three interlinked aspects of work: a nationwide survey and expert interviews to characterise KAP and perceptions of drone-based dengue surveillance; detailed GIS-based analysis of vegetation, shade, and land cover derived from drone orthomosaics in Shah Alam; and ML outputs as complementary lines of evidence for assessing the use of drones in dengue surveillance in Malaysia. Overall, this study provides a rigorous, policy-relevant foundation for developing more targeted, acceptable, and data-informed strategies for drone-assisted dengue vector management.

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction

Dengue remains a primary vector-borne disease in many tropical and subtropical regions, including Malaysia, where rapid urbanisation and dense residential development create favourable conditions for *Aedes* mosquitoes. As a result, vector control, particularly the elimination or management of mosquito breeding habitats, remains the basis of dengue prevention programmes. Furthermore, *Aedes* mosquitoes have adapted closely to human environments and commonly breed in natural and artificial water-holding containers around houses (Haddawy *et al.*, 2019). Recent advances in drones, high-resolution imagery, and Machine Learning (ML) have opened new possibilities for mapping environmental conditions associated with potential *Aedes* breeding sites. As such, drones can rapidly survey large or inaccessible areas, reduce field labour and costs, and generate detailed orthomosaics that support land-cover and environmental analysis (Annan *et al.*, 2022; Passos *et al.*, 2022). Therefore, this literature review is organised into several key themes. It first outlines the current dengue prevention and control strategies in Malaysia, with particular attention to Selangor, a state with a high burden of dengue.

Issues of feasibility, community and stakeholder perceptions, regulatory constraints, and operational strengths and weaknesses of drone-based approaches are considered through a scoping review and Strengths, Weaknesses, Opportunities, and Threats (SWOT) analysis. Subsequently, the ecology of *Aedes* mosquitoes and the general characteristics of breeding sites in urban environments are examined, followed by a synthesis of emerging evidence on the use of Unmanned Aerial Vehicles (UAVs), Geographic Information System (GIS)-based environmental indicators, and ML approaches, such as Random Forest (RF) models, for mosquito habitat mapping and risk classification. The chapter concludes by identifying key research gaps that can be addressed by incorporating a mixed-methods, stakeholder-informed, drone, and ML framework as a coherent response.

2.2 Dengue Epidemiology and Control: Global and Malaysian Context

Despite this growing burden, therapeutic and preventive options remain constrained. A comprehensive review of dengue antiviral research concluded that there are currently no licensed, direct-acting antivirals for dengue, and available vaccines have limited indications, typically restricted to seropositive individuals in specific age groups (Obi *et al.*, 2021). As a result, national and subnational dengue programmes continue to rely heavily on vector control and environmental management, including source reduction, larviciding, space spraying, and community mobilisation. However, many programmes struggle with limited resources, operational challenges, and the difficulty of sustaining community engagement. At the same time, conventional ground-based surveillance often provides incomplete or delayed information on the spatial distribution of vector habitats. As a result, it hampered targeted and proactive responses. These constraints have prompted growing interest in enhanced surveillance tools, including GIS-based risk mapping, remote sensing, and, more recently, drone-based environmental monitoring.

Malaysia is among the countries most affected by dengue in Southeast Asia. Indeed, a systematic review of national epidemiology and costs reported consistently high incidence rates between 2012 and 2019. This is with dengue fever and dengue haemorrhagic fever, typically ranging from approximately 244 to 398 cases per 100,000 population annually (AbuBakar *et al.*, 2022). The highest number of reported cases during that period occurred in 2019, with over 130,000 cases nationwide. In addition, dengue imposes substantial economic costs, estimated at around US$175.7 million in 2009 to 2010 for prevention and illness combined (AbuBakar *et al.*, 2022). Molecular epidemiology work further highlights the intensity and persistence of transmission. Specifically, more than 600,000 dengue cases and approximately 1,200 associated deaths were reported in Malaysia between 2015 and 2021. This is roughly double the cumulative total from 2008 to 2014, with all four serotypes co-circulating and frequent genotype replacements (Yenamandra *et al.*, 2024).

The COVID-19 pandemic highlighted the intricate relationship between dengue dynamics and broader social and mobility patterns in Malaysia. During the Movement Control Order (MCO) period in 2020, weekly dengue case counts fell markedly from pre-MCO levels, only to rebound as restrictions were eased (Zaki & Xin, 2023). Subsequent analyses suggest that changes in human movement, vector control operations, and health service utilisation all contributed to these fluctuations (Md Iderus *et al.*, 2023). More recently, official reports indicate that dengue cases and deaths have again increased, with over 100,000 cases and more than 100 deaths reported in 2024. The burden is concentrated in highly urbanised states, such as Selangor (AbuBakar *et al.*, 2022). Concurrently, these trends place sustained pressure on health services, emphasising the need for more precise, spatially explicit approaches to risk stratification and vector control, particularly in urban and peri-urban environments. Within this global and national context, this thesis develops a framework that integrates stakeholder perspectives, drone-based land-cover mapping, and ML. Specifically, it aims to contribute to more targeted dengue vector surveillance and environmental risk assessment in Malaysia.

2.3 Current Dengue Prevention and Control in Malaysia

Dengue fever has been known in Malaysia since 1902. The disease emerged as a public health concern in the 1970s, with the first major outbreak occurring in 1973 (Salim *et al.*, 2021). Due to environmental factors, rapid urbanisation, and serotype switching, the number of national dengue cases in Malaysia quadrupled in 2014. Since then, dengue has been a significant public health threat in Malaysia, with all four serotypes circulating (Selvarajoo *et al.*, 2022). In general, there are two components of mosquito control: control strategies and control methods. Mosquito control strategies determine the optimal relationship between humans, mosquitoes, and the environment. Accordingly, mosquito control strategies encompass a range of techniques, including prevention, modification, and eradication. Preventive methods focus first on eliminating mosquito breeding sites and creating environments that are uninhabitable for mosquitoes. Second, modification strategies, such as infecting mosquitoes with Wolbachia, aim to alter mosquito characteristics. Finally, eradication methods include insecticides, larvicides, and insect traps. These strategies can be implemented at small or large scales for individuals and communities (Joshi & Miller, 2021). Still, environmental and ecosystem management remain critical for disease control. Without sufficient technical support, mosquito control and surveillance efforts can become costly, time-consuming, and inefficient (Passos *et al.*, 2022).

Dengue prevention and control in Malaysia continue to rely predominantly on suppression of the two main vectors, *Ae. aegypti* and *Ae. albopictus*, in line with WHO recommendations for Integrated Vector Management (IVM). In particular, routine activities implemented by the Ministry of Health (MOH) and local authorities include larval source reduction (such as environmental clean-up campaigns, solid waste management, and elimination of water-holding containers), larviciding with temephos or other larvicides, and adult mosquito control through space spraying and fogging during outbreaks (Salleh *et al.*, 2022; Tham, 1993). Furthermore, vector surveillance is conducted using larval surveys, ovitraps, and entomological indices to guide responses. Indeed, recent work has highlighted the value of ovitrap surveillance as a core component of routine monitoring and targeted control (Hamdan *et al.*, 2021). Health education campaigns and the enforcement of public health regulations, such as fines for premises with positive breeding sites, complement these conventional approaches. Nevertheless, sustaining community participation and compliance remains a persistent challenge (Salleh *et al.*, 2022).

In 2020, Malaysia formally adopted IVM as a national strategy for *Aedes* control, emphasising the combined use of multiple tools and the integration of entomological, epidemiological, and community data to prioritise interventions (Halim *et al.*, 2025; Saadatian-Elahi *et al.*, 2025). The Intervention for Dengue Epidemiology in Malaysia (iDEM) cluster-randomised trial in urban Malaysia evaluated an IVM package that combined targeted outdoor residual spraying, deployment of auto-dissemination devices, and active community engagement. This is compared with routine vector control activities (Saadatian-Elahi *et al.*, 2025). Although the trial faced implementation challenges during the COVID-19 pandemic, it demonstrated the operational feasibility of coordinated, multi-component interventions in high-density urban settings.

In parallel, Malaysia has implemented Communication for Behavioural Impact (COMBI) programmes to increase community engagement in source reduction and environmental management. The Malaysian MOH administers COMBI. Fundamentally, COMBI is a dynamic method that utilises strategic social and communication mobilisation to promote healthy behaviour change among individuals, families, and communities. Moreover, it is grounded in theories of behaviour change, communication, and marketing. Consequently, COMBI provides a comprehensive and adaptable strategy for designing, implementing, and monitoring social and communication mobilisation interventions. This is tailored to achieve desired behaviour change outcomes (Ministry of Health Malaysia, 2023). In addition, a recent systematic review of COMBI in Malaysia concluded that these interventions could improve knowledge and certain preventive practices. Nonetheless, their effects on entomological indices and sustainability vary and are highly dependent on the local context, leadership, and community ownership (Halim *et al.*, 2025).

Malaysia has also been at the forefront of deploying biological and innovative control tools. Since 2017, the national Wolbachia programme has released *Ae. aegypti* mosquitoes carrying the wAlbB strain in multiple dengue hotspots in the Klang Valley and other urban localities (Hoffmann *et al.*, 2024). Following this, field evaluations have demonstrated the rapid establishment of Wolbachia in local mosquito populations and substantial reductions in dengue incidence, often 50% to 80% in treated areas (Cheong *et al.*, 2023). The programme is being progressively expanded to additional localities, supported by national policy statements and cost-effectiveness analyses. At the same time, digital tools such as the iDengue (2025) hotspot portal provide real-time maps of reported cases and hotspot areas, aiming to increase public awareness and prompt local clean-up actions. Although dengue vaccines have become available globally, Malaysia has not yet incorporated dengue vaccination into the National Immunisation Programme. Therefore, prevention and control remain centred on vector control and environmental management.

Despite these extensive efforts and innovations, dengue incidence in Malaysia remains high, particularly in urban states such as Selangor. This suggests that current strategies are necessary, yet insufficient to interrupt transmission. Challenges include insecticide resistance, limited human and financial resources, difficulties in sustaining community engagement, and the inherently fine-scale and dynamic nature of *Aedes* breeding habitats in dense urban environments (Salleh *et al.*, 2022; Packierisamy *et al.*, 2015). In addition, the influence of the human social factor, irregular waste collection, and poor sanitation also contributes to the failure of control programmes. Community involvement in dengue control through active elimination of breeding sites has been demonstrated to control dengue outbreaks successfully (Madzlan *et al.*, 2016). Despite this, strategies for controlling mosquitoes vary across individual, community, and regional settings (Joshi & Miller, 2021).

The persistence of these high transmission rates is heavily driven by human mobility and social mixing within urban centres. This intricate relationship between dengue dynamics and human movement was most clearly highlighted during the COVID-19 pandemic that had a profound impact on dengue surveillance and control technicians in the field, as they now face a new occupational hazard (Valdez_Delagado *et al.*, 2021). Dengue surveillance and prevention procedures are based on human case identification and vector surveillance and control at the community level. Specifically, dengue surveillance in Malaysia relies mainly on surveys of *Aedes* larvae in households and reports of laboratory-confirmed human infections (Ismail *et al.*, 2022). Additionally, vector surveillance and control measures, such as house-to-house larval surveys by health inspectors, removal of mosquito breeding sites, larvicidal activities, and fogging, have been practised for decades (Selvarajoo *et al.*, 2022; Mustapha *et al.*, 2023). Currently, health inspectors must visit residences to identify and destroy mosquito breeding sites. However, this technique is challenging for officials to implement and is associated with several drawbacks, including time constraints, safety risks, and high costs (Passos *et al.*, 2022).

Malaysia has three laws and regulations that relate to the prevention and control of vector-borne diseases. These are the Destruction of Disease-Bearing Insects Act 1975 (Act 154) (DDBIA 1975); Prevention and Control of Infectious Diseases Act 1988 (Act 342) (PCIDA 1988); and Local Government Act 1976 (Act 171). In particular, the purpose of the DDBIA 1975 is to ensure the destruction and control of disease-carrying insects. It also authorises the appropriate authority to provide medical examinations and treatment for persons suffering from insect-borne diseases. Importantly, most of the provisions outlined in the DDBIA 1975 are strictly enforced for dengue prevention and control. Moreover, the DDBIA is supplemented by Section 18(d) of the PCIDA 1988, which provides for the closure of premises where disease-carrying insects are found (Seng, 2001). Meanwhile, there is increasing recognition of the need for more precise, spatially explicit tools to identify high-risk environments and guide targeted interventions. This has increased interest in integrating advanced surveillance technologies such as GIS-based risk mapping, remote sensing, and drone-derived imagery with existing vector control infrastructure. This ultimately directly informs the focus of this study.

2.4 Current Dengue Situation in Selangor

Selangor is one of the states in Malaysia. According to the Department of Statistics Malaysia (DOSM), the total area is 7,951 km^2, and the estimated population was 6.56 million in 2021 (3.39 million males and 3.17 million females). The state is located on Peninsular Malaysia, between latitudes 3°4'25" N and 101°31'5" E. It is bordered by four states: Perak to the north, Pahang to the east, Negeri Sembilan to the south, and the Strait of Malacca to the west. Selangor is divided into 9 districts, each of which is further divided into 56 sub-districts. Notably, Selangor is a highly urbanised state in Malaysia and consistently bears the highest dengue burden nationally.

In general, a dengue outbreak is an area where two or more dengue cases occur within a 200-metre radius of the index case within 14 days of the date the index case was reported. The dengue outbreak date began on the date the second case was reported. In contrast, a dengue hotspot, on the other hand, is a localised epidemic that lasts more than 30 days from the date of onset (Ministry of Health Malaysia, 2023). Analysis of national surveillance data from 2014 to 2021 revealed that Selangor recorded the highest dengue incidence rate among all states. This is with a median of 765.4 cases per 100,000 population and a peak incidence of 1,115.0 per 100,000 in 2019 (72,543 cases) (Iderus *et al.*, 2023). Molecular epidemiological work for 2015 to 2021 similarly identified Selangor as contributing more than half (53.2%) of all dengue cases in Malaysia during that period (Yenamandra *et al.*, 2024). Essentially, these findings emphasise Selangor's role as the principal dengue hotspot in Malaysia and highlight the particular significance of understanding dengue dynamics in its urban environments.

Selangor recorded the most cumulative dengue cases in Malaysia and contributed to 90% of the national dengue cases (Salim *et al.*, 2021). From December 29, 2019, to March 4, 2023, a total of 10,128 cases were reported. Data on weekly dengue cases in Selangor were obtained from the official website of the Selangor State Health Department (JKN). As of February 28, 2023 (Epidemiological Week (EW) 8/2023), a total of 9,126 dengue fever cases have been reported in Selangor, an increase of 143.3% (5,375) from the same EW last year (3,751 cases). Specifically, Hulu Selangor recorded the highest increase in cumulative dengue cases by EW 8/2023 among Selangor districts, with 1484.4% (507 cases) over the same period in 2022 (32 cases). This is followed by Sepang with an increase of 311.7% (317 cases in 2023 and 77 cases in 2022); Kuala Selangor with an increase of 310.3% (238 cases in 2023 and 58 cases in 2022); Kuala Langat with an increase of 204.9% (250 cases in 2023 and 82 cases in 2022); Gombak with an increase of 176.1% (1.234 cases in 2023 and 447 cases in 2022); Petaling with an increase of 134.1% (2,982 cases in 2023 and 1,274 cases in 2022); Hulu Langat, with an increase of 110.8% (2.062 cases in 2023 and 978 cases in 2022); Klang, with an increase of 92.7% (1,511 cases in 2023 and 784 cases in 2022);

and finally Sabak Bernam, with an increase of 31.6% (25 cases in 2023 and 11 cases in 2022). Overall, all districts in Selangor recorded an increase in dengue fever cases, with Petaling reporting the highest cumulative case count of 2,982 cases for EW 8/2023 (Selangor State Health Department, 2023).

Within Selangor, several studies have used geospatial and time-series methods to characterise the spatial and temporal patterns of dengue transmission. A five-year analysis of dengue hotspots from 2017 to 2021 revealed that hotspots were highly clustered and recurrent, with the greatest concentration in densely populated districts such as Gombak, Hulu Langat, Klang, and Petaling (Abdullah *et al.*, 2025). Hotspot occurrence presented clear seasonal peaks, with ≥ 70 hotspots per week during defined periods of the year, indicating prolonged, localised epidemics rather than short, sporadic outbreaks. Complementary work using ML to predict dengue outbreaks at the district level in Selangor indicated that most cases occurred in urban communities. Simultaneously, climate variables, particularly temperature and rainfall, were strongly associated with outbreak risk (Salim *et al.*, 2021).

A separate time-series analysis demonstrated that dengue dynamics in one district were significantly influenced by neighbouring districts, reflecting strong spatial dependence within the Selangor urban corridor (Thiruchelvam *et al.*, 2021). Together, these studies portray Selangor as a densely interconnected urban system with persistent dengue hotspots in high-density residential and commercial areas. At finer spatial scales, urban municipalities within Selangor, including Shah Alam, have been demonstrated to contain localised clusters of dengue cases associated with specific neighbourhood characteristics. A GIS-based case study of a dengue outbreak in Seksyen 7, Shah Alam, using 2,389 dengue cases and ovitrap data from 2013 to 2014, reported that cases were highly clustered with an average nearest-neighbour distance of about 219 metres. Moreover, hotspots were concentrated around high-density residential and student areas (Mohd Hazrin Hasim *et al.*, 2018). Taken together, the evidence suggests that Selangor experiences persistently high dengue incidence, with strongly clustered hotspots in urban districts and marked heterogeneity between neighbourhoods. This pattern poses significant challenges to traditional, broad-spectrum vector control strategies. It also underscores the significance of implementing spatially targeted methods capable of identifying high-risk areas within urban areas.

2.5 Overview of Dengue Cases in Seksyen 24, Shah Alam, Selangor

Across the observation period from 2022 to July 2024, Seksyen 24, Shah Alam, recorded 431 notified dengue cases. Annual totals rose from 119 cases in 2022 to 183 cases in 2023, representing a 53.8% year-on-year increase, while 2024 recorded 129 cases from January to July only (Table 2.1). Although this partial-year figure already exceeds the full-year total for 2022 by 10 cases, it is not directly comparable to full-year totals. Within the same period, January to July 2024 (129) was 10.4% lower than January to July 2023 (144), indicating that the early 2024 burden was not uniformly higher than the preceding year.

Table 2.1
Annual Dengue Cases in Seksyen 24, Shah Alam

Year	Cases	Period Covered	Average Cases per Month
2022	119	Jan-Dec	9.92
2023	183	Jan-Dec	15.25
2024	129	Jan-Jul	18.43

Monthly patterns further clarify when notifications are clustered. Across 2022 to July 2024, cumulative counts were highest in March (63) and April (56), followed by June (53) and July (43) (Figure 2.1). In 2022, notifications rose after March, peaked in June (17 cases), and then remained at a sustained moderate level from July to December (11 to 15 cases per month). In 2023, the peak was sustained across March to May (25, 26, and 24 cases), whereas 2024 exhibited a sharper, more concentrated peak in March (36 cases). This is followed by declines in April (16) and May (12), with March contributing 27.9% of all notifications recorded in 2024 up to July.

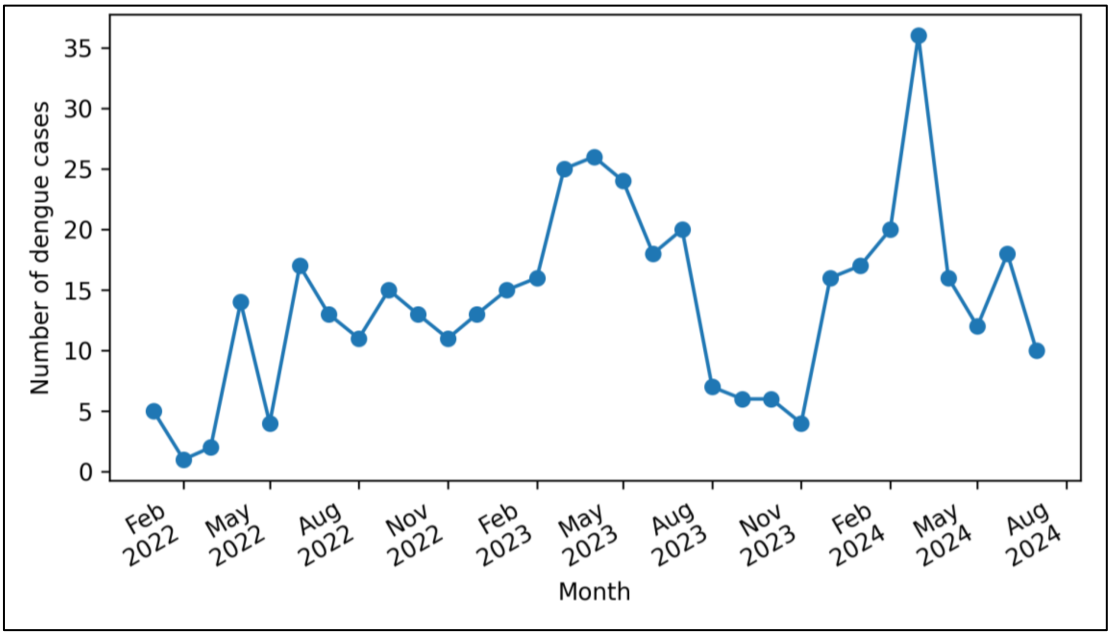

Figure 2.1 Monthly Dengue Cases in Seksyen 24 (Jan 2022-Jul 2024)

Spatially, dengue notifications in Seksyen 24 were not evenly distributed across localities. As summarised in Figure 2.2, the 10 highest-contributing localities accounted for 337 cases, representing 78.2% of all notifications. Accordingly, the three highest-burden localities were Flat G (54 cases; 12.5%), Flat B (52 cases; 12.1%), and Flat H (52 cases; 12.1%). This indicates that a substantial proportion of the dengue burden is concentrated in a small number of residential micro settings.

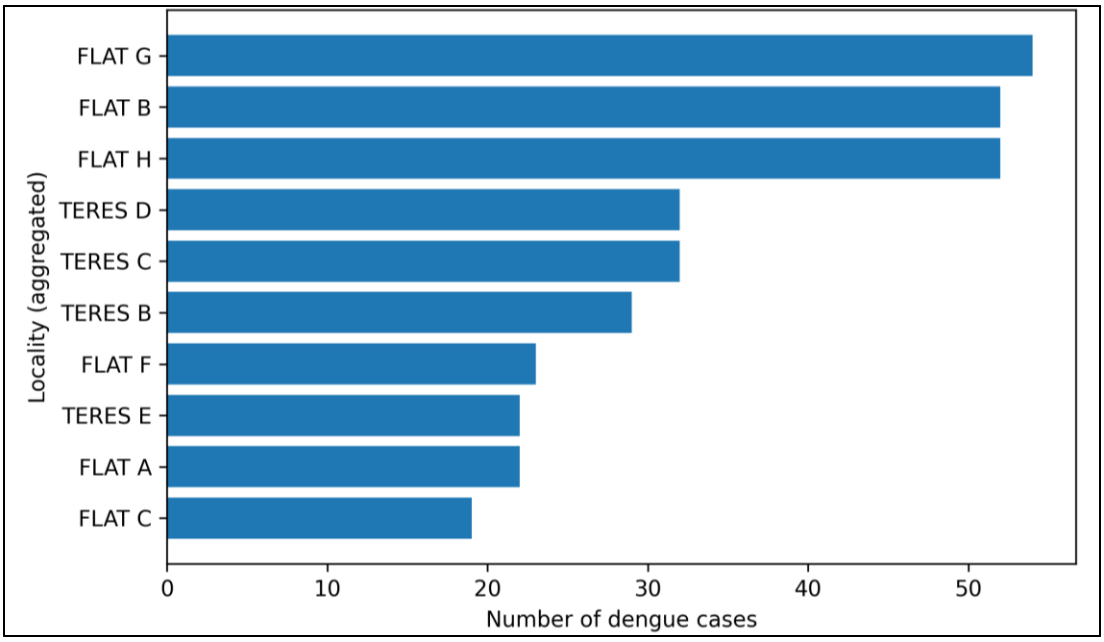

Figure 2.2 Top 10 Localities by Dengue Cases in Seksyen 24, Shah Alam (2022-Jul 2024)

Table 2.2 presents dengue cases by housing typology. Overall, high-rise housing (flats and apartments) accounted for 282 cases (65.4%), terrace housing for 142 cases (32.9%), and other settings (for example, shop-house areas) for a small residual proportion (1.6%). The predominance of high-rise settings was consistent across years, comprising 62.3% to 68.2% of annual notifications.

Table 2.2
Dengue Cases by Housing Typology in Seksyen 24, Shah Alam

Housing Typology	**Cases**	**% of Total**
High-rise (flats/apartments)	282	65.4%
Terrace houses	142	32.9%
Other	7	1.6%

The four study areas were selected to represent two high-rise settings (Flat B and Flat H) and two landed-terrace settings (Teres B and Teres D). From 2022 to July 2024, Flat B and Flat H each recorded 52 cases, while Teres D recorded 32 cases and Teres B recorded 29 cases (Figure 2.3). In total, these four localities contributed 165 cases, accounting for 38.3% of all dengue notifications in Seksyen 24 (Table 2.5). This proportion is substantial and indicates that the study areas capture a meaningful component of the dengue epidemiology in Seksyen 24 rather than representing marginal or sporadic transmission settings.

Year-specific trends varied across the four study areas (Table 2.3). Flat B reported its highest number of cases in 2023 with 23 cases, mirroring the year in which Seksyen 24 recorded its highest annual total. Conversely, Flat H remained comparatively low in 2023, with nine cases, though it rose sharply in 2024, with 25 cases reported by early July. This indicates that it contributed strongly to the increase observed in 2024. In the terrace localities, Teres D recorded 16 cases in 2023 and demonstrated a more sustained run of notifications from late 2022 through mid-2023, while Teres B increased steadily over time, reaching 13 cases in 2024 from January to July.

Table 2.3
Total Dengue Cases Contributed by the Study Areas

Study Area	**2022**	**2023**	**2024 (Jan-Jul)**	**Total Cases**	**% of Total**
Flat B	15	23	14	52	12.1%
Flat H	18	9	25	52	12.1%
Teres B	7	9	13	32	7.4%
Teres D	9	16	7	29	6.7%

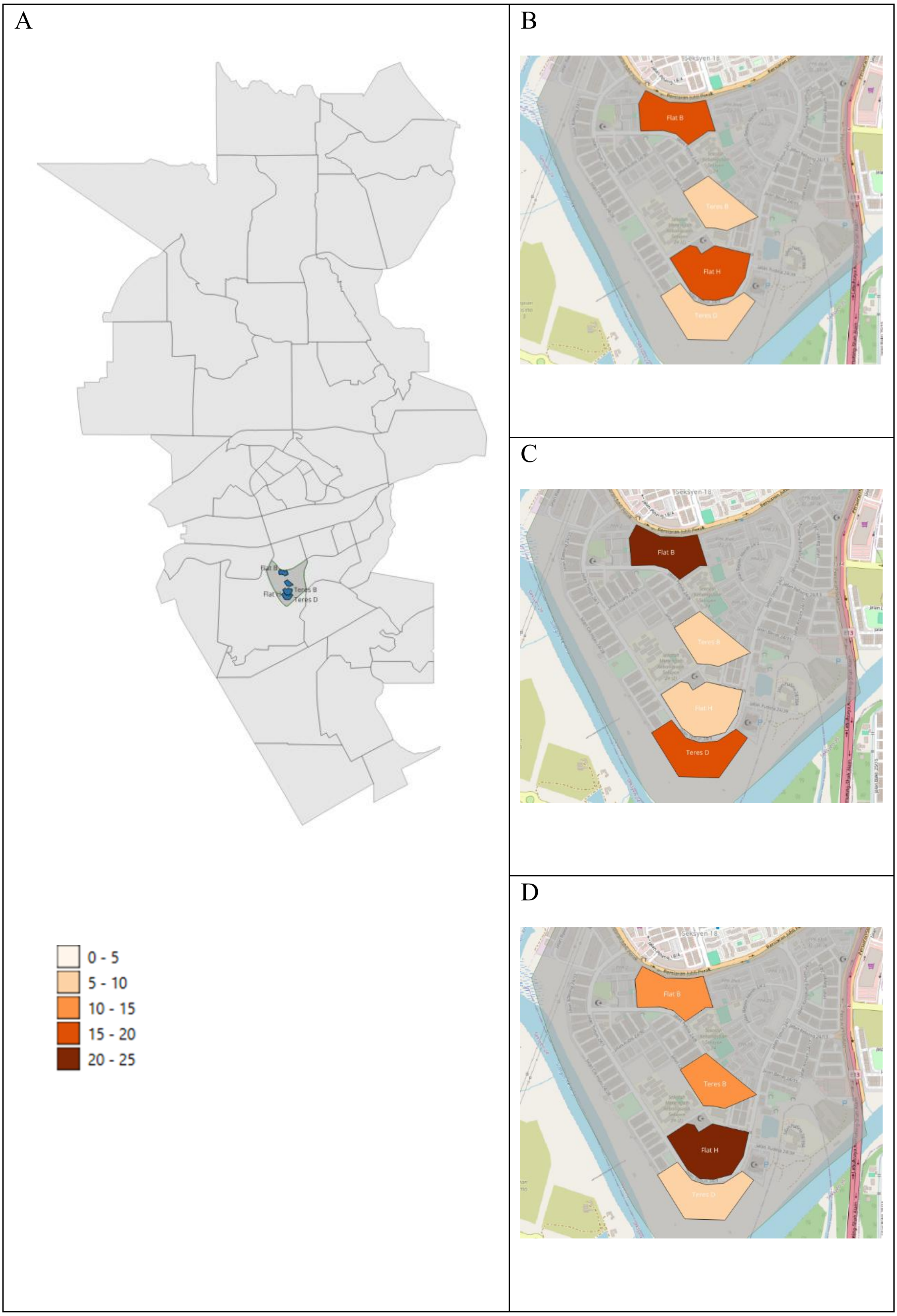

Figure 2.3 (A) Location of Seksyen 24, Shah Alam and Delineation of the Four Study Subareas (Flat B, Flat H, Teres B, Teres D); Spatial Distribution of Dengue Cases by Sub-area in (B) 2022, (C) 2023, and (D) 2024 (January-July)

2.6 Community Knowledge, Attitudes, Practices, and Stakeholder Perspectives

Many studies in Malaysia and across Asia have demonstrated that community KAP are central to the success of dengue prevention. This is mainly due to the fact that most control measures depend on household and community actions such as container management and environmental cleanliness (Guad *et al.*, 2021; Selvarajoo *et al.*, 2020; Arham *et al.*, 2025). In Malaysia, recent Knowledge, Attitude, and Practice (KAP) studies in urban and peri-urban hotspots consistently report that general awareness about dengue, its symptoms, and its mosquito vectors is often moderate to high. However, this knowledge does not reliably translate into sustained preventive practices such as regular container inspection, elimination of breeding sites, and active participation in control campaigns (Selvarajoo *et al.*, 2020; Hasrin & Ali, 2023). For example, work in a Selangor hotspot noted that approximately half of the respondents had good dengue knowledge.

Nevertheless, more than half reported poor attitudes and inadequate preventive practices, despite high Immunoglobulin G (IgG) seroprevalence indicating substantial past infection (Selvarajoo *et al.*, 2020). More recent studies in Kota Setar and other Malaysian communities presented similar patterns of acceptable knowledge, though with variable or suboptimal behaviour. Meanwhile, socio-economic status, education, and prior dengue experience emerged as important determinants of KAP (Andoy-Galvan *et al.*, 2024). At the same time, methodological advances, including validated KAP instruments for adults and adolescents, have improved the psychometric robustness of KAP assessment. This, in turn, offers more reliable tools for both research and programme evaluation (Guad *et al.*, 2021; Dapari *et al.*, 2024).

Within this landscape, behavioural and psychosocial frameworks have been increasingly applied to understand why KAP gaps persist despite repeated outbreaks and national communication campaigns. Studies using the Health Belief Model (HBM) and related constructs in Selangor and other states suggest that perceived susceptibility, perceived severity, self-efficacy, and cues to action all shape whether residents translate dengue knowledge into routine preventive practice (Othman *et al.*, 2019; Samsudin *et al.*, 2025). Additionally, qualitative work in recurrent hotspot communities further indicates that residents often normalise dengue as an unavoidable part of urban living, and are fatigued by repeated messaging. They may also view vector control as primarily a government responsibility rather than a shared duty (Samsudin *et al.*, 2024).

Conversely, school-based and theory-driven interventions such as the Integrated Dengue Education and Learning (iDEAL) module demonstrate that structured education programmes can improve KAP, environmental cleanliness indices, and entomological indicators among schoolchildren. This highlights the potential of targeted, context-sensitive education to modify behaviours when well designed and adequately resourced (Dapari *et al.*, 2024). Thus, these findings collectively underscore that KAP is dynamic, multi-determinant, and strongly mediated by risk perception, social norms, and local governance arrangements. This is rather than driven solely by knowledge (Andoy-Galvan *et al.*, 2024; Samsudin *et al.*, 2025).

In addition to local communities, the views of policymakers, local authorities, and technical staff are now widely acknowledged as vital in shaping how dengue interventions are planned, implemented, and accepted by society. Studies of stakeholder engagement and governance in Malaysia reveal moderate yet uneven levels of involvement in dengue control. This includes gaps in inter-sectoral coordination, role clarity, and long-term strategic planning (Arham & Amin, 2021; Manaf *et al.*, 2021). Surveys and qualitative research indicate that stakeholders may support innovative tools such as outdoor residual spraying, autocidal traps, or new chemical interventions.

Nevertheless, their attitudes are strongly mediated by perceived effectiveness, operational feasibility, regulatory clarity, and anticipated community reactions (Arham *et al.*, 2021; Rusly *et al.*, 2025). Furthermore, emerging evidence on drones and other digital tools further suggests that social acceptance cannot be assumed. On a similar note, a cross-country study reported high willingness among tech-savvy groups to accept UAVs for dengue surveillance. Respondents also expressed concerns regarding privacy, safety, data use, and regulatory oversight (Annan *et al.*, 2022). More recently, work in rural Malaysia has identified specific barriers to community engagement in UAV-based dengue management. This includes issues of trust, communication, perceived intrusiveness, and expectations for feedback on surveillance results (Dom *et al.*, 2025). Overall, it is a complex yet critical interface between community KAP, stakeholder perspectives, and the willingness to accept novel technologies such as drones. This also highlights the need for empirical, context-specific evidence on how Malaysian residents and experts perceive drone-assisted dengue surveillance.

2.7 General Characteristics of *Aedes* Mosquitoes' Breeding Sites in Urban Areas

In Malaysia and neighbouring Southeast Asian countries, *Ae. aegypti* and *Ae. albopictus* have adapted exceptionally well to dense urban environments, exploiting a wide range of artificial and natural containers that hold clean or slightly polluted water. The majority of dengue patients are aged 15 to 49 years, and 80% of cases occur in urban areas (Salim *et al.*, 2021). Note that increased population mixing due to the country's modern transportation network may have contributed to the increasing homogeneity of dengue risk between urban and rural areas and across all age groups over time (Chew *et al.*, 2016).

Container surveys in Kuala Terengganu, for example, indicate that water tanks, glass containers, and used paint buckets are among the most productive habitats. Correspondingly, *Ae. aegypti* predominates in urban areas, while *Ae. albopictus* more common in rural localities (Basari *et al.*, 2016). These findings are consistent with the broader understanding that *Ae. aegypti* is highly domesticated, favouring human dwellings and peridomestic spaces. Conversely, *Ae. albopictus* often exploits more vegetated, peri-urban environments. In practice, nonetheless, both species commonly co-occur across Malaysian towns and cities, colonising containers such as storage drums, discarded plastic items, construction materials, and ornamental receptacles in residential compounds, corridors, and small green patches (Basari *et al.*, 2016; Maamor *et al.*, 2023).

Due to urbanisation, globalisation, and the growth of mosquito populations, preventing mosquito-borne diseases will remain a challenge in the coming decades (Messina *et al.*, 2019). Proximity to low-income urban and peri-urban centres is also associated with a higher risk, especially in highly connected areas. This suggests that movement of people between population centres is an important factor in the spread of dengue (Bhatt *et al.*, 2013). Thus, mosquito control may reduce the future impact of mosquito-borne diseases (Joshi & Miller, 2021).

According to Getachew *et al.* (2015), prolonged storage of water in containers, extended rainfall during the recent rainy season, and ambient relative humidity and temperature favour the reproduction of *Ae. aegypti* and other *Aedes* mosquitoes. However, more *Ae. aegypti* mosquitoes breed in areas with high vegetation cover. Note that *Aedes* mosquitoes have a unique adaptation that allows them to survive in a range of habitats. *Aedes* mosquitoes are commonly found in natural and manufactured containers of clear, pure water. Furthermore, population densities of *Ae. albopictus*, previously considered a rural vector, has increased in suburban and urban areas in recent years due to factors such as water depth, specific study sites, area, and canopy cover (Annan *et al.*, 2022). In addition, *Ae. albopictus* is widespread in suburban and rural areas; nevertheless, it generally does not inhabit indoor water reservoirs. In contrast, the indoor and outdoor breeding habitats of these two vector species overlap in several countries, including Malaysia (Sairi *et al.*, 2016; Roslan *et al.*, 2022).

Urban housing typologies in Malaysia also shape the vertical and horizontal distribution of *Aedes* breeding. For instance, studies in high-rise residential settings demonstrate that vector infestation is not confined to ground floors. Ovitrap surveys in selected urban apartments indicate that *Aedes* eggs and larvae can be detected across multiple storeys. This includes appreciable infestation in mid- and upper-level corridors and common areas (Ab Hamid *et al.*, 2020). Similarly, a detailed case study of a dengue outbreak in Malacca high-rise buildings reports that a substantial proportion of positive containers are located in semi-indoor communal spaces. Corridors, stair landings, and service areas are locations where small water-holding items, poor housekeeping, and limited sun exposure combine to sustain breeding (Yahya & Che Dom, 2020). Hence, these studies emphasise that in high-density Malaysian cities, *Aedes* breeding cannot be considered solely a ground-level problem. Instead, vertical stratification, access to light, airflow, and shade, and the distribution of micro-habitats across floors are all relevant.

According to the study by Selvarajoo *et al.* (2022), apartments and floors with a high number of *Ae. aegypti* captures also indicate an increase in dengue cases. Since *Ae. aegypti* is a more efficient dengue vector than *Ae. albopictus*, it is possible that the prevalence of *Ae. aegypti* increases the risk of dengue transmission. Recent research indicates that *Ae. aegypti* prefers to lay its eggs near the ground and rarely travels more than 100 metres after feeding. Therefore, the spatial heterogeneity of the *Ae. aegypti* population across various locations may be a factor in the differential transmission and occurrence of dengue cases. In dengue-endemic regions, environmental factors such as standing water where mosquitoes lay their eggs, poor housing quality, lack of air conditioning, and climatic factors (such as temperature, precipitation, and humidity) increase the frequency, distribution, and risk of exposure to *Ae. aegypti*, the primary vector for dengue transmission (Wong *et al.*, 2022).

In urban environments, mosquitoes are more likely to use water containers in early developmental stages (Madzlan *et al.*, 2016). There are two types of potential mosquito breeding sites: artificial (man-made) and natural containers. *Aedes* mosquitoes breed in standing and clean water. Consequently, all water-bearing containers, including water tanks, buckets, ornamental fountains, planters, animal water bowls, and car tyres, can serve as breeding sites (Madzlan *et al.*, 2016; Amarasinghe *et al.*, 2017). Building on this, the relationship between mosquitoes and human populations is a dynamic phenomenon that depends on several variables, including global temperature and heterogeneity (Tay *et al.*, 2022). Based on environmental conditions, whether indoors or outdoors, residential areas are often potential breeding sites. That is, important mosquito habitats are located near common areas, primarily residential areas. When vegetation exists between a residential area and a mosquito breeding site, it provides a pathway for biting insects to enter community areas (Azura *et al.*, 2021). Some studies reported that the invasion of *Aedes* mosquitoes in high-rise apartments could promote the spread of the Dengue Virus (DENV). As such, new vector management strategies should be developed for this type of residential area (Hamid *et al.*, 2020; Lau *et al.*, 2013).

Beyond established residential neighbourhoods, *Aedes* breeding is also documented in public urban spaces. At residential construction sites in Malaysia, entomological surveys reveal abundant *Aedes*-positive containers in areas with incomplete drainage, stored construction materials, irregular waste management, and pockets of vegetation. This highlights the entomological significance of active development fronts within cities (Maamor *et al.*, 2023). In Kuala Lumpur, a study of major urban parks near dengue outbreak areas indicates that rain-filled, uncovered containers in shaded, vegetated zones constitute key larval habitats. Simultaneously, spatial analysis suggests clustered breeding patterns within specific park sectors (Mahmud *et al.*, 2023). Together, these findings suggest that urban *Aedes* risk in Malaysia extends across a mosaic of land-use types. This includes landed housing, flats, high-rise blocks, construction sites, and public green spaces, where water-holding containers interact with shade, vegetation, and human activity.

In Singapore, an environmental case-control study using gravitrap indices reports that high *Ae. aegypti* abundance in high-rise public apartments is associated with older building age, the presence of gully traps, and poorer corridor cleanliness. At the same time, vegetation and structural design can modulate the suitability of surrounding spaces for *Aedes* oviposition (Fernandez *et al.*, 2023). Evidence from Malaysia and other Southeast Asian cities reinforces the role of fine-scale built-environment and micro-environmental features in shaping *Aedes* breeding patterns. Such work aligns with Malaysian studies in emphasising that dengue vector breeding is concentrated where structural features (such as drainage, building age, housing type) intersect with environmental factors (such as vegetation, shade, rainfall) and human behaviours (such as storage practices, waste handling, maintenance). Concurrently, this study focuses on (i) residential typologies (flat versus terrace housing), (ii) land-cover characteristics (such as vegetation, built surfaces), and (iii) shade. These can be mapped and quantified using drone imagery and GIS in order to identify potential breeding sites in urban areas.

2.8 Use of Geographic Information System (GIS) and Land-Cover Mapping in Dengue Risk Assessment

GIS has become a core component of contemporary dengue surveillance, as it enables case data, environmental factors, and vector information to be visualised, analysed, and modelled explicitly in spatial terms. A recent scoping review of GIS in dengue surveillance highlighted that the most common applications include mapping incidence, identifying spatial and spatio-temporal clusters, generating hotspot maps, and integrating climatic and socio-environmental data. All these can support targeted control (Nayak *et al.*, 2025). Across endemic countries, GIS-based workflows typically start from geocoded dengue case data at the household, neighbourhood, or district level. Subsequently, it applies spatial statistics such as Kernel Density Estimation (KDE), Moran's I, or space-time scan statistics to delineate persistent transmission foci and guide prioritisation of vector-control resources (Masrani *et al.*, 2022; Abd Naeeim *et al.*, 2022; Majid *et al.*, 2019; Majid *et al.*, 2021).

In Malaysia, a growing body of work has utilised GIS to examine dengue dynamics in diverse settings. This implies that cases tend to cluster in densely built-up, rapidly urbanising areas. In addition, spatio-temporal clustering analyses can anticipate where outbreaks are likely to intensify if no additional control measures are implemented (Foad *et al.*, 2023; Hadi *et al.*, 2025; Abdullah *et al.*, 2025). Beyond mapping case counts, an important evolution has been the integration of land-cover and landscape indicators derived from remote-sensing data into dengue risk assessment. For instance, a systematic review of remote-sensing applications in dengue research established that satellite imagery at varying spatial resolutions has been used to characterise urbanisation, vegetation cover, surface water, built-up density, and thermal patterns. These environmental indicators are then linked statistically to dengue incidence or vector indices.

In Brazil, Lorenz *et al.* (2020) employed very high-resolution WorldView imagery data to present *Ae. aegypti* infestations. They discovered that mosquito presence was positively associated with specific land-cover types, such as asbestos roofs and exposed soil, and with thermal features indicative of warmer microenvironments. Conversely, infestations were being negatively associated with green areas and certain pavements. More recently, Teillet *et al.* (2024) used fine-scale satellite data to demonstrate that urban landscape metrics, including building density, vegetation structure, and road patterns, could accurately predict the spatial distribution of potential *Aedes* breeding sites. This, in turn, supports the use of land-cover proxies as a complement to conventional field surveillance.

At broader spatial scales, land-cover and climate-derived indicators have also been incorporated into regional or national risk models. For example, Galeana-Pizaña *et al.* (2024) applied a Bayesian spatial model in Mexico. They reported that municipal-level forest loss, precipitation, and temperature jointly influenced dengue incidence, with even small reductions in forest cover associated with marked increases in risk. Similarly, studies in South and Southeast Asia have exploited land-surface temperature and urban heat island metrics from thermal remote sensing to establish that warmer urban cores often coincide with higher dengue incidence. This is presumably due to their effects on *Aedes* survival and viral replication (Sureshkumar & Shekhar, 2025).

More recently, work in Rio de Janeiro has used geospatial big data combining satellite imagery, street-network features, and census data to derive urban *Ae. aegypti* suitability indicators. This illustrates how composite land-cover and built-environment metrics can be translated into operational indicators for vector surveillance and control (Knoblauch *et al.*, 2025). GIS and land-cover mapping now extend far beyond simple case plotting, towards integrated, multi-source risk assessment that links dengue transmission to the configuration of the urban environment. However, most of this work relies on satellite imagery resolution, which may overlook fine-scale environmental heterogeneity within neighbourhoods and individual housing typologies. In the Malaysian context, GIS-based studies have primarily focused on district or city scales and have rarely incorporated very high-resolution land-cover mapping or vegetation-shade indices. This creates a methodological niche for approaches that combine GIS with higher-resolution imagery, such as drone-derived orthomosaics, to characterise micro-environmental patterns within specific urban residential areas.

2.9 Scoping Review on the Viability of Unmanned Aerial Vehicles in Identifying Potential Breeding Sites of Mosquitoes[1]

The DENV infects humans through a bite from a female mosquito. Dengue fever is now deemed endemic in over 100 countries, with Asia bearing more than two-thirds of the burden (Haddawy *et al.* 2019). The principal vector of dengue, yellow fever, and chikungunya is *Ae. aegypti* (Passos *et al.*, 2022). The spread of *Ae. aegypti* is a severe public health issue. This relationship is further increased by the mosquito's ability to disperse and adapt to new surroundings and poor sanitation (Aragao *et al.*, 2020). Consequently, targeted environmental and ecosystem management remains critical for controlling dengue, given the lack of effective vaccines or antiviral treatments (Haddawy *et al.* 2019). Notably, dengue can thrive in either artificial containers or naturally occurring environments (Amarasinghe *et al.*, 2017). Specifically, stagnant and unpolluted water is ideal for the reproduction of *Aedes* mosquitoes (Mehra *et al.*, 2016). Moreover, they have adapted to human environments and can now be seen breeding in various small containers (Haddawy *et al.* 2019).

Nevertheless, the prevention of mosquito-borne diseases will continue to pose difficulties in the coming years due to rapid urbanisation and globalisation, coupled with the dynamic changes in mosquito populations (Messina *et al.*, 2019). Various strategies for controlling mosquitoes can be tailored to suit individual, community, and regional environments. Note that mitigating mosquito proliferation can lessen the future effects of diseases transmitted by mosquitoes (Joshi & Miller, 2021). Such efforts could result in costly, time-consuming, ineffective monitoring and control without an efficient mosquito management strategy (Fernandes *et al.*, 2018; Passos *et al.*, 2022). In addition, field technicians have encountered a new occupational risk while performing dengue surveillance and control during the COVID-19 pandemic (Valdez-Delgado *et al.*, 2021). At the same time, health inspectors must visit residences to identify and eliminate potential mosquito breeding sites. However, this technique poses a significant challenge

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[1] Mahfodz, Z., Dom, N. C., Abdullah, S., & Precha, N. (2024). Viability of unmanned aerial vehicles in identifying potential breeding sites for mosquito. *The Medical Journal of Malaysia*, *79* (Suppl 1), 148-157.

for officials and has several drawbacks, including time constraints, safety concerns, and cost (Mehra *et al.*, 2016; Passos *et al.*, 2022).

Drones are rotary or fixed-wing aircraft operated remotely. When equipped with suitable sensors, drones can be used in a wide range of public health, agricultural, forestry, and ecological monitoring applications (Stanton *et al.*, 2021; Passos *et al.*, 2022). As such, drones are viable alternatives to manual assessment, as they can be manoeuvred to overcome obstacles that impede human access. It can also be used as a suitable platform for remote photography, mapping, and data collection (Aragao *et al.*, 2020). Accordingly, drones can capture images or recordings at higher spatial or temporal resolutions from various angles and altitudes (Grubesic *et al.*, 2018). Finally, using a programmable drone enhances the auditors' safety by reducing their exposure to potentially hazardous situations or locations (Hardy *et al.*, 2017; Haas-Stapleton *et al.*, 2019; Carrasco-Escobar *et al.*, 2019).

This study aims to review existing research on the viability of using drones to identify potential breeding sites for *Aedes* mosquitoes. In particular, the advancement of drone technology and its integration with ML have made drones promising tools to complement current dengue prevention strategies. Concurrently, this review highlighted the issues, challenges, and limitations of recent drone research as a guideline for future studies before field implementation.

2.9.1 Methodology

This research adhered to the framework by Arksey *et al.* (2005) to conduct a scoping review, which provides a comprehensive perspective on a complex topic by mapping available data from different sources. The five stages of this approach include identifying the research question, identifying relevant studies, selecting studies, charting the data, and collating, summarising, and reporting the results. This review also follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) recommendations (Figure 2.6).

A literature search was conducted in December 2022 across the following online databases: Scopus, Web of Science, ScienceDirect, and IEEE Xplore. Importantly, no time constraints were imposed on the literature search strategy. To maximise the scope of the initial literature search, a two-block search strategy was used and modified from Hiebert *et al.* (2020). Correspondingly, block one contained drone-related nomenclature, whereas block two contained mosquito-related nomenclature (Table 2.4).

Table 2.4
Terms Used in the Initial Document Search Strategy to Identify Articles

Block 1 - Drone-related Nomenclature	**Block 2 - Mosquito Surveillance Nomenclature**
Unmanned Aerial Vehicle	Mosquito
Unmanned Aircraft System	Vector control
Drone	Breeding site

The search was constructed in three steps: (1) the Boolean operator "OR" was used to connect all terms in block one; (2) the Boolean operator "OR" was used to connect all terms in block (2); and (3) the Boolean operator "AND" was used to connect all terms in block one with all terms in block two to ensure all documents retrieved included both drone and mosquito related nomenclatures. The exact search string was used for all online databases selected (Figure 2.4).

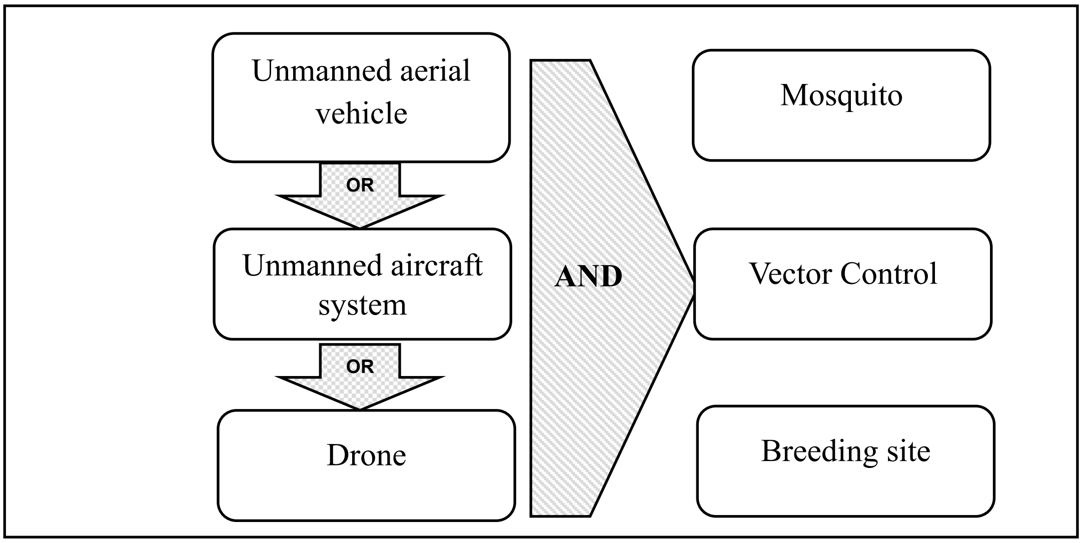

Figure 2.4 Boolean Operators Used to Connect the Term Search

Following the article search strategy (Figure 2.5), the significance and relevance of the selected literature were evaluated based on its subject matter and publication format. During title and abstract screening (Figure 2.6), documents were maintained for full-text review if they fulfilled the following inclusion criteria; (i) The title or abstract emphasises the application of drones for surveillance and control of mosquitoes breeding sites; (ii) The studies conducted for any species of mosquito regardless of any stage of the life cycle; and (iii) The document must be a full research paper and written in English.

At this stage, documents were omitted from analysis if any of the subsequent conditions were met; (i) The document was not related to the application of drones for surveillance of mosquitoes breeding sites; (ii) The document was a review article, operational note, newsletter, book chapter, commentary, editorial note, unpublished manuscript, or conference abstract; (iii) The document was authored in a language other than English; and (iv) The document was duplicate or non-availability of the full text articles.

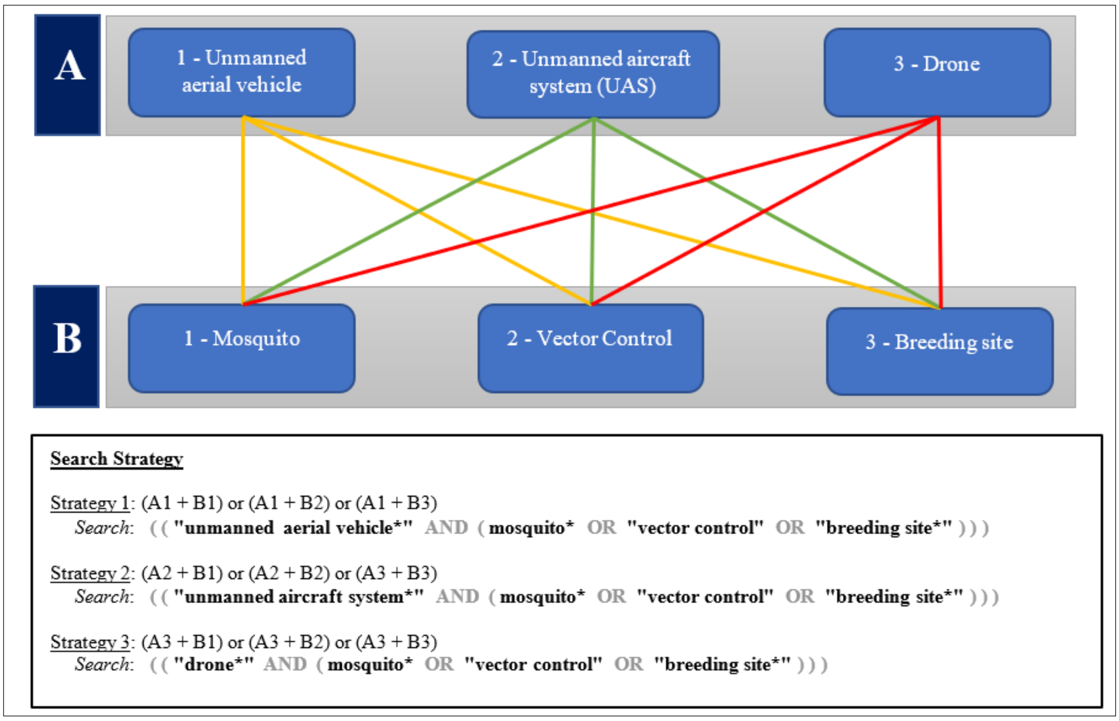

Figure 2.5 Article Search Strategy. A: Block One Contained Drone-related Nomenclatures. B: Block Two Contained Mosquito Surveillance Nomenclatures

Following the identification of articles in the aforementioned databases, they were imported into EndNote Version 20.4.1 (Clarivate, Philadelphia, Pennsylvania, United States), where duplicates were removed. Only documents that appeared relevant to the topic at hand and met the inclusion criteria were retained for a more in-depth read. The full texts of articles were then retrieved to identify which were eligible for inclusion in the review, as presented in the PRISMA flowchart (Figure 2.6). A data extraction form (Table 2.6) was used to extract study details such as the paper identification (ID), the author(s), the year of publication, the study objectives, the study sites, the mosquito species, and the disease studied (if specified), the methodological approaches, and the application of drones.

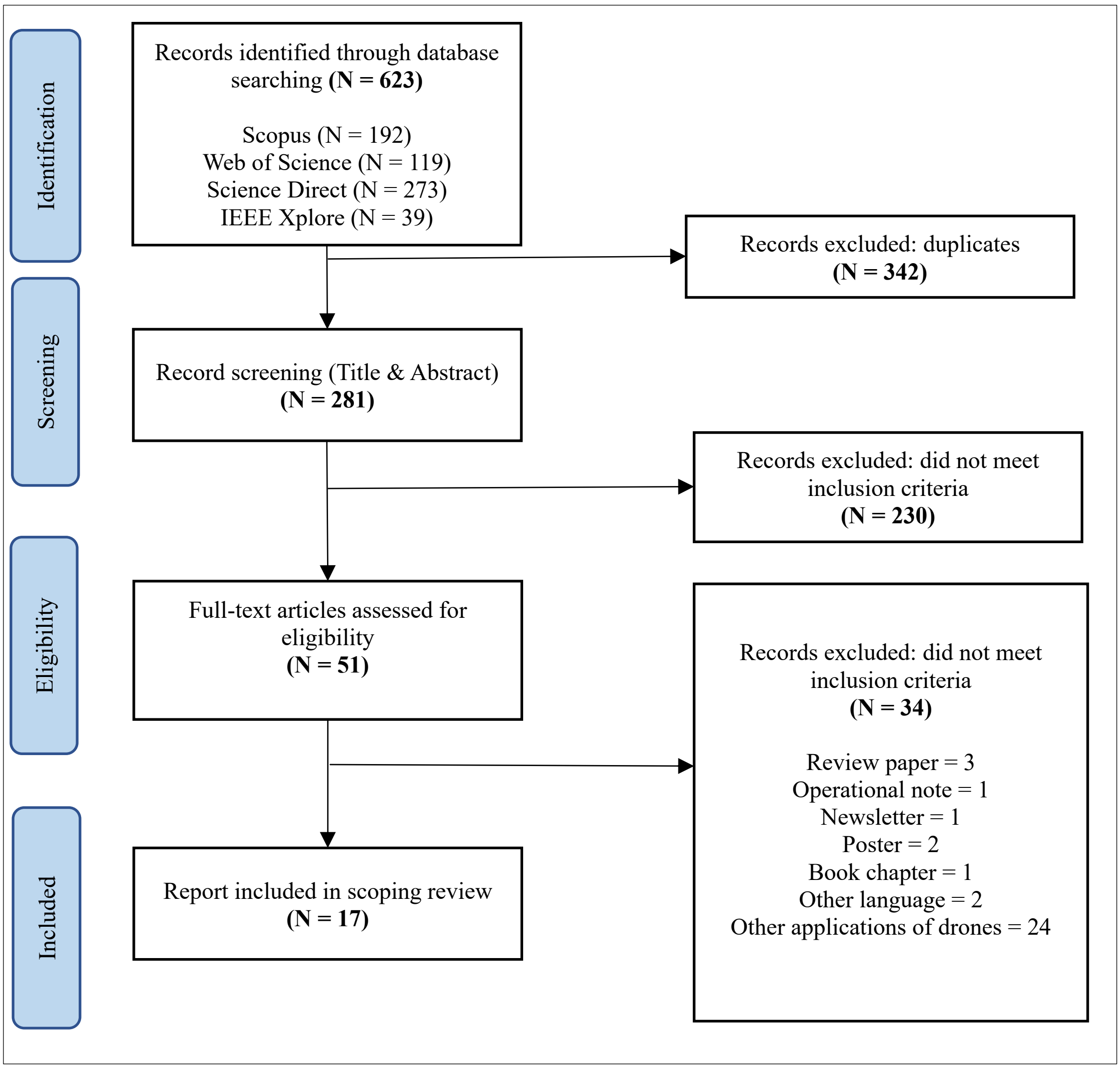

Figure 2.6 Flowchart of Article Selection using PRISMA Guidelines

2.9.2 Results

The initial search using the keywords yielded 623 documents across four databases: Scopus (*n* = 192), Web of Science (*n* = 119), ScienceDirect (*n* = 273), and IEEE Xplore (*n* = 39). A total of 342 articles were excluded after title, abstract, and duplicate screening. The remaining 51 articles were assessed for eligibility individually. Finally, only 17 full-text articles met the inclusion criteria. The comprehensive review process for the study collection is depicted in Figure 2.6. Table 2.5 summarises the articles included in the scoping review. The included publications were published between 2016 and 2022. There were two studies in 2016, three in 2017, one each in 2018 and 2019, two in 2020, five in 2021, and three in 2022, with 71% published within the last five years. Most of the articles reviewed were from Brazil. Sri Lanka was second with three articles, followed by Tanzania and Malawi with two articles each. Meanwhile, the United States, Ecuador, India, Mexico, and Peru each contributed one article. Dengue fever treatment has a significant economic impact in several countries, particularly Brazil. Hence, a study conducted across 17 Latin and Central American countries estimated that the annual cost of dengue outbreaks exceeds US $3 billion, with Brazil alone accounting for US $1.4 billion (Laserna *et al.,* 2018). There has also been considerable international collaboration, with some authors studying regions outside their own. As mosquito populations continue to expand, greater international collaboration is expected.

The objectives of the selected studies can be summarised under four main headings. First, nine documents (50%) focused on identifying and mapping potential mosquito breeding sites using high-resolution drone imagery. Following this, seven documents (38.9%) addressed computer-based approaches, including ML and remote sensing, to map mosquito breeding sites using aerial drone imagery. Moreover, one paper (5.6%) examined the effectiveness of the two technologies for surveying a study area, which are drones and Global Positioning System (GPS)-based receivers. In addition, one document (5.6%) examined the relationship between socioeconomic status and mosquito breeding sites. Dengue fever is endemic in many of the regions studied. In particular, the most studied species is the *Aedes* mosquito *(Ae. aegypti* and *Ae. albopictus*). *Aedes* sp. accounted for 64.7% of the mosquito species analysed; *Anopheles* sp. accounted for 29.4%, and one study did not report any of the mosquito species involved (5.9%). Building on this, dengue was the most frequently discussed disease (41.7%), followed by Zika (25%), malaria (20.8%), and chikungunya (12.5%). Since a single mosquito species can serve as a vector for multiple mosquito-borne diseases, some studies addressed multiple diseases. Most studies were conducted in urban areas or in a combination of suburban and rural areas. Accordingly, 52% of the study focused on urban areas, 33% on most suburban areas, and 14% on rural areas.

Integrating ML techniques into surveillance activities has gained interest in many studies. That is, 70.6% of the selected articles used ML in their research. Another 29.4% analysed high-resolution imagery from drone technology. Most of the study was conducted using a DJI drone from Shenzhen, China. The DJI Phantom 4 was the most widely used, accounting for 47.1%, followed by the DJI Phantom 3 (23.5%), and only one study utilised the DJI Phantom 2 (5.9%). Another type of drone from the French company Parrot, the AR, was also employed in one study (5.9%). In the remaining three studies (17.6%), the type of drone used was not specified. All studies (100%) were at the same implementation level, namely proof of concept, with a descriptive study design. However, the application of drones in the study was either for surveillance purposes (82.4%) or larval control (17.6%).

Table 2.5
General Characteristics of Articles Included in Scoping Reviews

Characteristic	***n* (%)**
1.Publication Year	
a. < 2018	5 (29.4)
b. 2018 - 2022	12 (70.5)
2.Study Objective (can be more than 1 objective per article)	
a. Identify and map the potential breeding sites of mosquitoes using a drone	9 (50)
b. Study computational approaches, including ML and remote sensing, for the automatic identification of objects and mapping mosquito breeding sites using aerial images from drones	7 (38.9)
c. Investigate the effectiveness of drones and GPS in identifying potential mosquito breeding sites.	1 (5.6)
d. Investigate the socioeconomic level associated with identified mosquito breeding sites.	1 (5.6)
3.Study sites	
a. Brazil	5 (29.4)
b. Sri Lanka	3 (17.6)
c. Tanzania	2 (11.8)
d. Malawi	2 (11.8)
e. USA	1 (5.9)
f. Ecuador	1 (5.9)
g. India	1 (5.9)
h. Mexico	1 (5.9)
i. Peru	1 (5.9)
4.Species of mosquito studied	
a. *Aedes* sp.	11 (64.7)
b. *Anopheles* sp.	5 (29.4)
c. Not specified (general)	1 (5.9)
5.Type of disease concerned (can be more than 1 disease per article)	
a. Dengue	10 (41.7)
b. Zika	6 (20.8)
c. Malaria	5 (25.0)
d. Chikungunya	3 (12.5)
6.Integrate Machine Learning Techniques	
a. Yes	12 (70.6)
b. No	5 (29.4)
7.Type of Study Area (can be more than 1 type of study area per article)	
a. Urban	11 (52)
b. Suburban	7 (33)
c. Rural	3 (14)
8.Type of drone	
a. DJI Phantom 4	8 (47.1)
b. DJI Phantom 3	4 (23.5)
c. DJI Phantom 2	1 (5.9)
d. Parrot's AR	1 (5.9)
e. Not specified	3 (17.6)
9.Type of drone activity (can be more than 1 activity per article)	
a. Surveillance	14 (82.4)
b. Control (larva)	3 (17.6)

Table 2.6
Summary Findings of Eligible Articles

			Methodology						Application of a Drone	
ID	**Author (Year)**	**Objective**	**Study Site**	**Species of Mosquito Studied**	**Disease Concerned**	**Study Design/Area**	**Integrate Machine Learning Techniques (YES/NO)**	**Summary - Data Processing/Software Used**	**Type of Drone**	**Type of Activity**
1	Mehra *et al.* (2016)	To identify the presence of stagnant water bodies in images taken from UAVs.	Brazil	*Aedes* sp.	Zika	Descriptive/Urban	YES	Naive Bayes Classifier (NBC), Ensemble Method, Adaptive Boosting	Not specified	Surveillance
2	Prasad *et al.* (2016)	To inspect and identify stagnant water patches in hard-to-access areas using a quadcopter.	India	*Not specified*	Dengue	Descriptive/Urban	YES	Support Vector Machine (SVM), optical flow classifier	Parrot's AR drone	Surveillance
3	Amarasinghe *et al.* (2017)	To capture the images of the water retention areas via a drone and generate a map.	Sri Lanka	*Aedes* sp.	Dengue	Descriptive/Urban & Suburban	YES	SVM, Histogram of Oriented Gradients (HOG) feature extraction	DJI Phantom 4 and DJI FC330 (DJI, Shenzhen, China)	Surveillance
4	Suduwella *et al.* (2017)	To identify the possible water retention in inaccessible areas via drone images.	Sri Lanka	*Aedes* sp.	Dengue & Zika	Descriptive/Urban	NO	Waypoint generator	DJI Phantom 4 and DJI FC330 (DJI, Shenzhen, China)	Surveillance

ID	Author (Year)	Objective	Methodology						Application of a Drone	
			Study Site	Species of Mosquito Studied	Disease Concerned	Study Design/Area	Integrate Machine Learning Techniques (YES/NO)	Summary - Data Processing/Software Used	Type of Drone	Type of Activity
5	Hardy *et al.* (2017)	To map water bodies as targets for Larval Source Management (LSM) using low-cost drones.	Tanzania	*Anopheles* sp.	Malaria	Descriptive/Suburban	NO	Quantum Geographic Information System (QGIS), Agisoft	DJI Phantom 3 and DJI 4K Edition camera	Control (Larva)
6	Dias *et al.* (2018)	To determine mosquito-breeding habitats' location by employing computer vision tools on aerial images using UAVs.	Brazil	*Aedes* sp.	Dengue, Chikungunya, Zika	Descriptive/Suburban	YES	RF Classifier	DJI Phantom Vision 2 Plus (DJI, Shenzhen, China)	Surveillance
7	Carrasco-Escobar *et al.* (2019)	To identify mosquito breeding sites with high-resolution imagery (~0.02m/pixel) and their multispectral profile from a drone.	Peru	*Anopheles* sp.	Malaria	Descriptive/Suburban	YES	ArcGIS, Pix4D, Agisoft, RF Classification	DJI Phantom 4 Pro (DJI, Shenzhen, China)	Control (Larva)

ID	Author (Year)	Objective	Methodology						Application of a Drone	
			Study Site	Species of Mosquito Studied	Disease Concerned	Study Design/Area	Integrate Machine Learning Techniques (YES/NO)	Summary – Data Processing/Software Used	Type of Drone	Type of Activity
8	Schenkel *et al.* (2020)	To investigate the effectiveness metrics between the two technologies of interest in surveying a study area: drones and GPS-based receivers.	USA	*Aedes* sp.	Zika	Descriptive/Urban	NO	ArcMap in ArcGIS	DJI Phantom 3 Standard (DJI, Shenzhen, China)	Surveillance
9	Amarasinghe & Wijesuriya (2020)	To identify possible mosquito breeding grounds using drone images and propose two algorithms to identify small-scale standing water bodies.	Sri Lanka	*Aedes* sp.	Dengue, Zika, Chikungunya	Descriptive/Urban	YES	Classifier - SVM & HOG feature extraction	DJI Phantom IV (DJI, Shenzhen, China)	Surveillance
10	Bravo *et al.* (2021)	To propose computational approaches for the automatic identification of objects and scenarios suspected of being mosquito breeding sites using aerial images from drones.	Brazil	*Aedes* sp.	Dengue	Descriptive/Urban & Suburban	YES	Convolutional Neural Networks (CNN) and Bag of Visual Words combined with the Support Vector Machine classifier (BoVW + SVM)	DJI Phantom 3 (DJI, Shenzhen, China)	Surveillance

ID	Author (Year)	Objective	Methodology						Application of a Drone	
			Study Site	**Species of Mosquito Studied**	**Disease Concerned**	**Study Design/Area**	**Integrate Machine Learning Techniques (YES/NO)**	**Summary – Data Processing/Software Used**	**Type of Drone**	**Type of Activity**
11	Stanton *et al.* (2021)	To identify larval habitat using a drone as a method for collecting very high-resolution (< 10 cm), contemporary imagery of an area.	Malawi	*Anopheles* sp.	Malaria	Descriptive/Suburban	YES	Agisoft, Geographical Object-Based Image Analysis (GeoOBIA), RF classification	Phantom Pro 4 (DJI, Shenzhen, China); eBeeSQ	Control (Larva)
12	Valdez-Delgado *et al.* (2021)	To evaluate the effectiveness of low-cost drone images in identifying mosquito breeding sites on the roofs of buildings and backyards.	Mexico	*Aedes* sp.	Dengue	Descriptive/Urban	NO	ArcGIS, GNU Image Manipulation Programme (GIMP)	Phantom 4 Pro DJI (DJI, Shenzhen, China)	Surveillance
13	Cunha *et al.* (2021)	To detect swimming pools and water tanks installed on the roof using remote sensing and deep learning, to investigate the area's socioeconomic level, and to discuss the possible application of the obtained results in the control of dengue.	Brazil	*Aedes* sp.	Dengue, Zika, Chikungunya	Descriptive/Urban & Suburban	YES	Faster R-CNN framework, Python, Agisoft, ArcGIS	DJI Phantom 3 and 12.1 MP Canon PowerShot S100	Surveillance

ID	Author (Year)	Objective	Methodology						Application of a Drone	
			Study Site	Species of Mosquito Studied	Disease concerned	Study Design/Area	Integrate Machine Learning Techniques (YES/NO)	Summary – Data Processing/Software Used	Type of Drone	Type of Activity
14	Lee *et al.* (2021)	To explore the use of UAV mapping as a tool to identify spatial risk factors for symptomatic dengue.	Ecuador	*Aedes* sp.	Dengue	Descriptive/Urban & Rural	NO	Green Red Vegetation Index (GRVI), Pix4D, Agisoft	Not specified	Surveillance
15	Passos *et al.* (2022)	To have a comprehensive dataset of aerial videos, from a drone, containing possible mosquito breeding sites. All frames of the video dataset were manually annotated with bounding boxes identifying all objects of interest.	Brazil	*Aedes* sp.	Dengue	Descriptive/Urban	YES	All videos are manually annotated in a frame-by-frame manner using the Faster R-CNN architecture	Phantom Vision 4 PRO (DJI, Shenzhen, China)	Surveillance
16	Hardy *et al.* (2022)	To compare the results of two mapping approaches, supervised image classification using ML, and Technology-Assisted Digitising (TAD) mapping.	Tanzania	*Anopheles* sp.	Malaria	Descriptive/Rural	YES	QGIS, TAD, RF classifier	DJI Phantom 4 Advanced+ (DJI, Shenzhen, China)	Control (Larva)
17	Stanton *et al.* (2022)	To detect larval habitats using high-resolution earth observation data captured by drones.	Malawi	*Anopheles* sp.	Malaria	Descriptive/Rural	YES	GeoOBIA, RF classification	Not specified	Surveillance

2.9.3 Discussion

The applications of drones are primarily governed by variables such as size, power, and operating conditions, which vary widely across drone types (Daud *et al.*, 2022). Notably, the application of drone technology has already led to numerous remarkable results. Concurrently, the images of water bodies are examined to identify potential mosquito breeding sites (Carrasco-Escobar *et al.*, 2019). Furthermore, drone surveying approaches for artificial containers are becoming more accurate by combining GPS receivers with ML techniques and imaging technologies such as multispectral imaging (Schenkel *et al.*, 2020). In other research, they merged the Internet of Medical Things and GIS (Ali *et al.*, 2022). They contain and manage DENV outbreaks by analysing call records. In addition, Hardy *et al.* (2022) analysed drone data using a mix of mapping methods: supervised image classification with ML and technology-enabled digitising mapping accessible to those without a technical background.

ML can detect patterns in data at or above human levels, which is helpful for classification, prediction, and clustering (Joshi & Miller, 2021). In a similar vein, Artificial Intelligence (AI) can accurately estimate the number of larvae and pupae in a sample by automating repetitive learning processes (Haas-Stapleton *et al.*, 2019). Many studies used orthomosaic maps that are constructed by stitching together Two-Dimensional (2D) aerial photographs with at least 70% picture overlap as reference points (Truong & Clavel, 2022). Consistent with this, drones were used to collect many aerial photo configurations for a database (Dias *et al.*, 2018). The proposed system was assessed and trained using the collected photos and the annotated database. Remarkably, this technology allows the detection of tiny objects that existing remote sensing methods cannot detect (Bravo *et al.*, 2021). In an example of architectural innovation that combines and applies two established technologies to a new market and context (Mukabana *et al.*, 2022). Results revealed that drone deployment and insecticides could reduce mosquito populations in an irrigated rice agroecosystem. However, improving the precision of the technology requires extensive engagement and data from many images representing a wide range of situations. Hence, this review has highlighted and grouped operational issues in drone use into seven themes: hardware, software, law and regulation, operating time, expertise, geography, and community involvement (Table 2.7). Additionally, the ability of drones to fly in inaccessible areas is their most important advantage. Since drones are available in various sizes and configurations, specific criteria must be considered to determine which model is best suited for searching breeding habitats (Aragao *et al.*, 2020).

Table 2.7
Issues, Challenges, and Limitations of Using Drones

Issues & Challenges	**Paper ID**																
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
Hardware (*Specification, flight duration, Height, Signal Strength, spare parts*)		☑	☑	☑	☑		☑	☑	☑	☑	☑	☑	☑	☑	☑	☑	☑
Software (*piloting drone, formatting, data & image processing/classification*)	☑	☑	☑	☑	☑	☑	☑	☑	☑	☑	☑	☑	☑	☑	☑	☑	☑
Law & Regulation (*licensing, no-fly zone, military deployment*)								☑	☑			☑		☑		☑	☑
Operating time (*weather, shadow effect, time-consuming*)			☑	☑	☑		☑				☑		☑	☑	☑		
Expertise (*Skill/training hours/previous research & data*)		☑	☑	☑	☑	☑	☑	☑	☑	☑	☑	☑	☑	☑		☑	☑
Geographical (*hard-to-reach locations, tree canopies, area covered*)			☑				☑	☑	☑	☑			☑	☑	☑	☑	
Community involvement	☑										☑	☑	☑	☑		☑	

The most frequently highlighted issue among many authors is software (22%) (Figure 2.7), including drone control software, formatting, data processing, and image classification. For instance, the study by Prasad *et al.* (2016) highlighted the failure of Support Vector Machine (SVM)-based approaches and optical flow, after which a combined method, the horizon mask, was developed to address this issue. Moreover, identifying waters in the resulting orthomosaic can be challenging, especially when waters with significant suspended sediment are the same colour as bare ground (Hardy *et al.*, 2017). Thus, there is a need for more techniques for rapid data processing and solutions for accelerated image processing (Carrasco-Escobar *et al.*, 2019). Although obtaining unbiased, ethical, comprehensive, and global datasets is challenging, they are necessary for practical ML applications in mosquito control (Rund *et al.*, 2019; Joshi & Miller, 2021). In essence, creating orthomosaics from drone imagery is a time-consuming process that requires a powerful computer, ample storage, and specialised software (Stanton *et al.*, 2021).

Regarding hardware (20%), key issues include specifications, flight duration, maximum altitude, signal strength, spare parts supply, data management, and cost efficiency. Note that a drone can only stay in the air for up to 20 minutes before its battery runs out (Amarasinghe *et al.*, 2017). Therefore, numerous flights over the area are required to create a single map, though this may result in some temporal variation between scenes on the single map and affect the spectral signature. However, this effect is likely minimal (Haddawy *et al.*, 2019).

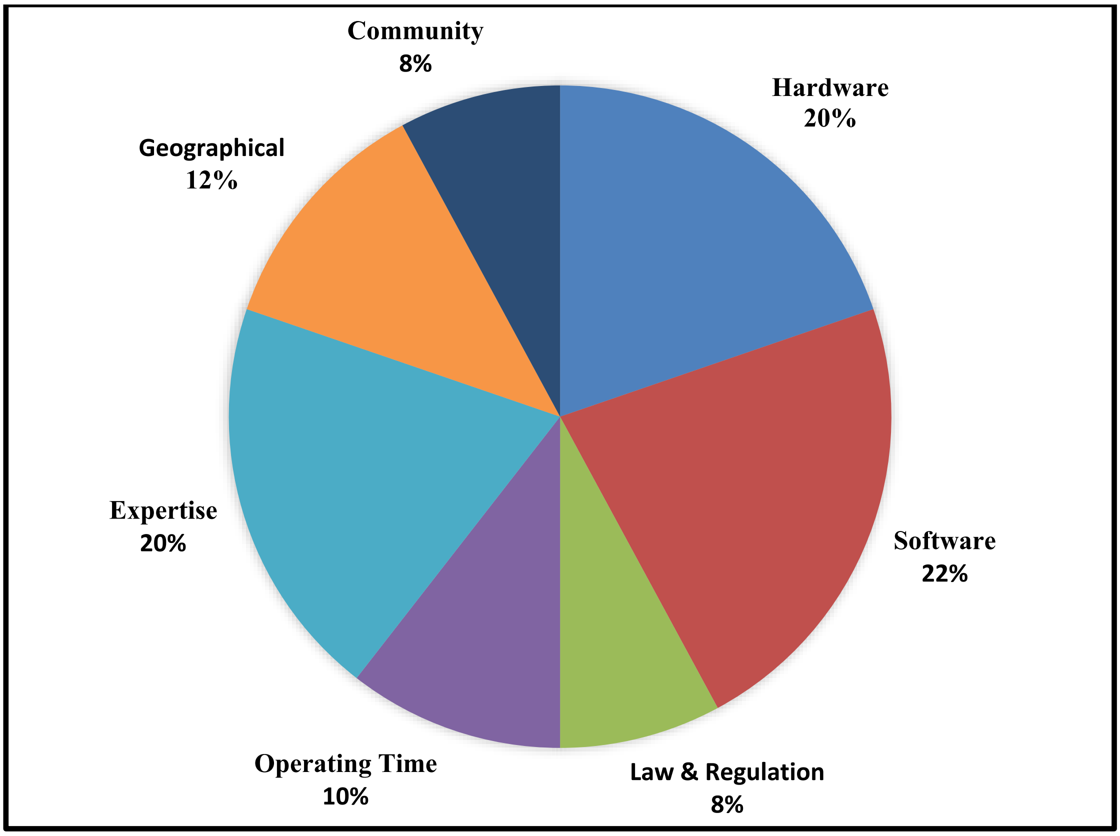

Figure 2.7 Issues, Challenges, and Limitations of Using Drones

Drone signals are lost when there is a large body of water or telecommunications towers between the drone pilot and the drone, as these areas absorb drone signals (Amarasinghe *et al.*, 2017). Although purchasing commercially available drones in the country is possible, obtaining replacement parts or repairs becomes challenging and expensive when technical problems occur (Stanton *et al.*, 2021). In addition, expertise issues (20%) include incompetence, training hours for drone pilots, and insufficient previous research data. Since the aerial inspection is manually controlled, it depends on the drone pilot's ability to fly the drone (Amarasinghe *et al.*, 2017), requiring a certain level of skill (Hardy *et al.*, 2017). When searching for water bodies in a rural setting, drone imagery inevitably presents technical and skill-based challenges (Wyngaard *et al.*, 2018; Stanton *et al.*, 2021). Nevertheless, the lack of comprehensive research on this topic in the past and the small sample sizes in the training phase of deep learning posed significant challenges for researchers (Mehra et al., 2016; Aragao *et al.*, 2020).

Regarding geographic limitations (12%), drones cannot be used in highly difficult-to-access locations, such as areas with high plant density or tree canopies. Due to the dynamic nature of water bodies, conducting large-scale surveys from the ground has not been possible (Hardy *et al.*, 2017). Other obstacles, such as power lines and telecommunications towers, prevent the use of auto-fly mode in urban areas (Amarasinghe *et al.*, 2017), limiting the drone's application. The drone's flight time (10%) was another factor to be considered. Since a drone cannot be flown in wet or windy conditions, the flight experience is critical for determining optimal flight times (Stanton *et al.*, 2021). Furthermore, the drone camera's tilt angle should be 90 degrees, and the drone should fly around midday to reduce the shadow effect (Suduwella *et al.*, 2017). Shadows cast by large trees and structures can obscure potential water sources (Hardy *et al.*, 2017). Hence, avoid conducting drone surveys when the sun is low in the early morning or evening to mitigate this effect.

Regarding law and regulation (8%), the authors emphasised the licensing process, no-fly zones, and control over military deployment. Prior to utilising drones for any activities, national civil aviation authorities require drone pilots to obtain approved qualifications and secure relevant authorisation, even though rules differ by country (Stanton *et al.* 2021). The importance of community involvement (8%) was also addressed in several studies. This is mainly due to the fact that researchers are experimenting with community-based monitoring systems that integrate technology into communities. Partnering with communities to collect surveillance data was also an effective data-collecting technique for public health practitioners and epidemiologists (Lee *et al.*, 2021). At the same time, concerns have been raised regarding how local communities will respond to drone use, the number of drones required, the area of coverage, when drones will be used, and how human privacy will be protected. Therefore, community members must be involved to help address all these potential future issues (Annan *et al.*, 2022). With recent advancements in drone technology, particularly the Internet of Things (IoT), smaller drones can capture high-resolution photos and upload them to the cloud in real time for rapid data processing. These drones are energy efficient and can cover large areas without losing connectivity to their base station (Annan *et al.*, 2022). However, there is a need for additional consultations between experts and stakeholders in the field of drones. This includes image analysis and vector control to develop more specific recommendations for how this technology can be utilised most effectively (Stanton *et al.*, 2021).

2.10 SWOT Analysis for Assessing the Field Efficiency of Drones in Identifying Potential Breeding Sites of *Aedes* Mosquitoes[2]

SWOT analysis (Figure 2.8) of the viability of using drones for surveillance was conducted based on the related articles identified in the scoping review (Table 2.6). While drones were initially envisioned as simple tools, their sophistication has evolved as their intended tasks have grown more complex. Accordingly, the applications of drones are primarily determined by variables such as size, power, and operating conditions, which vary greatly depending on the type of drone (Mohd Daud *et al.*, 2022). A drone is a remotely piloted rotary or fixed-wing aircraft without a pilot on board. When equipped with the proper sensors, drones are used to photograph the landscape and measure vegetation indices, surface water areas, and wildlife populations. Correspondingly, drones are being adapted to inspect mosquito breeding in a range of environments (Carrasco-Escobar *et al.*, 2019). A drone equipped with a multispectral camera and a high-magnification zoom video camera can be used to quantify and map surface water accumulated in a tidal marsh and to observe mosquito larvae, respectively (Haas-Stapleton *et al.*, 2019). Following this, there are eight drone categories, each with its own advantages and limitations. These include fixed-wing, flapping-wing, rotary-wing, tilt-rotor, ventilator, helicopter, ornithopter, and unconventional aircraft (Shahmoradi *et al.*, 2020). Drones are used in health research for a variety of purposes, including locating survivors after natural disasters, transporting medical supplies to remote areas, and providing early treatment in emergencies (Hiebert *et al.*, 2020; Passos *et al.*, 2022). Drones are also used in a variety of other fields, including agriculture, forestry, ecology, and environmental monitoring (Stanton *et al.*, 2021).

The ability of drones to fly in difficult-to-access areas is their most significant advantage. According to Hardy *et al.* (2022), drones can capture images or videos with greater spatial or temporal resolution from a variety of angles and heights. In addition, deploying programmable drones increases health inspectors’ safety by reducing their exposure to potentially hazardous incidents or situations. The initial cost of drone hardware is considerable. Nevertheless, it is feasible, as a small team can cover a vast

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[2] Mahfodz, Z., Dom, N. C., Salim, H., & Precha, N. (2024). A conceptual framework for assessing the field efficiency of drones in identifying potential breeding sites of the *Aedes* mosquito. *Alam Cipta: International Journal on Sustainable Tropical Design Research & Practice*, *17*(1).

area from the air at minimal operating costs (Chiroli *et al.*, 2017). Despite this, drone implementation for mosquito breeding site surveillance may face numerous challenges. For example, the laws and guidelines for flying drones vary by region. There is no standard set of guidelines for operating or regulating drones; there are restricted zones where drones cannot be used; there are topographic and climate differences; there are privacy concerns; and community attitudes towards and acceptance of drones vary across cultures (Annan *et al.*, 2022; Mohd Daud *et al.*, 2022; Poljak & Šterbenc, 2020). Thus, the scalability of the proposed method may be limited by the geographic area a single drone can cover (Bravo *et al.*, 2021).

Nonetheless, Hardy *et al.* (2017) demonstrated that a low-cost drone can be used to map water bodies in various settings, including natural water bodies, rice paddies, and urban areas, to identify and map aquatic mosquito habitats. A well-organised database for identifying and categorising objects in aerial videos is also an essential element. Among the features highlighted by Passos *et al.* (2022), a database should include a large number of samples per target group, be free of image distortions, and provide precise object annotation.

Detecting water bodies in remote areas using drone-captured images requires several technological and competence hurdles. Creating orthomosaics from drone imagery is a time-consuming process that requires a powerful computer, ample storage, and specialised software (Stanton *et al.*, 2021; Wyngaard *et al.*, 2018). In addition to hardware and software concerns, misconfigured drones can pose risks and vulnerabilities (Wyngaard *et al.*, 2018). Flight experience was essential for calculating the ideal flight hours, as the drone could not be piloted in rainy weather, and adverse weather could cause the equipment to overheat on hot days. Hence, more engagements between stakeholders and specialists across disciplines are required to provide more specific recommendations on how this technology can be used most efficiently (Stanton *et al.*, 2021).

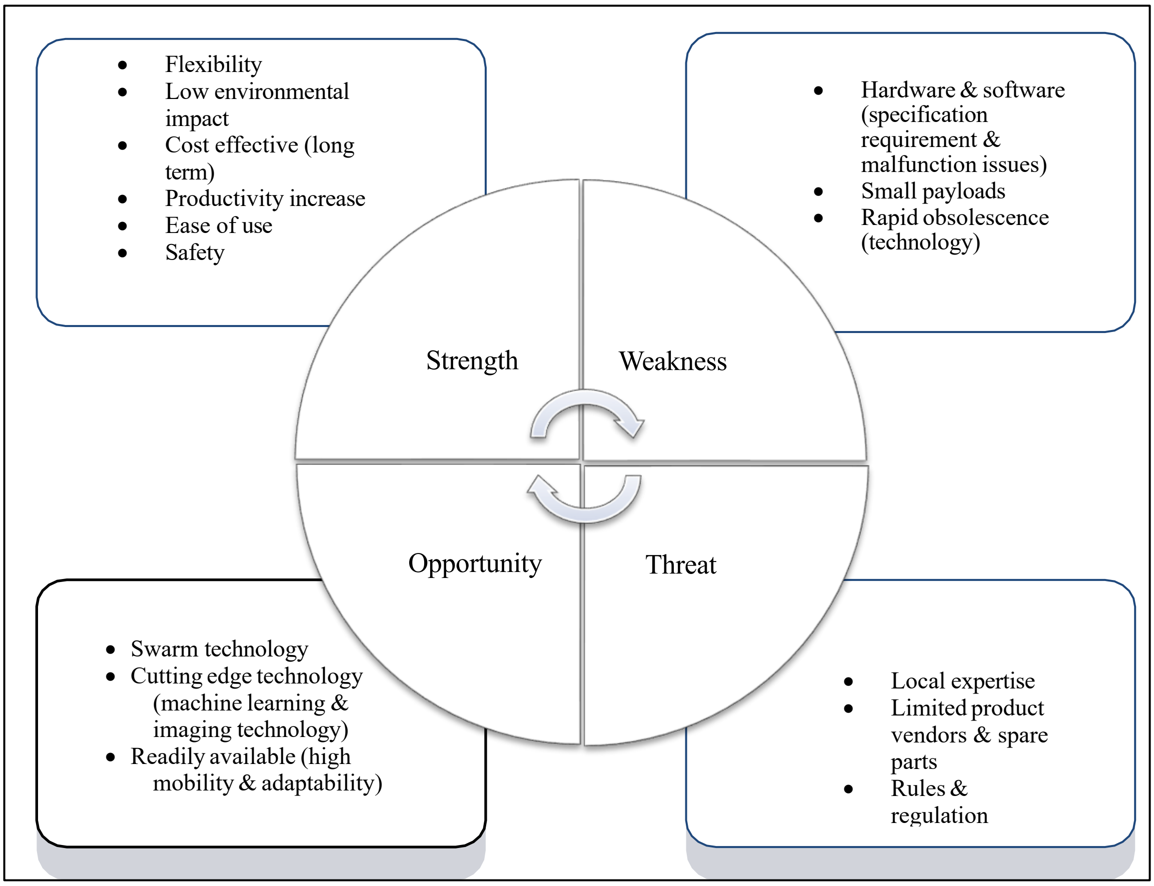


Figure 2.8 SWOT Analysis on the Viability of Using Drones for Surveillance Activities

The feasibility of using drone technology in mosquito breeding control programmes should be further explored, as it can complement the traditional, labour-intensive method of larval habitat inspection. In Malaysia, rigorous dengue control measures are implemented in certain localities based on the notification of lab-confirmed human cases and the location of dengue hotspots. Currently, house-to-house larval inspections by the health inspector, removal of mosquito breeding sites, larvicide activities, and fogging are among the control measures taken by the MOH in Malaysia. Still, the feasibility of using drone technology in mosquito breeding control programmes should be considered an effective alternative, as it could replace the time-consuming conventional process of observing larval habitats.

In Malaysia, the application of ML to dengue has thus far focused mainly on predicting case counts and entomological indices rather than on analysing drone imagery. Salim *et al.* (2021) developed dengue outbreak prediction models for Selangor using SVM, RF, and other algorithms. This indicates that ML can outperform traditional statistical approaches when integrating meteorological and epidemiological data. More recently, Majeed *et al.* (2023) used a Long Short-Term Memory (LSTM) deep learning model with spatial attention to forecast dengue cases at the state level in Malaysia. The study similarly demonstrated the value of non-linear, data-driven methods for early warning systems. At a finer spatial resolution, Dom *et al.* (2025) combined microclimatic variables (temperature, humidity, rainfall) with artificial neural networks, RF, and SVM to predict *Aedes* indices and a dengue-positive trap index. This highlights that ML can capture species-specific responses to environmental variability at the neighbourhood scale. Collectively, these studies indicate that ML is feasible and valuable for predicting dengue risk. However, they are based on time-series cases or microclimate data and do not yet incorporate high-resolution drone-derived land-cover information or explicitly map potential breeding environments in real urban areas.

By contrast, work from Malaysia and the wider SEAR on ML with spatial imagery has primarily relied on satellite or street-view data rather than UAV imagery. For instance, Knoblauch *et al.* (2024) used state-of-the-art object detection (YOLOv5) applied to satellite and street-view images. The study aimed to detect breeding-relevant container types and to generate high-resolution maps of *Ae. aegypti* immature abundance in Rio de Janeiro. This demonstrates how computer vision outputs can be linked to ovitrap-based entomological indices at the city scale. Likewise, Haddawy *et al.* (2019) trained Convolutional Neural Networks (CNNs) on Google Street View images in Thailand to detect outdoor containers (e.g., jars, tyres, buckets). They produced detailed container density maps that correlated strongly with Breteau indices from manual surveys. Su Yin *et al.* (2021) extended this work by revealing that including container counts derived from street-view images improved the performance of dengue risk models. This is compared with models using only conventional environmental and socio-demographic predictors. Overall, these studies are highly relevant conceptually to the present study since they illustrate how ML-based image analysis can transform raw imagery into operational indicators of breeding-site density and dengue risk. Nonetheless, they do not use UAVs, and very little of this work has yet been adapted to Malaysian urban settings.

Globally, there is a rapidly growing body of work that combines UAV imagery and ML to identify mosquito habitats and risk environments. Nevertheless, much of it concerns malaria vectors rather than *Aedes*. Several studies synthesised in the review by Carrasco-Escobar *et al.* (2022) noted that ML algorithms such as RF, SVM, and deep neural networks can classify UAV-based multispectral data into water, vegetation, and infrastructure classes that are strongly associated with larval habitats across malaria-endemic landscapes. More directly relevant to *Aedes* surveillance, several recent studies have applied ML to drone imagery and other high-resolution images to detect containers and other trash that may serve as breeding sites. Meanwhile, Valdez-Delgado *et al.* (2021) evaluated the field effectiveness of drones for identifying potential *Ae. aegypti* breeding sites around households in Tapachula, Mexico. The authors reported that UAV-based surveys could detect elevated containers and roof-level sites that were frequently missed by ground teams. Additionally, Rosser *et al.* (2024) developed an image-based trash classification system using UAV photographs and ML to map container-like trash objects associated with *Ae. aegypti* breeding. In comparison, Tarpenning *et al.* (2025) compared UAV-derived classifications with systematic ground walkthroughs. The study also highlighted trade-offs between aerial coverage and detection accuracy for small containers.

Passos *et al.* (2022) proposed a deep learning pipeline with spatiotemporal consistency constraints to detect *Ae. aegypti* breeding grounds in aerial video sequences. This demonstrates that temporal information can reduce false positives in complex urban scenes. Hence, these studies indicate that convolutional and ensemble-based ML methods can extract breeding-relevant features from UAV imagery. Still, they tend to focus either on container-level detection or on proof-of-concept performance metrics. This is as opposed to integrating these outputs with broader land-cover and stakeholder perspectives. From another perspective, ML-based image analysis is increasingly used to detect specific breeding containers and build richer environmental indicators that directly link to entomological outcomes. Su Yin *et al.* (2021) similarly established that including container information from street-view imagery improved the predictive power of dengue risk models. This emphasises the added value of image-derived features in spatial risk mapping.

2.11 Systematic Review on Drone-Based Machine Learning Approaches for Mosquito Vector Surveillance[3]

Mosquito-borne diseases remain among the most significant global public health challenges, with dengue fever, malaria, Zika, and chikungunya contributing substantially to morbidity and mortality worldwide. Dengue fever, transmitted predominantly by *Ae. aegypti* and *Ae. albopictus*, continues to escalate as one of the most pressing global public health threats, placing more than half of the world's population at risk (Lwande *et al.*, 2020; Naslund *et al.*, 2021). The burden is disproportionately concentrated in tropical and subtropical regions, where rapid urbanisation, inadequate waste management, and climate variability amplify mosquito proliferation (Ligsay *et al.*, 2021). Despite decades of vector control programmes, dengue incidence has nearly tenfold since the 1970s, underscoring the limitations of conventional surveillance methods (Barrera, 2025). Larval surveys, ovitraps, and human-led inspections, while foundational, are resource-intensive, spatially restricted, and often too reactive to support timely interventions in densely populated environments (Collins *et al.*, 2022). Similar challenges have been reported for *Anopheles* surveillance in rural and agricultural landscapes, where larval habitats are spatially dispersed and difficult to monitor consistently. These limitations underscore the need for innovative surveillance tools capable of providing timely, scalable, and fine-resolution information to support proactive vector control strategies across mosquito genera.

In this context, UAVs, or drones, have emerged as transformative tools for public health entomology (Mechan *et al.*, 2023). Equipped with high-resolution sensors, drones enable rapid, scalable, and fine-grained mapping of landscapes, with unprecedented potential to detect and monitor mosquito breeding habitats in both urban and peri-urban settings (Carrasco-Escobar *et al.*, 2022; Vanhuysse *et al.*, 2023). However, the full promise of drone-based surveillance is realised only when coupled with ML techniques that transform raw imagery into actionable intelligence (Heidari et al., 2023). ML algorithms ranging from classical approaches such as RF, SVM, and GeoOBIA to advanced deep learning architectures like CNNs and object detection frameworks such as You Only Look Once (YOLO) are reshaping the landscape of

[3] Mahfodz, Z., Naba, A., Isawasan, P., Ngesom, A. M. M., & Dom, N. C. (2026). Drone-based machine learning approaches for mosquito vector surveillance. *Discover Applied Sciences,* 8, 657.

vector surveillance (Liu *et al.*, 2018; Jozdani *et al.*, 2019). These models not only enhance automated classification and ecological characterisation but also enable predictive risk modelling with greater accuracy and efficiency than human operators (Binetti *et al.*, 2024).

Nevertheless, the integration of drone-derived imagery and ML applications in *Aedes* surveillance remains fragmented and nascent (Carrasco-Escobar *et al.*, 2022). Methodological heterogeneity, inconsistent validation practices, and limited generalisability hinder the scalability of existing studies (Njotto *et al.*, 2024; Lim *et al.*, 2023). While previous systematic reviews have examined drones in environmental monitoring or ML entomology more broadly, none have comprehensively synthesised evidence at the nexus of drone-based surveillance and ML-enabled vector control (Ogab *et al.*, 2025). Critically, contextualised evidence from hyperendemic regions such as Southeast Asia and Malaysia in particular is scarce, despite the region's urgent need for innovative surveillance strategies to curb recurrent dengue outbreaks.

Against this backdrop, the present systematic review was undertaken to consolidate and critically appraise global evidence on drone-based machine learning applications for mosquito vector surveillance, with a primary focus on *Aedes* mosquitoes while incorporating methodologically relevant studies involving other vector genera such as *Anopheles*. The review aims to: (i) classify existing applications across detection, ecological characterisation, and feasibility assessments; (ii) map the diversity of ML models employed, spanning traditional classifiers to deep learning frameworks; (iii) evaluate methodological rigour using an adapted quality appraisal framework; and (iv) highlight research gaps and future opportunities for operational deployment. By bridging global innovations with local challenges, this review seeks to advance the development of scalable, cost-effective, and technologically robust surveillance frameworks to strengthen dengue prevention and control programmes in endemic regions.

2.11.1 Methodology

2.11.1.1 Systematic Review Protocol

This systematic review was conducted in accordance with the PRISMA 2020 guidelines to ensure methodological rigour, transparency, and reproducibility (O'Dea *et al.*, 2021). The protocol was designed to address the overarching research question: *How have ML approaches been applied in drone-based Aedes surveillance and vector control strategies?* The review process encompassed structured search, eligibility screening, data extraction, and quality assessment.

2.11.1.2 Literature Search Strategy

A comprehensive literature search was conducted in Web of Science (Core Collection), Scopus, PubMed, and IEEE Xplore to identify relevant studies published between January 2000 and December 2024. Searches were performed between January 2000 and December 2024 using database-specific search strings combining terms related to mosquito vectors, drone-based imagery, and machine learning approaches. The exact search strategies, including Boolean operators, database-specific syntax, search dates, and applied limits, are detailed in Table 2.8. Searches were limited to English-language publications, and no restrictions were applied on study design at the search stage. Conference proceedings were included only when indexed in IEEE Xplore and when full papers reporting primary empirical data were available. No additional grey literature databases were searched. Reference lists of included studies were manually screened to identify any additional eligible articles.

Table 2.8
Database-specific Search Strategy for Identification of Relevant Studies

Database	Search String	Limits / Filters
Web of Science (Core Collection)	(*Aedes* OR *Anopheles* OR mosquito*) AND (drone* OR UAV* OR "unmanned aerial vehicle*" OR "aerial imagery") AND ("machine learning" OR "deep learning" OR CNN OR "convolutional neural network*" OR YOLO OR "random forest" OR SVM OR GeoOBIA)	English language; publication years 2000–2024

Scopus	(*Aedes* OR *Anopheles* OR mosquito*) AND (drone* OR UAV* OR "unmanned aerial vehicle*" OR "aerial imagery") AND ("machine learning" OR "deep learning" OR CNN OR "convolutional neural network*" OR YOLO OR "random forest" OR SVM OR GeoOBIA)	English language; publication years 2000–2024
PubMed	(*Aedes*[Title/Abstract] OR *Anopheles*[Title/Abstract] OR mosquito*[Title/Abstract]) AND (drone*[Title/Abstract] OR UAV*[Title/Abstract] OR "unmanned aerial vehicle"[Title/Abstract]) AND ("machine learning"[Title/Abstract] OR "deep learning"[Title/Abstract] OR CNN[Title/Abstract] OR YOLO[Title/Abstract] OR "random forest"[Title/Abstract] OR SVM[Title/Abstract])	English language
IEEE Xplore	("mosquito" OR *Aedes* OR *Anopheles*) AND (drone OR UAV OR "unmanned aerial vehicle") AND ("machine learning" OR "deep learning" OR CNN OR YOLO)	English language; conference papers and journal articles

2.11.1.3 Eligibility Criteria

Studies were considered eligible for inclusion if they reported primary empirical data and employed drone-based imagery for mosquito vector surveillance or larval habitat detection and characterization. Eligible studies were required to integrate at least one machine learning (ML) approach, including either traditional classifiers (such as Random Forest, Support Vector Machines, or Geographic Object-Based Image Analysis) or deep learning architectures (such as convolutional neural networks and object detection frameworks). Studies targeting mosquito vectors of public health importance, including *Aedes*, *Anopheles*, or other medically relevant genera, were included, provided that the methodological focus was relevant to vector surveillance applications. Only articles published in English were considered. Studies were excluded if they were purely theoretical in nature, review articles, editorials, commentaries, book chapters, or conference abstracts lacking full empirical results, as well as investigations that applied drone or ML techniques outside the context of mosquito vector surveillance. Although *Aedes*-focused studies constituted the majority of the included literature, selected *Anopheles* studies were retained due to their methodological relevance and direct applicability to drone-based larval habitat detection and environmental characterization, ensuring a comprehensive synthesis of transferable surveillance approaches.

2.11.1.4 Study Screening and Selection

All records retrieved from Web of Science (n = 47), Scopus (n = 50), PubMed (n = 30), and IEEE Xplore (n = 25) were imported into EndNote X9 for reference management and duplicate removal. A total of 152 records were initially identified across the four databases. Following deduplication, 55 duplicate records were removed prior to screening. The remaining 97 records were screened at the title and abstract level, resulting in the exclusion of 56 records that did not meet the inclusion criteria. Subsequently, 41 reports were sought for retrieval, of which 23 reports could not be retrieved. The remaining 18 full-text articles were assessed for eligibility, and 10 articles were excluded with documented reasons, including review papers (n = 2), book chapters (n = 2), encyclopaedia editorials (n = 4), and studies addressing non-relevant applications (n = 2). Ultimately, eight studies (n = 8) met all inclusion criteria and were included in the final synthesis. The complete study selection process is summarized in the PRISMA 2020 flow diagram (Fig. 2.9).

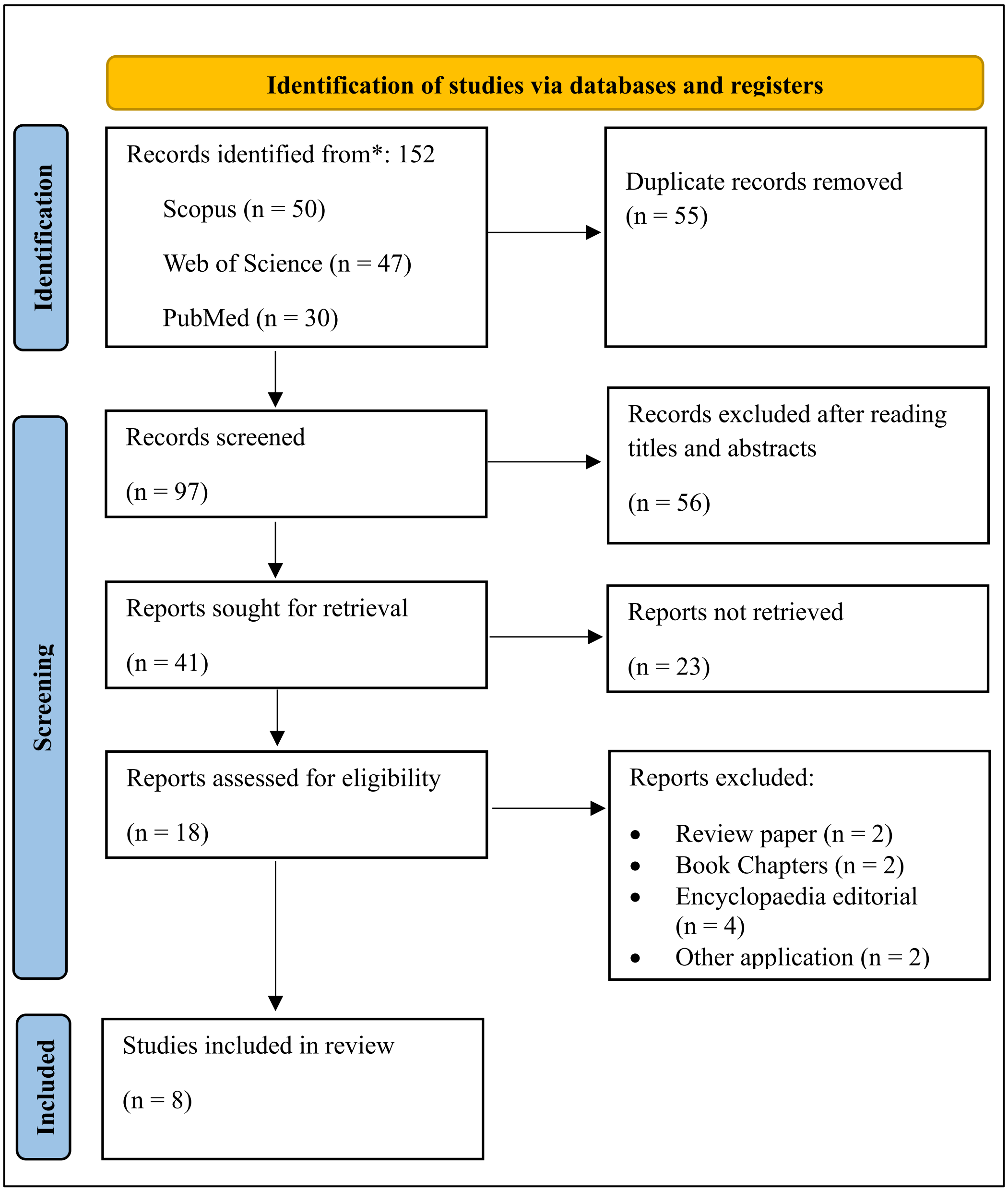


Figure 2.9 The PRISMA Flow Diagram Summarizes the Process of Study Identification, Screening, Eligibility, and Inclusion

2.11.1.5 Data Extraction

A standardized data extraction template was developed in Microsoft Excel to ensure consistency, transparency, and reproducibility across studies. For each eligible article, bibliographic information (author, year of publication, and country) was recorded. Study objectives were classified according to their primary analytical focus, including breeding habitat detection, ecological or environmental characterization, and feasibility or pilot assessment. Information on machine learning (ML) approaches was systematically extracted, encompassing deep learning architectures, Random Forest, Geographic Object-Based Image Analysis (GeoOBIA), Support Vector Machines (SVM), and any reported hybrid models.

Methodological details related to data sources were captured, including imagery type, sensor modality, and spatial resolution, to reflect variability in drone-based data acquisition. Validation strategies were also documented, such as train–test splits, cross-validation, and independent field-based ground-truth verification, where applicable. In addition, performance outcomes were extracted, including reported accuracy, precision/recall, F1-score, intersection over union (IoU), and indicators of operational feasibility, as reported by the original studies. This structured extraction approach enabled a comprehensive descriptive synthesis of methodological practices and empirical outcomes across the included literature. Image resolution was extracted primarily from the reported ground sampling distance (GSD) in the original studies. When GSD was not explicitly stated, resolution was inferred from flight altitude and sensor specifications, provided sufficient information was available. For analytical synthesis, image resolution was categorized into < 5 cm and > 5 cm bins, reflecting operational distinctions between fine-scale detection of small breeding containers and broader environmental or habitat mapping.

2.11.1.6 Quality Assessment

Methodological quality was appraised using a customized checklist designed for drone-based remote sensing and machine learning (ML) workflow studies, to ensure domain relevance and transparent reporting. The tool assessed five key domains: (1) data representativeness and sampling context (e.g., site diversity, capture conditions, and generalizability), (2) ground-truth and labelling quality (e.g., field verification, annotation protocol, and inter-annotator checks where applicable), (3) data partitioning and leakage prevention (e.g., spatial/temporal independence between training and test data), (4) validation design and robustness (e.g., train–test split strategy, cross-validation, external/field validation), and (5) reporting transparency and reproducibility (e.g., model specification, hyperparameters, metrics, and availability of code/data or sufficient procedural detail) (Hong *et al*., 2018). Each domain was rated as High, Moderate, or Low quality according to predefined criteria, and an overall judgment was derived by considering the pattern of domain ratings rather than a summed score (Appendix 1).

2.11.1.7 Data Synthesis and Analysis

The extracted data were synthesized using a mixed narrative–quantitative descriptive approach, designed to summarize methodological patterns without formal statistical inference. A narrative synthesis was first undertaken to describe study characteristics, methodological orientations, and contextual applications of machine learning (ML) in drone-assisted mosquito vector surveillance. This was complemented by descriptive quantitative cross-tabulations to examine the distribution of study objectives, ML approaches, and validation strategies across the included studies. Given the small number of included studies ($n = 8$) and the resulting low expected cell counts, no formal hypothesis testing was performed. Analyses were therefore restricted to descriptive synthesis and visual cross-tabulation, with results presented as frequency-based patterns rather than statistically inferred associations. Cross-tabulated summaries were used to illustrate how different ML approaches were applied across study objectives such as breeding habitat detection, habitat or environmental characterization, and feasibility assessment. These descriptive patterns were intended to highlight methodological tendencies and areas of convergence within the existing literature, rather than to establish statistically significant relationships.

To enhance interpretability, multiple visualization outputs were generated. Stacked bar charts were used to display the frequency distribution of ML approaches across study objectives, while heatmaps provided an overview of methodological quality and reporting gaps. In addition, bubble plots were used to map ML attributes (accuracy, interpretability, scalability, feasibility) against vector control strategies, highlighting the balance between methodological strengths and applied utility. Together, these synthesis techniques allowed for a nuanced interpretation of the evidence base, enabling the identification of dominant methodological patterns, underexplored strategies, and critical gaps for future research.

2.11.2 Results

A total of eight studies met the inclusion criteria and were synthesized in this review. Most studies focused on the detection and characterization of *Aedes* mosquito breeding habitats, predominantly in urban and peri-urban environments, consistent with the public health priority of dengue surveillance. A smaller subset examined larval habitats of *Anopheles* mosquitoes in rural or agricultural settings, where drone-based imagery was applied to identify broader aquatic environments. These non-*Aedes* studies were retained because they employed comparable UAV platforms, image acquisition strategies, and machine learning workflows, providing methodologically transferable evidence relevant to mosquito vector surveillance. Accordingly, findings are reported and interpreted in relation to surveillance methodologies rather than species-specific disease outcomes, and no stratified analyses by pathogen or disease endpoint were undertaken.

The methodological quality of the included studies was generally high. All studies demonstrated strong internal validity, reflected by clearly defined study objectives, systematic UAV flight protocols, transparent data processing pipelines, and detailed reporting of machine learning performance metrics. However, external validity was moderate, as most investigations were conducted in geographically limited settings and focused primarily on artificial or semi-artificial water-holding containers. Common methodological constraints included environmental interference such as shading and vegetation occlusion, limited incorporation of explanatory environmental variables, and the absence of temporal validation or cost-effectiveness assessments.

Table 2.9 presents the characteristics of studies included in this systematic review on the use of drones and ML for mosquito control. Overall, the table highlights the diversity of geographical settings, study objectives, UAV platforms, and analytical approaches employed across the literature. Despite differences in scale and methodology, a clear trend emerges. Researchers are increasingly leveraging drone imagery in combination with ML to enhance the detection and mapping of mosquito breeding habitats. Furthermore, the synthesis highlights the rapid evolution of this field, with studies transitioning from proof-of-concept applications to more operationally relevant tools for vector surveillance. In addition, this consolidated view provides the foundation for further analysis of methodological strengths, limitations, and future opportunities, which will be explored in the subsequent sections. A methodological quality appraisal tailored to ML/UAV workflow studies indicated generally strong reporting of model performance and imagery acquisition, but variability in labeling transparency, leakage prevention, and external validation across studies (Appendix 1).

Table 2.9

Systematic Literature Review of Drone-Based ML Applications for Mosquito Vector Surveillance and Control

Author (Year)	Country/ Region	Objective	Drone Platform & Sensor	Image Resolution/ Coverage	Target Habitat /Vector	Annotation Method	ML Approach (Model/Algorithm)	Validation Strategy	Evaluation Metrics	Integration with GIS/Epidemiology	Key Findings
Passos *et al.* (2023)	Rio de Janeiro, Brazil	Improve detection of *Ae. aegypti* breeding grounds using drone imagery with data augmentation.	DJI Phantom 4 Pro, RGB video (4k)	Flight altitudes: 10 m, 25 m, 40 m; speed 15 km/h; serpentine flight plan	Artificial containers: tyres (primary), bottles, buckets, pools, puddles, MBG dataset water tanks	Manual frame-by-frame annotation; MBG dataset (13 videos, 11 sites)	Faster R-CNN (ResNet50-FPN) and YOLOv5; pretrained on COCO; with vs. without augmentation (grayscale, HSV gain, CLAHE, scaling)	8-fold leave-one-out cross-validation on 13 videos (8 train/val, 5 test)	Faster R-CNN + augmentation: AP50 = 74.8, F1 = 0.79; YOLOv5 + augmentation: AP50 = 80.7, F1 = 0.81 (improvement of up to +14.1% F1 over baseline)	Not explicitly linked to epidemiologic indices; designed for operational mosquito surveillance	Data augmentation significantly improved robustness and reduced overfitting; both YOLOv5 and Faster R-CNN achieved high detection rates for tyres.
Shen *et al.* (2021)	Not explicitly stated	Estimate shallow water depth in potential mosquito habitats using multispectral UAV imagery and CNN.	Multirotor UAV with multispectral sensor	cm-level GSD at low altitude (< 50 m)	Shallow water bodies (potential larval habitats)	Ground-truth water depth measurement in situ	CNN regression model	Train/test split with repeated validation	$R^2 \approx 0.89$; RMSE $\approx$ 6–7 cm	Intended for integration with mosquito risk mapping	CNN accurately predicted shallow water depth, suitable for mapping habitats.

Author (Year)	Country/ Region	Objective	Drone Platform & Sensor	Image Resolution/Coverage	Target Habitat /Vector	Annotation Method	ML Approach (Model/Algorithm)	Validation Strategy	Evaluation Metrics	Integration with GIS/Epidemiology	Key Findings
Passos *et al.* (2021)	Brazil	Develop and validate an automatic deep learning model for detecting *Ae. aegypti* breeding grounds	DJI Phantom 4 Pro (RGB sensor)	~1-2 cm/pixel, covering an urban neighbourhood	Containers (e.g., tyres, tanks, small vessels) in peridomestic environments	Manual labelling of containers in aerial images	CNN (YOLOv3 object detection)	Dataset split into training/validation/test sets; k-fold cross-validation	Precision = 0.92; Recall = 0.85; mAP ≈ 0.89	Intended to support municipal dengue control campaigns through container surveillance	Demonstrated feasibility of UAV + DL for vector control; high accuracy in urban container detection.
Hardy *et al.* (2019)	Unguja Island, Zanzibar, Tanzania	Evaluate drone imagery for mapping *Anopheles* mosquito larval habitats	DJI Phantom 3 (RGB sensor)	~2-5 cm/pixel, covering rice fields, ponds, drainage ditches	*Anopheles* larval habitats in rural/agricultural landscapes	Manual delineation of water bodies and habitat features	Supervised classification (RF with NDVI, NDWI indices)	Ground-truthing with field larval surveys	Accuracy > 85% for larval habitat classification	Direct integration with malaria vector control programmes	UAV imagery enhanced identification of larval habitats, supporting targeted control.
Bravo *et al.* (2021)	Sao Paulo, Brazil	Automatically detect objects (domestic water tanks) and scenarios (garbage accumulations that can hold water) from UAV imagery	DJI Phantom 3 + Sony EXMOR 12.4 MP RGB (DS1-DS2); DJI Phantom 4 20 MP RGB; GoPro HERO4 Silver (DS4)	DS1: 50 m, ~2.2 cm/px, 66,312 m²; DS2: 70 m, ~2.45 cm/px, 91,344 m²; DS3: 7-13 m, 0.30-0.56 cm/px; DS4: 3-5 m, < 0.30 cm/px; overlap 60-70%	Potential mosquito breeding sites (esp. *Aedes*): water tanks, mixed solid-waste scenarios	Manual bounding boxes & sub-images; 7 water-tank classes; 9 scenario classes	YOLOv3 (objects), tiny-YOLOv3 (scenarios); baseline BoVW+SVM (CH, CLCM, HOG, LBP)	70/30 split; Objects: 73 test images (DS1-2); Scenarios: 69 test images (DS3-4); augmentation applied	Objects (YOLOv3): mAP-50 = 0.9651, recall = 0.9211; Scenarios (tiny-YOLOv3): mAP-50 = 0.9028, recall = 0.8649; BoVW+SVM best mAP-50 = 0.6453	Georeferenced by UAV GPS (accuracy <1.8 m); orthomosaic generation feasible	CNNs greatly outperformed BoVW+SVM; detection fast enough for near-real-time.

Author (Year)	Country/ Region	Objective	Drone Platform & Sensor	Image Resolution/Coverage	Target Habitat /Vector	Annotation Method	ML Approach (Model/Algorithm)	Validation Strategy	Evaluation Metrics	Integration with GIS/Epidemiology	Key Findings
Stanton *et al.* (2021)	Kasungu District, Malawi	Assess the feasibility of drone imagery to identify larval habitats for LSM.	DJI Phantom 4 Pro (RGB + NIR) and eBee SQ (Parrot Sequoia NIR)	RGB ~3.3 cm/px (Phantom 4 Pro), ~3.7 cm/px (eBee SQ); NIR ~11 cm/px; 8.9 km² across 8 sites	*Anopheles* larval habitats (reservoir, water bodies, aquatic vegetation)	326 larval survey sites; manual annotation of imagery	GeoOBIA (object-based segmentation in OTB/QGIS) + supervised classification (RF-style)	Interpolated vs extrapolated classification; GLMM for larval presence	Interpolated OA ≈ 0.91; Extrapolated OA ≈ 0.76–0.80; user/producer accuracy >80% (interpolated)	Outputs linked to LSM planning	Larval presence significantly associated with aquatic vegetation; RGB alone nearly as strong as RGB+NIR.
Cunha *et al.* (2021)	Campinas & Sao Paulo, Brazil	Detect water tanks (rooftops) and swimming pools, and relate object densities to socioeconomic level to support dengue/*Aedes* control.	DJI Phantom 3 carrying Canon PowerShot S100 (12.1 MP, 5.2 mm); flight planned in MissionPlanner; 60% lateral/80% longitudinal overlap; processing in Agisoft PhotoScan	GSD ≈ 0.03 m/pixel at 100 m altitude; 3.05 km² total coverage (Campinas); patches 240×240 px; BH satellite imagery via Google Earth Pro (≈0.15 m/pixel) for pretraining	Swimming pools & rooftop water tanks (*Aedes*-relevant sites)	Manual annotation (Labelme). Campinas: pools 74 patches (52 train/val, 22 test; 65 pools); tanks 146 patches (102 train/val, 44 test; 196 tanks). BH: 3980 pools, 16,216 tanks	Faster R-CNN (MobileNetV2 backbone) in PyTorch; transfer learning from BH→Campinas; Adam (typical lr = 1e-4; fine-tuning lr = 0.005; batch = 1)	AP computed at IoU=0.5 and 0.5:0.95; detection threshold 0.8; independent Campinas subset used for validation	With fine-tuning: Pools AP50 = 90.23, AP50:95 = 56.9; Tanks AP50 = 87.53, AP50:95 = 46.8. Without fine-tuning: Pools AP50 = 80.27 (AP50:95 = 51.65); Tanks AP50 = 0. Campinas only (no TL): Pools 33.81, Tanks 46.12 (AP50)	Densities computed per km² and per 100 households across 4 areas; $\chi^2 = 89.159$; $p = 0.05$; used to infer socioeconomic patterns	Area 4 (poorest): water tanks/km² = 360.8; tanks/100 households = 18.2; few pools. Area 1 (wealthiest): pools/km² = 116.7; pools/100 households = 9.8; A few tanks. Transfer learning markedly improved detection performance.

Author (Year)	Country/ Region	Objective	Drone Platform & Sensor	Image Resolution/Coverage	Target Habitat /Vector	Annotation Method	ML Approach (Model/Algorithm)	Validation Strategy	Evaluation Metrics	Integration with GIS/Epidemiology	Key Findings
Case *et al.* (2020)	USA; New York	Test whether UAV imagery + CNNs can (i) detect container habitats of *Aedes albopictus* and (ii) predict property-level larval presence to aid integrated mosquito management.	DJI Mavic Pro (RGB); custom quadcopter (3DR Pixhawk 1) + GoPro Hero5; flights at 50 m, ~5 m/s	Theoretical GSD: <1 cm/px (Mavic) 1.5–4 cm/px (GoPro). Effective smallest objects identified: ~2–5 cm (Mavic), ~10–15 cm (GoPro). Neighbourhood areas: 5 ha and 14 ha	*Ae. Albopictus* container habitats (47 Object categories (e.g., flowerpots, bins, gutters, toys)	12,281 tiles processed; >125 properties and 1,925 containers imaged; ground surveys on 28 properties with 629 containers; labels via LabelImg; IoU (Jaccard) used for TP/FP/FN; larval/pupal ID from field surveys	SSD300 (VGG16 base) object detection with transfer learning (first 11 layers frozen); Adam; data augmentation; also property-level FCN (VGG16-based) for larvae presence	Held-out test tiles for detection; GLMM linking UAV-seen containers to ground totals/water/larvae; property-level classification on 34 properties	Object detection: precision ~59%/recall ~35% (strict classes); counting any "container" boosts to precision ~67%/recall ~40% (conf ≥ 0.2). Property classification accuracy ~80% (larvae present/absent). Container visibility: 64% fully, 14% partially visible from the air. Properties with ≥ 15 UAV-seen containers all had water; with ≥ 35 had larvae	Intended to prioritise houses for inspection, UAV imaging dramatically increases coverage vs. ground alone	UAV cannot reliably see water/larvae at this resolution; occlusion by trees/awnings/walls; small training set (overfitting ~25 epochs); performance varies by neighbourhood canopy.

Note: This table collates detailed information from published studies, including: author and year, study site/country, research objectives, UAV platform and sensor specifications, image resolution and coverage, target vector habitats, annotation and ground-truthing strategies, ML architectures (e.g., CNN, YOLO, Faster R-CNN, SSD, RF), validation design, evaluation metrics (precision, recall, mAP, accuracy), GIS/epidemiological integration, key findings, limitations, and identified research gaps. By consolidating these elements, the table enables direct comparison of methodological approaches, technical performance, and the contextual applications of UAV-ML pipelines, while also highlighting gaps in small-object detection, multispectral/thermal integration, and operational scalability.

2.11.2.1 Characteristics of Included Studies

A total of eight studies were included and systematically analysed for their methodological and technical characteristics (Table 2.10). Most studies focused on breeding habitat detection (n = 5, 62.5%), reflecting the predominant application of drone–machine learning approaches for identifying mosquito breeding sites. Fewer studies addressed habitat or environmental characterization (n = 1, 12.5%) or feasibility and pilot assessments (n = 2, 25.0%), indicating that research in this field remains largely oriented toward detection rather than broader operational evaluation.

In terms of aerial platforms, DJI Phantom series drones were the most commonly used (n = 4, 50.0%), followed by the DJI Mavic series (n = 3, 37.5%) and custom or other UAV platforms (n = 2, 25.0%). Sensor deployment was dominated by RGB cameras, which were used in all studies (100%). Only a minority incorporated multispectral sensors (n = 2, 25.0%) or thermal sensors (n = 1, 12.5%), suggesting that most applications relied on visible-spectrum imagery rather than advanced spectral data. Most studies employed high spatial resolution imagery (≤ 5 cm ground sampling distance) (n = 6, 75.0%), consistent with the need to detect small and heterogeneous mosquito breeding habitats. The remaining studies used coarser resolutions (> 5 cm; n = 2, 25.0%) to balance spatial coverage and operational efficiency. With respect to target vectors and habitats, *Aedes* breeding habitats were the primary focus (n = 6, 75.0%), while *Anopheles* larval habitats were included in a smaller subset of studies (n = 2, 25.0%), reflecting the dominant emphasis on urban dengue vectors.

Regarding analytical methods, deep learning approaches including convolutional neural networks, YOLO, and related architectures were reported in most studies (n = 7, 87.5%). Random Forest methods were used in n = 2 (25.0%) of studies, while GeoOBIA and support vector machines were each reported in one study (12.5%). This distribution highlights the widespread adoption of deep learning for drone-based mosquito surveillance, alongside continued use of traditional classifiers for specific analytical tasks. Annotation procedures were primarily manual (n = 6, 75.0%), with semi-automated annotation reported less frequently (n = 2, 25.0%), underscoring the ongoing reliance on labour-intensive data preparation. Validation strategies varied across studies, with train–test splits most commonly reported (n = 6, 75.0%), followed by cross-validation (n = 3, 37.5%) and independent field validation (n = 2, 25.0%). Evaluation metrics were similarly heterogeneous. Accuracy was the most frequently reported metric (*n* = 7, 87.5%), while precision and recall (*n* = 4, 50.0%), F1-score (*n* = 3, 37.5%), and intersection over union (IoU) (*n* = 2, 25.0%) were reported less consistently, reflecting the absence of a standardized evaluation framework for drone-based mosquito surveillance.

Overall, the included studies consistently reported high performance in breeding habitat detection and demonstrated the technical feasibility of integrating drone imagery with machine learning for mosquito surveillance. However, several recurring challenges were identified, including small-object detection, occlusion by vegetation, scalability constraints, and the burden of manual annotation. Taken together, these findings suggest that while existing studies provide strong proof-of-concept evidence, further methodological refinement and operational integration are required to support sustained deployment within vector control programmes.

Table 2.10
Summary of Methodological Characteristics of Included Studies

Key Characteristics	**No. of studies**	**% of studies**
A. Study objective		
▪ Breeding habitat detection	5	62.5
▪ Habitat / environmental characterization	1	12.5
▪ Feasibility / pilot assessment	2	25.0
B. Drone platform		
▪ DJI Phantom series	4	50.0
▪ DJI Mavic series	3	37.5
▪ Custom / other UAV platforms	2	25.0
C. Sensor type		
▪ RGB camera	8	100.0
▪ Multispectral sensor	2	25.0
▪ Thermal sensor	1	12.5
D. Ground sampling distance (GSD)		
▪ ≤ 5 cm	6	75.0
▪ > 5 cm	2	25.0
E. Target Vector / Habitat		
▪ *Aedes* breeding habitats	6	75.0
▪ *Anopheles* larval habitats	2	25.0
F. Machine Learning Approaches		
▪ Deep learning (CNN, YOLO, related architectures)	7	87.5
▪ Random Forest	2	25.0
▪ GeoOBIA	1	12.5
▪ Support Vector Machine	1	12.5
G. Annotation method		
▪ Manual annotation	6	75.0
▪ Semi-automated annotation	2	25.0
H. Validation strategy		
▪ Train–test split	6	75.0
▪ Cross-validation	3	37.5
▪ Independent field validation	2	25.0
I. Evaluation Metrics		
▪ Accuracy	7	87.5
▪ Precision / Recall	4	50.0
▪ F1-score	3	37.5
▪ Intersection over Union (IoU)	2	25.0

Note: Percentages are calculated using the total number of included studies (n = 8). For categories where individual studies could report more than one characteristic (e.g., drone platforms, sensor types, machine learning approaches, annotation methods, validation strategies, and evaluation metrics), percentages represent the proportion of studies reporting each feature and do not sum to 100%. Categories are mutually exclusive only where explicitly stated.

2.11.2.2 Technical Characteristics of Drone-Based Mosquito Surveillance

Figure 2.10 synthesises cross-tabulated characteristics across the included studies, providing insights into how technical decisions in drone deployment shape research outcomes. Meanwhile, Figure 2.10A demonstrates that image resolution is closely aligned with the ecological niche of interest. Studies employing high-resolution imagery (< 5 cm/pixel) overwhelmingly targeted container-breeding *Aedes* habitats. This reflects the need for fine-grained imagery to detect small, discrete water-holding structures such as tanks, buckets, and discarded containers. In contrast, studies using moderate resolution (5-15 cm/pixel) have extended their focus to larger habitats. This includes rice fields, puddles, and wetlands, which are often associated with *Anopheles* breeding. Essentially, this trend suggests that resolution requirements are habitat-dependent, with greater spatial detail being indispensable for detecting urban containers.

On the other hand, coarser resolutions suffice for expansive, rural water bodies. Figure 2.10B highlights a clear technological preference in drone-sensor pairings. Commercial multirotor drones (e.g., DJI Phantom series) dominate the field, especially when equipped with RGB sensors, underscoring their accessibility, affordability, and ease of deployment. By contrast, custom-built multirotor platforms are more frequently associated with multispectral sensors, suggesting that research groups pursuing more specialised ecological questions often resort to bespoke hardware. Notably, fixed-wing platforms and advanced imaging sensors (e.g., thermal or hyperspectral cameras) remain underrepresented. This highlights a methodological gap in surveying large or inaccessible habitats at scale. Together, these heatmaps reveal a research landscape heavily skewed toward urban container-breeding *Aedes* surveillance using consumer-grade drones and RGB imagery, with relatively limited diversification into alternative habitats, platforms, or sensors. Furthermore, this concentration reflects both the practicality of accessible technology and the epidemiological priority of dengue vectors. Nevertheless, the underutilisation of advanced sensing modalities and alternative drone platforms presents a clear opportunity for methodological innovation. This is particularly true in integrating aerial surveillance with GIS-epidemiological models to inform broader vector control strategies.

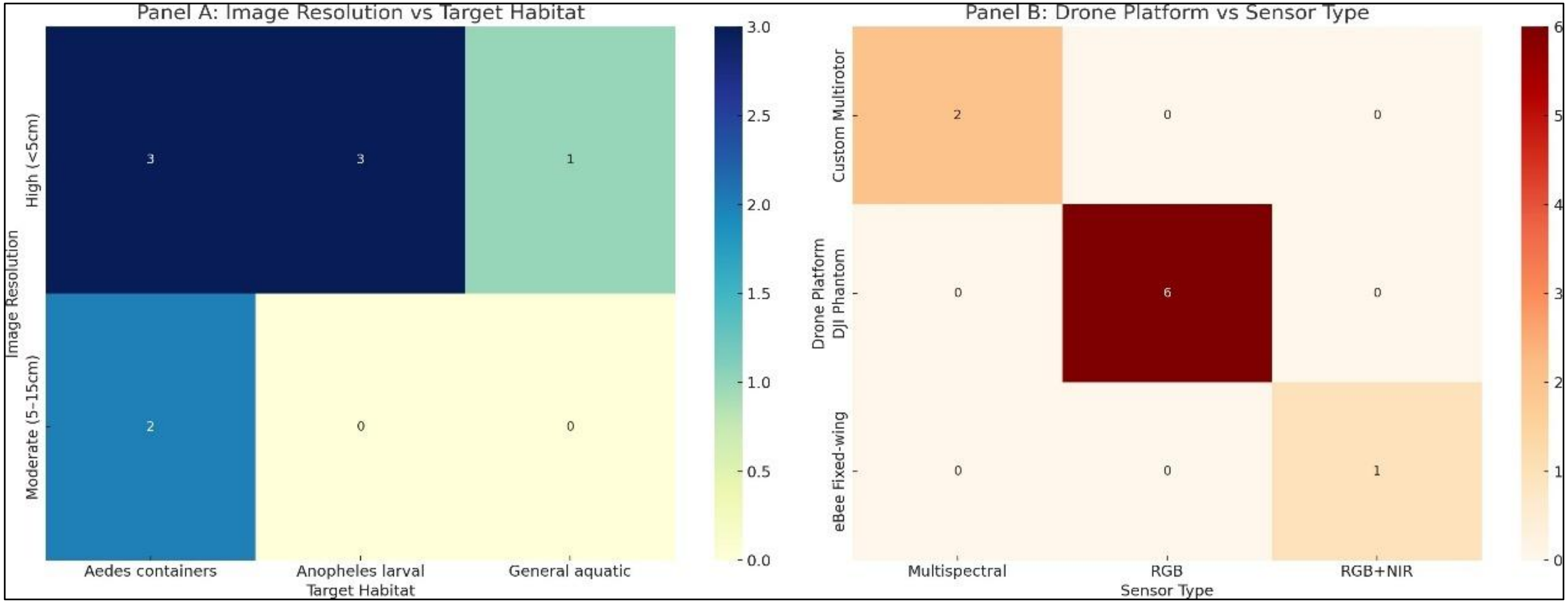


Figure 2.10 Cross-Tabulation of Technical Characteristics in Drone-Based Mosquito Surveillance Studies

Note: Panel A compares image resolution with target habitats, showing that high-resolution imagery (< 5 cm/pixel) is primarily applied to *Aedes* container habitats. In comparison, moderate resolution (5-15 cm/pixel) is shared across *Aedes* and *Anopheles* habitats. Panel B links drone platforms to sensor types, revealing a dominance of DJI Phantom with RGB sensors and custom multirotor with multispectral cameras. All analyses are based on the eight included studies (n = 8). Counts reflect the number of studies reporting each characteristic. Values lower than eight indicate that the respective characteristic was not examined or not reported in all studies. Categories are not mutually exclusive, and individual studies may contribute to more than one category

2.11.2.3 Association Between Study Objectives and Machine Learning Approaches in Drone-Based Aedes Surveillance

The distribution of study objectives across machine learning (ML) approaches in drone-based mosquito vector surveillance demonstrates clear methodological patterning (Figure 2.11A). Deep learning methods, including convolutional neural networks and YOLO-based architectures, were predominantly applied to breeding habitat detection (n = 5), reflecting their suitability for high-resolution image analysis and automated object recognition tasks. In contrast, traditional ML approaches, such as Random Forest and GeoOBIA, were more commonly used for habitat characterization (n = 1), consistent with their strength in feature-based classification and spatial segmentation. Studies focusing on feasibility assessments were largely supported by deep learning approaches (n = 2), indicating their frequent use in exploratory evaluations and pilot-scale implementations. Overall, the observed distribution highlights that analytical approaches were selected in alignment with specific study objectives, with detection-oriented applications favoring deep learning techniques and habitat-focused analyses more often utilizing traditional ML methods.

To further illustrate these trends, Figure 2.11B presents a heatmap cross-tabulating study objectives with ML approaches. The visualisation reinforces the dominance of deep learning in detection-related studies and feasibility trials, while highlighting the niche yet persistent role of RF in ecological assessments. Together, these findings suggest an emerging methodological specialisation in drone-based vector surveillance: deep learning is becoming the preferred tool for detection tasks where speed and accuracy are critical. By contrast, traditional classifiers continue to play a role in environmental feature classification, where interpretability and structured analysis remain advantageous.

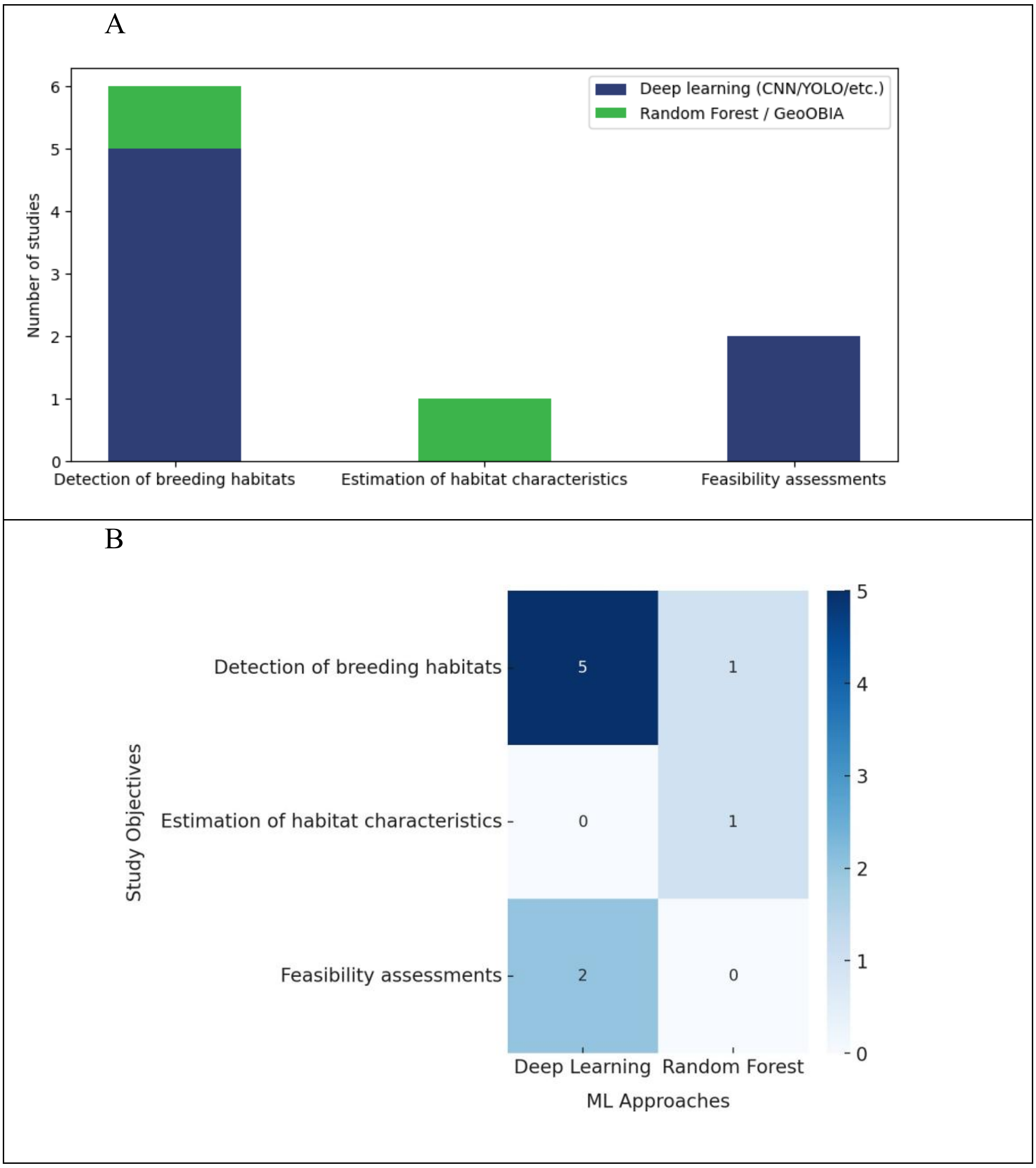


Figure 2.11 Association Between Study Objectives and ML Approaches in Drone-Based *Aedes* Surveillance

Note: (A) Descriptive cross-tabulation of study objectives and machine learning (ML) approaches in drone-based mosquito vector surveillance studies. Bars represent the number of studies applying deep learning methods (e.g., CNN/YOLO) and traditional machine learning approaches (e.g., Random Forest/GeoOBIA) across different study objectives. The figure is presented for descriptive purposes only. (B) Heatmap cross-tabulating study objectives with ML approaches. All analyses are based on the eight included studies (N = 8). Counts represent the number of studies reporting each study objective–machine learning approach combination. Values lower than eight reflect that not all studies addressed every objective or employed every analytical approach. Categories are not mutually exclusive, and individual studies may contribute to more than one category.

2.11.2.4 Machine Learning Attributes in Vector Control Strategies

The bubble plot illustrates the distribution of ML attributes, including high accuracy, interpretability, scalability, and feasibility in field applications. This can be observed across four major vector control strategies: breeding site detection, environmental risk characterisation, feasibility assessments, and predictive early warning (Figure 2.12). In particular, breeding site detection exhibited the strongest association with high accuracy (n = 5) and scalability (n = 4). This underscores the reliance on precision algorithms, such as CNNs, for the reliable identification of *Aedes* breeding habitats. Nonetheless, interpretability was limited (n = 2), reflecting the "black-box" challenge of deep learning methods in operational contexts. Following this, environmental risk characterisation was more evenly distributed, with a moderate emphasis on accuracy (n = 4) and interpretability (n = 4). This suggests that models in this domain often strike a balance between predictive power and explainability to inform ecological and epidemiological decision-making. In addition, scalability remained a challenge (n = 3), particularly in heterogeneous environments. Feasibility assessments were primarily driven by the field feasibility attribute (n = 5), emphasising the importance of evaluating whether ML-driven systems can be practically deployed in resource-limited settings. In line with this, accuracy and interpretability were moderate (n = 3 each). At the same time, scalability remained low (n = 2), reflecting early-phase validation studies rather than broad operational integration.

Finally, predictive early warning demonstrated strong associations with accuracy (n = 5) and scalability (n = 4). This aligns with the demand for high-performing, scalable models that can process large volumes of epidemiological and climatic data for real-time outbreak forecasting. However, interpretability (n = 3) and feasibility (n = 2) were less emphasised, reflecting the current prioritisation of predictive performance over operational implementation.

Therefore, these patterns suggest that while accuracy and scalability are paramount in breeding detection and early warning systems, feasibility in field settings is crucial for assessment studies, and interpretability plays a vital role in characterising environmental risk. This uneven distribution of attributes suggests significant evidence gaps, particularly in developing interpretable, scalable models that can be feasibly deployed in community-level vector control programmes.

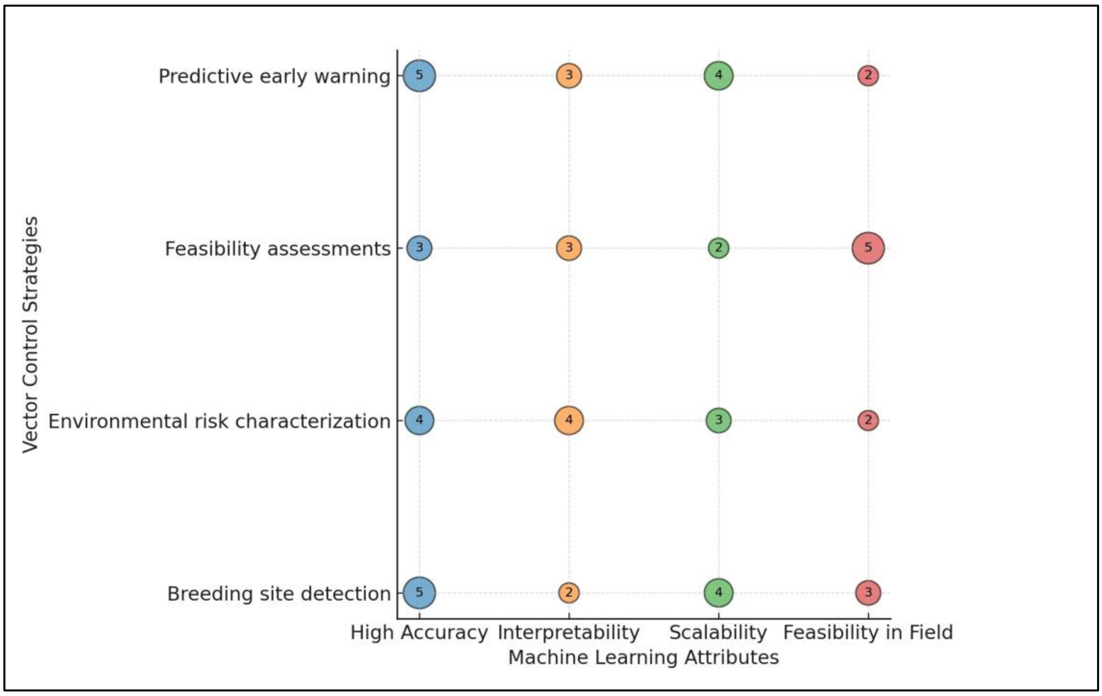


Figure 2.12 Bubble Plot Illustrating Machine Learning (ML) Attributes in Relation to Vector Control Strategy Domains Synthesized from the Included Studies

Note: Bubble size reflects the frequency with which specific ML attributes (e.g., accuracy, interpretability, scalability, feasibility) were reported or discussed in association with each strategy domain. Empirical evidence from the included studies primarily informs breeding site detection, environmental risk characterization, and feasibility assessment, while predictive early warning is presented as a conceptual synthesis domain derived from cross-study interpretation rather than a standalone study objective. This figure is based on the eight included studies (N = 8). Bubble sizes represent the frequency of reported attribute–strategy associations, not unique study counts. Counts may exceed eight because individual studies often addressed multiple attributes and contributed to more than one strategy domain. Categories are not mutually exclusive, and values reflect reported methodological coverage rather than direct evidence of operational implementation

The evidence synthesized from the eight included studies primarily pertains to breeding habitat detection, environmental or ecological characterization, and feasibility assessment of drone-based machine learning applications for mosquito vector surveillance. Concepts such as predictive early warning were not reported as explicit empirical objectives within the included studies but were instead identified through cross-study synthesis of methodological attributes and reported applications. Accordingly, results are presented to distinguish directly observed empirical outcomes from conceptual extensions, ensuring that quantitative findings are not overstated while allowing broader interpretation of how drone-based machine learning approaches may inform integrated vector control frameworks.

2.11.3 Discussion

This systematic review highlights the growing role of ML in advancing drone-based *Aedes* surveillance, revealing a methodological landscape that is becoming increasingly specialised and aligned with both technical capabilities and vector control priorities. Deep learning architectures, particularly CNNs and object detection frameworks such as YOLO, emerged as the dominant tools for breeding habitat detection. Moreover, their ability to process high-resolution imagery and deliver rapid, automated classification explains their predominance in detection-oriented studies (Shahzadi *et al.*, 2025). In contrast, traditional ML approaches, including RF and GeoOBIA, were consistently employed for ecological characterisation, reflecting their interpretability and robustness in structured feature-based classification tasks (Rajbhandari *et al.*, 2019). Feasibility-focused studies also leaned toward deep learning, highlighting its flexibility for proof-of-concept applications and experimental deployment (Muñoz *et al.*, 2019).

The descriptive synthesis further indicates that methodological choices were closely aligned with study objectives, rather than applied uniformly across surveillance tasks. Detection-oriented studies consistently favored deep learning methods, reflecting their suitability for automated object detection and image-based pattern recognition in drone imagery. In contrast, studies addressing ecological characterization more often relied on RF and GeoOBIA, which offer greater transparency and explanatory power for structured environmental analyses. These patterns are presented as descriptive tendencies, as no formal hypothesis testing was performed due to the small number of included studies, and analyses were restricted to narrative synthesis and visual cross-tabulation. Similar objective-driven methodological alignment has been reported in adjacent domains such as precision agriculture, environmental monitoring, and wildlife ecology, where deep learning dominates detection-focused applications, while traditional classifiers remain central to interpretable ecological mapping (Hashali *et al.*, 2024). Such cross-domain parallels suggest that the observed patterns are not unique to mosquito surveillance but reflect broader trends in applied remote sensing and ML research.

From a public health perspective, the integration of ML-driven analytics into drone-based surveillance represents more than a technological advancement. It reflects an operational transformation in vector control (Hassan, 2024). Detection-oriented strategies gain from the precision and automation of deep learning, enabling rapid hotspot identification and faster intervention cycles (Maican *et al.*, 2025). Conversely, ecological characterisation studies benefit from the ecological validity and interpretability of RF and GeoOBIA. This, in turn, provides insights that support long-term environmental management and urban planning (Sharma *et al.*, 2024). These distinctions map directly onto the principles of the WHO's IVM framework, where the dual priorities of rapid response and sustainable ecological monitoring are equally vital (Tiffin *et al.*, 2025).

Despite these advances, several critical gaps remain. First, hybrid modelling frameworks that integrate the predictive strength of deep learning with the interpretability of traditional ML approaches remain underexplored yet may offer balanced solutions that are both powerful and transparent an important consideration for adoption by public health agencies. Second, external validation and scalability are limited, with most studies confined to pilot settings or geographically restricted sites. Robust validation across diverse ecological and socio-environmental contexts is necessary to demonstrate reliability under real-world operational conditions. Third, economic considerations are rarely addressed; few studies evaluate the cost, infrastructure requirements, or sustainability of deploying advanced ML-driven drone surveillance in resource-constrained settings. Finally, the translational pathway from technical outputs to policy integration and community engagement remains poorly developed, limiting the impact of these technologies within national and local vector control programs.

Overall, this review demonstrates that methodological specialisation in drone-based *Aedes* surveillance is guided by study objectives, technical requirements, and operational priorities rather than random selection. Correspondingly, deep learning has established itself as the dominant approach for detection and feasibility assessments. In contrast, traditional ML approaches remain highly relevant for ecological characterisation. Thus, addressing current gaps through hybrid modeling, large-scale validation, cost-effectiveness analyses, and stronger linkages with policy and community frameworks will be essential to move the field beyond proof-of-concept studies. Such advances are necessary to realize the full potential of ML-integrated drone surveillance as a scalable, sustainable, and impactful component of vector control in the context of climate change, urban expansion, and increasing arboviral risk.

2.12 Research Gap

While previous studies in Malaysia and Southeast Asia have substantially advanced understanding of dengue-related KAP, as well as *Aedes* ecology across different urban settings, important gaps remain when viewed through the lens of drone-assisted environmental surveillance. Notably, KAP studies in Malaysian hotspots consistently report moderate to sound knowledge. However, inconsistent preventive behaviour (Selvarajoo *et al.*, 2020; Guad *et al.*, 2021; Andoy-Galvan *et al.*, 2024), and theory-informed work have demonstrated that risk perception, self-efficacy, and social norms strongly shape community responses to dengue (Othman *et al.*, 2019; Samsudin *et al.*, 2024, 2025). Stakeholder research has identified governance challenges and mixed attitudes towards conventional and innovative interventions (Arham & Amin, 2021; Manaf *et al.*, 2021; Rusly *et al.*, 2025). Conversely, early work on UAVs has demonstrated general acceptability, though it raises concerns regarding privacy, trust, and communication (Annan *et al.*, 2022; Dom *et al.*, 2025).

At the same time, entomological and environmental studies in Malaysia and other regions have described *Aedes* breeding in diverse urban micro-environments ranging from domestic containers and high-rise corridors to construction sites and urban parks (Basari *et al.*, 2016; Ab Hamid *et al.*, 2020; Yahya & Che Dom, 2020; Maamor *et al.*, 2023; Mahmud *et al.*, 2023; Fernandez *et al.*, 2023). Moreover, GIS-based work has mapped dengue hotspots at city and district scales, and several studies have linked satellite-derived land-cover and thermal features to *Aedes* infestation (Lorenz *et al.*, 2020; Kolimenakis *et al.*, 2021; Teillet *et al.*, 2024). Despite this, there is still little empirical work in Malaysia that uses drone-derived orthomosaics and vegetation-shade metrics to characterise fine-scale land-cover patterns in real neighbourhoods (such as flat versus terrace housing) as potential *Aedes* breeding sites. This includes documenting community and stakeholder perceptions of drone-based surveillance systematically.

In parallel, ML has been successfully applied to dengue case prediction and entomological indices in Malaysia (Salim *et al.*, 2021; Majeed *et al.*, 2023; Dom *et al.*, 2025). Nonetheless, these models are primarily built on time-series epidemiological or microclimatic data and do not yet incorporate high-resolution drone imagery for land-cover classification. Concurrently, RF and deep-learning approaches have been utilised to detect breeding-relevant containers from street-view, satellite, and UAV imagery, and to relate image-derived features to *Aedes* abundance (Haddawy *et al.*, 2019; Su Yin *et al.*, 2021; Passos *et al.*, 2022; Knoblauch *et al.*, 2024; Valdez-Delgado *et al.*, 2021; Rosser *et al.*, 2024; Tarpenning *et al.*, 2025; Carrasco-Escobar *et al.*, 2022). Still, these applications are mostly outside Malaysia, often highly technical, and rarely embedded in the realities of local vector control strategies.

Hence, this study addresses a clear gap by developing and applying a framework that links: (i) national-level community KAP and institutional stakeholder perspectives on drones; (ii) drone-based environmental mapping of land cover, vegetation, and shade in specific Malaysian urban areas; and (iii) RF-based land-cover classification implemented in QGIS to delineate potential *Aedes* breeding risk areas.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Introduction

This chapter details the research methodology employed in this study, which integrates drone technology and Machine Learning (ML) to support dengue prevention strategies at the community level. The overall research process was organised into three main phases, with each phase corresponding to a specific research objective.

The first objective was to identify the perception, specific needs, preferences, and challenges of households and experts in utilising drone technology for dengue prevention strategies. There were four aims under this objective: (i) to identify sociodemographic determinants of public perception and engagement in drone-assisted dengue surveillance; (ii) to identify sociodemographic determinants of willingness to adopt surveillance technology and mosquito control training for dengue; (iii) to evaluate community knowledge and practices on mosquito control at the state level and across urban-rural settings for sustainable dengue prevention; and (iv) to determine expert perspectives on drone-based surveillance of mosquito breeding sites. The outcomes of this objective informed the design of the subsequent phases. This is particularly true in tailoring drone applications and analytical approaches to meet community needs and stakeholder expectations.

The second objective was to evaluate the effectiveness of drone-based imaging in profiling potential breeding sites of *Aedes* mosquitoes. There were two aims in this objective: (i) to determine vegetation-shade interactions for *Aedes* habitat risk in urban areas using drone-based geospatial modelling; and (ii) to evaluate vegetation-shade interactions and housing typology using drone-based microclimate modelling and a Composite Risk Index (CRI). The field and imaging data generated in this phase provided the spatial and environmental profile required for the final phase of the study. Meanwhile, the third specific objective was to evaluate the accuracy of ML algorithms in classifying land-cover types associated with potential mosquito breeding sites. This objective aimed to evaluate ML-based classification of potential *Aedes* breeding habitats using RGB drone imagery. This final phase integrated the outputs from the previous objectives to develop and assess data-driven classification models for dengue risk profiling. The overall research flow and the linkages among these three phases, along with their respective aims, are depicted in Figure 3.1.

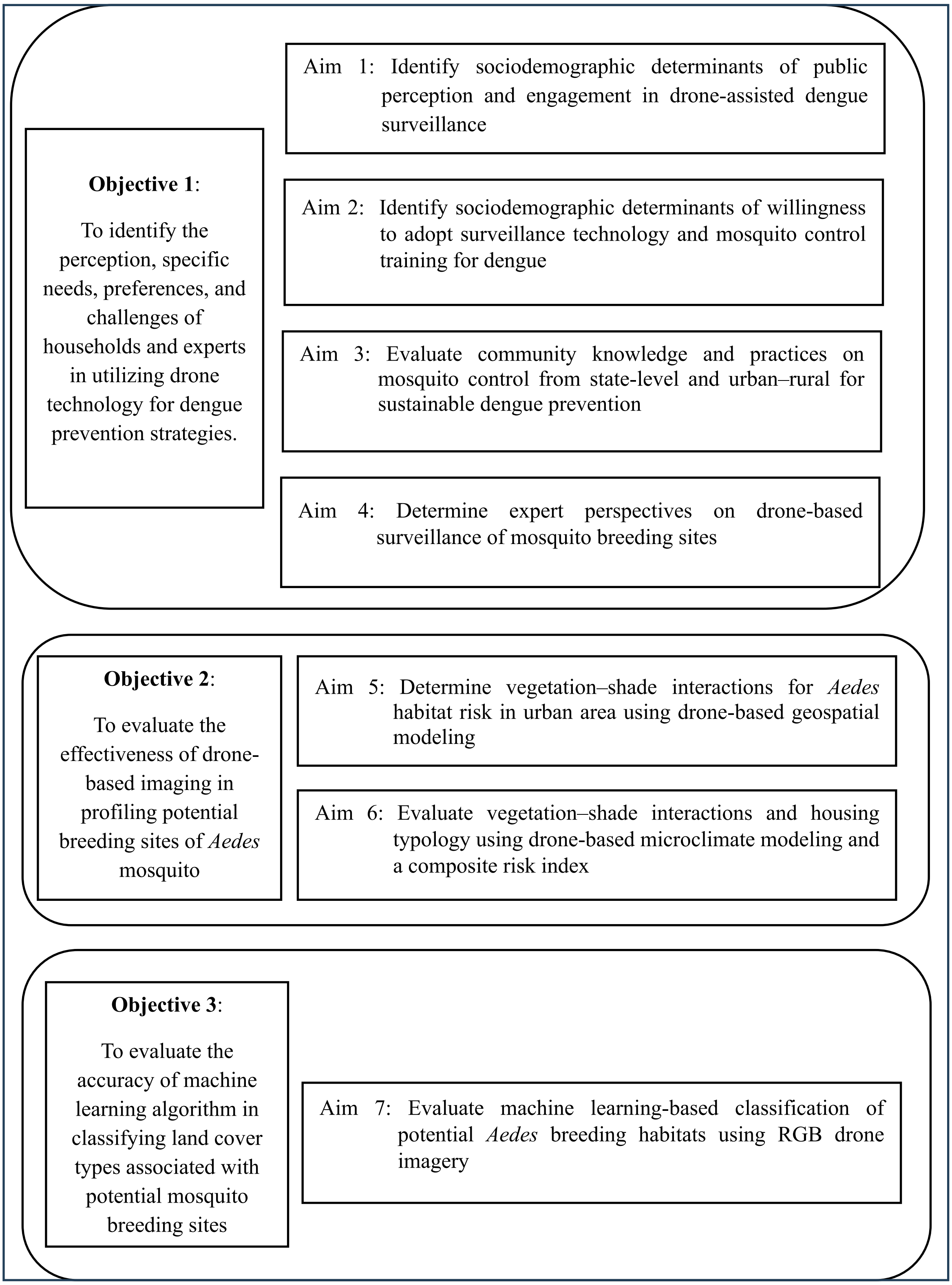


Figure 3.1 Research Flowchart

3.2 Objective 1: To Identify the Perception, Specific Needs, Preferences, and Challenges of Households and Experts in Utilising Drone Technology for Dengue Prevention Strategies

This study employed a cross-sectional survey design to investigate the sociodemographic factors influencing public perception and engagement with drone-based dengue surveillance in Malaysia. A cross-sectional approach was selected as it enables the assessment of associations between sociodemographic variables and public acceptance of drone technology at a specific point in time. It also facilitates a data-driven understanding of factors influencing community engagement in vector control initiatives. Accordingly, the study was conducted across multiple states in Peninsular Malaysia, focusing on areas identified as dengue hotspots based on epidemiological surveillance data from the Ministry of Health (MOH) Malaysia. These areas were selected based on historical dengue case reports over the past 3 years, ensuring the study targeted regions with persistent dengue outbreaks and a heightened need for innovative vector control measures. Note that the inclusion of both urban and rural communities was a key criterion to ensure a representative sample that captures variations in population density, digital engagement, and technology adoption.

The urban study locations included high-density metropolitan areas such as Shah Alam, Kuala Lumpur, Johor Bahru, and Penang. This is mainly attributed to the fact that the technological infrastructure is more developed, and public exposure to drone applications is likely higher in such areas. Furthermore, these urban centres represent economically active populations with greater access to digital health interventions and higher levels of social media usage. Such factors could influence engagement with drone-based surveillance systems. Conversely, the rural study sites were low-density regions in Kelantan, Pahang, and Terengganu, where traditional dengue control measures are more commonly relied upon, and digital technology adoption rates vary significantly compared to those in their urban counterparts. Thus, the urban-rural stratification was essential for assessing whether geographic location influences public perceptions of drone technology, willingness to participate in drone-assisted interventions, and concerns about privacy and surveillance. In addition, to ensure comprehensive sociodemographic representation, the study sample was stratified based on key variables. This includes age, gender, ethnicity, household type, and duration of residency in the area. On a similar note, the proportional sampling approach was used to align the distribution of respondents with the national demographic profile, thereby enhancing the generalisability of the findings.

Additionally, the study accounted for regional socioeconomic differences, ensuring that findings could be interpreted in the context of varying economic conditions, levels of education, and access to health information. The methodological approach of this study was designed to facilitate comparative analysis across geographic regions and demographic groups. This, in turn, provides valuable insights into how different populations perceive and engage with drone-based dengue surveillance. At the same time, the study's findings contribute to the broader discourse on technology adoption in vector control programmes. This ultimately offers evidence-based recommendations for integrating drone technology into national dengue prevention strategies.

3.2.1 Study Design and Setting

This study employed a community-based cross-sectional survey design to examine public perceptions and behavioural intentions regarding dengue vector control in Peninsular Malaysia. An emphasis has been placed on acceptance of drone-assisted dengue surveillance and willingness to engage in community-level prevention activities. Correspondingly, the cross-sectional approach was selected, as it enables the capture of population-level patterns of awareness, attitudes, and practices within a defined period. This provides baseline evidence to inform targeted interventions and risk communication strategies. Following this, data collection was conducted across dengue-prone regions in 12 states of Peninsular Malaysia. States were purposively selected using two criteria: (i) dengue endemicity, based on surveillance reports from the MOH Malaysia, and (ii) demographic heterogeneity, ensuring inclusion of both highly urbanised states (e.g., Selangor, Kuala Lumpur, Penang) and predominantly rural states (e.g., Kelantan, Terengganu, Pahang). This approach ensured representation of populations with different risk exposures, health system access, and socio-ecological contexts that influence mosquito breeding and control practices. Within each selected state, sampling was designed to capture both urban and rural populations. Districts were first stratified by urbanisation level using official classifications from the Department of Statistics Malaysia (DOSM).

Subsequently, communities were selected within each stratum to ensure balanced recruitment across diverse settlement types, including high-density metropolitan areas, semi-urban townships, and traditional villages. This stratification was crucial for accounting for the urban-rural divide, as previous studies have demonstrated differences in larval control practices, perceptions of mosquito risk, and reliance on adult mosquito interventions between these settings. The study setting, therefore, spanned a broad ecological and socio-economic spectrum, ranging from densely populated apartment complexes in Kuala Lumpur to coastal fishing villages in Terengganu. Such diversity enhances the external validity of the findings, allowing them to inform both national-level policy and state-tailored dengue prevention strategies.

3.2.2 Target Population

The target population for this study comprised residents aged 18 years and above residing in dengue-prone regions across 12 states in Peninsular Malaysia. These states were selected based on historical dengue incidence data from the MOH Malaysia. This ensures the inclusion of areas with persistent dengue outbreaks and high transmission risk. Note that the study population was diverse, encompassing urban and rural settlements, socioeconomic backgrounds, and digital literacy levels to assess public perceptions of drone-based dengue surveillance and intervention strategies.

A stratified random sampling technique was employed to ensure proportional representation of respondents across key demographic variables, including gender, age group, ethnicity, residence type (urban vs. rural), and socioeconomic background. In line with this, stratification was essential to mitigate selection bias and enhance the generalisability of findings to the broader Malaysian population. This approach enabled a comparative analysis of how sociodemographic factors influence public engagement with drone technology, willingness to participate in vector control measures, and concerns about drone surveillance. However, eligibility criteria were restricted to adults who had resided in their community for at least six months to ensure adequate exposure to local dengue risk and community-level mosquito control practices. Participation also required informed consent prior to completing the questionnaire. Individuals who declined consent or provided incomplete submissions that did not permit analysis were excluded from the final dataset.

3.2.3 Sampling Strategy

A stratified sampling strategy was employed to enhance representativeness and facilitate subgroup comparisons across key characteristics. Stratification was applied by state and by area of residence, specifically urban and rural. This ensures that the sample included respondents from settlement contexts with potentially different exposure patterns, prevention norms, and access to digital health tools. Within the selected states, districts, and communities, efforts were made to achieve balanced recruitment across urban, semi-urban, and rural areas, including high-density urban areas, semi-urban townships, and rural areas. Furthermore, the sample size was determined using Cochran's formula to ensure adequate statistical power for subgroup analyses (Cochran, 1977). Given the need for robust inferential statistics, a 95% confidence level and a 5% margin of error were applied, resulting in a minimum required sample size sufficient to detect significant associations between independent and dependent variables. An additional oversampling strategy (10%) was implemented to address non-response bias, ensuring the final dataset maintained statistical integrity and population representativeness.

In total, 1,000 individuals were approached, and 866 completed the survey, yielding an 86.6% response rate. The final sample retained representation across strata, with rural residents comprising 36.4% and urban residents comprising 63.6%. This stratified structure enabled a more granular analysis of how sociodemographic characteristics influence willingness to engage in both digital and traditional vector control interventions.

3.2.4 Survey Instrument

Data were collected using a structured questionnaire adapted from a validated instrument reported by Annan *et al.* (2022) and refined to reflect the Malaysian context of dengue control. In particular, the adaptation process aimed to preserve the meaning of the original constructs while improving relevance to local public health systems, terminology, and household prevention practices. In addition, to tailor the instrument for the Malaysian context, several modifications were made during the adaptation process. These included: (i) Translating the questionnaire into both Bahasa Malaysia and English to enhance comprehension and inclusivity; (ii) Adjusting phrasing to reflect local terminology (e.g., replacing "neighbourhood council" with “Majlis Perbandaran”); (iii) Including culturally relevant examples of mosquito control behaviours commonly practiced in Malaysian households; and (iv) Adding questions on housing type and local community engagement, which were deemed important based on expert consultations with public health officers, entomologists, and local stakeholders. The final instrument was designed to be comprehensive while maintaining respondent engagement, with an estimated completion time of 20 to 30 minutes. Concurrently, the English version of the questionnaire was prepared for inclusion as supplementary material to support transparency and reproducibility.

3.2.5 Questionnaire Structure

A structured, self-administered questionnaire, adapted from a validated instrument, served as the primary data collection instrument. It is also designed to assess public perceptions, behavioural engagement, and technology acceptance related to drone-based dengue surveillance and intervention strategies (Annan *et al.,* 2022). The questionnaire was structured to ensure clarity, comprehensiveness, and relevance, and to capture sociodemographic variations in public attitudes toward drone technology. Notably, the survey employed a combination of closed-ended and Likert scale questions to systematically assess the key determinants influencing respondents' willingness to engage in dengue vector control initiatives. Specifically, the structured questionnaire focused on three primary domains: sociodemographic characteristics, perceptions of technology adoption, and attitudes toward drone-based mosquito surveillance and participation in training. Each response was categorised into predefined options, enabling comparative analysis across demographic subgroups to identify significant predictors of engagement in vector control measures.

The first section of the survey collected sociodemographic information, which served as a critical foundation for understanding variations in willingness to adopt mosquito control strategies. Participants provided details on gender, age, ethnicity, area of residence, duration of residence, housing type, and household size. Gender was included to assess potential differences in mosquito control responsibilities, as previous research indicates that women are often more involved in domestic vector control efforts. At the same time, men may be more inclined toward outdoor surveillance activities. Age categories ranged from 18 to over 60 years, allowing for the examination of differences in technology adoption and traditional public health engagement across generations. At the same time, ethnicity was recorded to explore potential cultural variations in perceptions of vector control and disease risk. Additionally, participants were asked to identify whether they lived in an urban or rural setting, as environmental and infrastructure factors can influence the prevalence of mosquito breeding sites and access to digital health interventions. The duration of residence in a given area was also considered, as long-term residents are likely to have greater awareness of local mosquito risks and a stronger sense of community responsibility.

Lastly, housing type and household size were included to examine whether living conditions influence mosquito exposure and vector control behaviours, particularly in high-density residential settings. However, educational level was not included in the survey instrument. This decision was made to minimise respondent fatigue and maintain completion rates, considering that the survey already took 20 to 30 minutes to complete. Given the emphasis on perceptions and behavioural intentions, priority was given to demographic, housing, and digital access variables most relevant to the study objectives.

Following the sociodemographic assessment, the survey included a series of questions evaluating participants' access to technology and the internet, crucial factors in determining readiness for digital vector control interventions. Participants were asked about their ownership of technological devices, frequency of internet usage, and engagement with social media platforms, as these factors influence the likelihood of adopting a dengue surveillance application. The following section assessed perceptions of drone-based mosquito surveillance, including questions on prior exposure to drones, privacy concerns, and perceived risks associated with aerial surveillance for public health purposes. Moreover, to measure acceptance levels, participants were asked whether they would support drone monitoring in their residential areas. This includes whether they would be willing to download a rapid alert system application that provides real-time notifications on detected mosquito breeding sites. Responses were categorised as "No," "Maybe," or "Yes," enabling further analysis of adoption patterns across sociodemographic groups.

Another critical component of the survey examined willingness to participate in mosquito control training programmes, assessing respondents' interest in learning how to identify and eliminate breeding sites, use ovitraps, and implement preventive measures. Accordingly, participants were asked to indicate their level of interest in attending community-led dengue prevention programmes using the same three-option scale ("No," "Maybe," or "Yes"). The final section of the questionnaire focused on household mosquito control behaviours. This aims to capture self-reported engagement in preventive measures such as eliminating standing water, using insecticides, covering water storage containers, and employing non-chemical control methods.

Additionally, the frequency of mosquito control practices was recorded to evaluate the consistency of engagement in prevention efforts. The survey was designed to be comprehensive yet time-efficient, comprising approximately 40 structured questions across five core sections. The use of both closed-ended and Likert scale response formats facilitated the quantitative analysis of behavioural patterns and risk perceptions. This enables researchers to identify significant predictors of technology adoption and training participation. Thus, by incorporating a well-structured set of measures, the study provides a robust framework for assessing public engagement in dengue vector control. It also offers valuable insights for developing targeted, evidence-based interventions that align with community needs and preferences. In general, across the instrument, responses were primarily captured using closed-ended formats and scaled options to support quantitative analysis. This included a three-category intention format, with options for “No,” “Maybe,” and “Yes,” for key outcomes related to application adoption and training participation (Appendix 2).

3.2.6 Pilot Testing, Validity, and Reliability Procedures

A pilot test was conducted with a subsample of 30 respondents from diverse sociodemographic backgrounds (urban and rural, various age groups, and different housing types) to assess the clarity, reliability, and relevance of the instrument. Feedback from the pilot revealed minor issues related to ambiguous wording and redundancy, which were addressed through revisions to item phrasing and the removal or consolidation of overlapping items. The methods described by Yusoff (2019) were primarily used as guidelines for calculating the Face Validity Index (FVI). The primary objective of face validity was to ensure that the questionnaire items were clearly and effectively articulated, thereby preventing any confusion among participants due to excessive formality or vagueness (Yusoff, 2019). There were two types of FVI: FVI for Item Level Face Validity Index (I-FVI) and Scale Level Face Validity Index based on average (S-FVI/Ave). Essentially, the value for I-FVI was calculated using the formula

[I-FVI = (agreed item)/(number of raters)]. Meanwhile, the value for S-FVI/Ave was calculated using the formula [S-FVI/Ave = (sum of I-FVI scores)/(number of items)] (Yusoff, 2019).

The Content Validity Index (CVI) was calculated to determine the degree to which the questionnaire items accurately represented the entire domain or variable under study. This evaluation was conducted by subject-matter experts, who rated each questionnaire item on a 4-point scale. Two types of CVI were utilised. The Item-Content Validity Index (I-CVI) assessed the validity of individual items by calculating the proportion of content experts assigning a relevance rating of 3 or 4. Additionally, the Scale-Content Validity Index (S-CVI/Ave) was calculated by averaging the I-CVIs for all items on the scale (Polit & Beck, 2006).

Based on the preliminary face validity assessment conducted with ten randomly selected individuals from the target community, participants' feedback was systematically evaluated, and the findings indicated that all ten respondents clearly understood the questionnaire content and considered it relevant. The Content Validity Index (CVI) analysis, conducted by a panel of experts, showed that all items met the minimum content validity standard (CVI > 0.80) and adhered to the minimum acceptable Content Validity Ratio (CVR) requirement.

In line with this, internal consistency reliability was evaluated using Cronbach's alpha, with the overall instrument demonstrating good reliability. Subscales related to technology adoption and community participation also demonstrated acceptable internal consistency. This, in turn, supports the use of the instrument for central survey administration. Overall, these procedures supported the refinement of wording, alignment with the intended constructs, and coverage of the content domain relevant to dengue surveillance, acceptance, and participation in prevention (Appendix 3-5).

3.2.7 Data Collection Procedures

Data collection was conducted using both online and face-to-face methods to improve coverage and reduce bias arising from unequal digital access. Online distribution was implemented through social media platforms, WhatsApp groups, and community forums to reach respondents with higher digital engagement. Meanwhile, field-based recruitment and administration were used in areas with limited internet access to ensure the inclusion of rural and lower-income communities that may be underrepresented in online surveys. The questionnaire was available in both Bahasa Malaysia and English, allowing respondents to select their preferred language to minimise misunderstandings and enhance response accuracy. For face-to-face administration, trained bilingual data collectors were available to clarify questions when needed while following standardised guidance to maintain consistency of administration across sites. Following this, public gathering points such as markets, clinics, and community centres were used to approach potential participants across various demographic groups. Concurrently, recruitment was conducted to maintain proportional representation within the stratification structure. Upon completion of the survey, participants were provided with dengue prevention educational materials to reinforce public health messaging. However, no financial incentives were offered to minimise the risk that participation or responses were influenced by compensation.

3.2.8 Aim 1: Identify Sociodemographic Determinants of Public Perception and Engagement in Drone-Assisted Dengue Surveillance

All collected data were cleaned, coded, and analysed using Statistical Package for the Social Sciences (SPSS) (Version 29) to ensure accuracy, consistency, and completeness before statistical analysis. Descriptive statistics, including frequencies, means, and standard deviations, were used to summarise sociodemographic characteristics, technology usage patterns, and perceptions of drone-based dengue surveillance. Furthermore, to examine associations between sociodemographic factors and public perceptions of drone technology, chi-square tests were used for categorical variables. These were utilised to assess whether observed differences in attitudes and engagement levels were statistically significant across demographic groups. Additionally, logistic regression analyses were conducted to assess the predictive strength of sociodemographic characteristics for key outcome variables, including willingness to participate in drone-assisted dengue control activities, comfort in sharing drone-based data, and concerns about privacy and surveillance. The Odds Ratios (ORs) and 95% Confidence Intervals (CIs) were reported to quantify the magnitude and direction of the associations.

The statistical significance level was set at $p < 0.05$, ensuring results were interpreted with 95% confidence and minimising the likelihood of Type I errors. To provide a visual representation of the significance of relationships across multiple variables, a heatmap analysis was performed using R's ggplot2 and seaborn libraries in Python. This allows for rapid identification of key demographic predictors of drone technology acceptance and engagement. Note that all statistical tests were conducted in accordance with best practices for public health research, ensuring robust, reproducible, and interpretable findings. Remarkably, this analytical approach provides comprehensive insights into the role of sociodemographic factors in shaping public acceptance of drone-based dengue surveillance. This ultimately supports evidence-based policy recommendations and targeted intervention strategies.

3.2.9 Aim 2: Identify Sociodemographic Determinants of Willingness to Adopt Surveillance Technology and Mosquito Control Training for Dengue

A rigorous statistical approach was employed to analyse the determinants influencing respondents' willingness to engage in dengue vector control initiatives. The analysis was conducted in two stages: a descriptive statistical analysis to summarise sociodemographic characteristics and overall trends in technology adoption and training participation. This is followed by a multinomial logistic regression analysis to identify significant predictors of engagement in vector control strategies. As such, descriptive statistics were used to characterise the study population, providing a distribution of key sociodemographic variables. This includes gender, age, ethnicity, residential area, housing type, and household size. Furthermore, frequency and percentage distributions were computed for categorical variables to illustrate overall trends and subgroup variations. This initial analysis provided a comprehensive overview of participants' demographic profiles and engagement patterns, laying the groundwork for further inferential analysis. In addition, to examine the factors influencing willingness to participate in vector control measures, multinomial logistic regression analysis was performed. Given that the dependent variables, willingness to download a dengue surveillance application and willingness to participate in mosquito control training, were categorical with three response levels ("No," "Maybe," and "Yes"), multinomial regression was deemed the most appropriate analytical approach. This method allows for the simultaneous comparison of multiple response categories against a reference group, enabling a more comprehensive assessment of behavioural determinants.

The primary independent variables included age, gender, housing type, and duration of residence, selected based on their theoretical relevance in shaping health behaviour and vector control engagement. ORs with 95% CIs were calculated to estimate the likelihood of participants choosing "Maybe" or "Yes" compared to "No" for each of the two dependent variables. Accordingly, a statistical significance threshold of $p < 0.05$ was applied to determine meaningful associations. The model also accounted for potential interaction effects, enabling a nuanced exploration of how demographic variables collectively influence engagement. For instance, interaction terms were examined to assess whether gender moderated the association between age and technology adoption or whether housing type influenced engagement differently in urban and rural settings. Meanwhile, age was analysed as a binary variable using a 40-year threshold. This cut-off aligns with previous studies on digital health adoption that distinguish younger, tech-savvy populations from older cohorts with lower digital engagement and a higher preference for traditional public health interventions. This categorisation also corresponds to the approximate median age of the sample, providing a meaningful statistical split.

All statistical analyses were conducted using SPSS version 29.0, ensuring a robust and reproducible analytical framework. Prior to model estimation, data were screened for missing values, multicollinearity, and violations of assumptions, ensuring the validity of the regression outputs. Sensitivity analyses were also performed to assess the stability of findings across various model specifications. Additionally, the integration of descriptive and inferential statistical techniques provided a comprehensive evaluation of sociodemographic predictors of engagement in dengue control strategies. This offers valuable insights to inform targeted public health interventions and optimise community participation in both technology-driven and traditional mosquito control measures.

3.2.10 Aim 3: Evaluate Community Knowledge and Practices on Mosquito Control from State-Level and Urban-Rural for Sustainable Dengue

Data collection instrument: Data were collected using a structured questionnaire adapted from validated dengue Knowledge, Attitude, and Practice (KAP) surveys previously employed in Southeast Asia. It is subsequently tailored to the Malaysian sociocultural and epidemiological context (Annan et al., 2022). The adaptation process included consultation with entomologists, public health practitioners, and social scientists to ensure relevance to the local dengue control environment.

The final instrument was prepared in both Malay and English, with careful attention to semantic and conceptual equivalence. The questionnaire comprised four domains. First, sociodemographic characteristics were collected, including age, sex, ethnicity, education, occupation, household size, type of residence, and duration of stay at the current location. This enables the analysis of the social determinants of mosquito control behaviours. Second, knowledge indicators focused on perceived risk of mosquito-borne diseases and the ability to correctly identify *Aedes* larvae, representing essential cognitive determinants of vector control. Third, preventive practices were assessed using items measuring the frequency of cleaning water storage containers, the adoption of protective measures (e.g., insecticide use, repellents, mosquito nets), and active control against both larval stages (source reduction, larviciding), as well as adult mosquitoes (fogging, spraying). Responses were recorded using standardised frequency scales to enable quantification. Fourth, household environment characteristics included observations and self-reports on water storage practices, waste management, and potential breeding habitats, providing ecological context for reported behaviours.

Measurement of KAP indices: Composite indices were developed to quantify KAP levels across states. Knowledge Index: Derived from responses to perceived risk of mosquito-borne diseases and ability to identify mosquito larvae, standardised to a 0% to 100% scale. Practice Index: Constructed from reported frequencies of preventive behaviours, including container cleaning, larval source management, and use of adult mosquito control measures (mosquito nets, insecticide spraying, fogging, repellents). Responses on a 5-point Likert scale were normalised and averaged, then converted to a 0% to 100% scale. Overall KAP Index: The mean of Knowledge and Practice indices, categorised as Good ($\geq$ 80%), Moderate (60-79%), and Poor (< 60%). As for attitude it was analysed independently through the technology acceptance and willingness to adopt digital tools and training in Aim 2.

Statistical analysis: Descriptive statistics were used to characterise respondents. State-level differences in sociodemographic characteristics were visualised using heatmaps. Variation in knowledge and practices was assessed using chi-square tests of independence, with adjusted residuals indicating over- or under-representation. One-way ANOVA with post-hoc Tukey's tests was employed to assess differences in Knowledge, Practice, and Overall KAP indices across states. Effect sizes were expressed as eta-squared (η^2). To evaluate urban-rural disparities, independent-samples Welch's t-tests were performed when assumptions of normality and equal variances were met; otherwise, Mann-Whitney U tests were employed. At the same time, forest plots summarised mean differences (Urban-Rural) with 95% CIs, where values above zero indicated higher urban scores and values below zero indicated higher rural scores. All analyses were conducted using SPSS version 29.0 and R version 4.4, with significance set at $p < 0.05$.

3.2.11 Aim 4: Determine Expert Perspectives on Drone-Based Surveillance of Mosquito Breeding Sites

Study setting: This research was grounded within Malaysia's stratified healthcare system, comprising national, state, and district levels. Within this structure, the MOH oversees vector surveillance programmes, and the introduction of drone-based monitoring could represent a technological innovation to strengthen current dengue control strategies. Remarkably, the integration of drone-based monitoring into traditional vector control operations in this context offers insights into the operational feasibility, institutional readiness, and acceptability of such innovations among public health stakeholders.

Study design and stakeholder selection: A qualitative case study design was employed to explore the institutional, operational, and technological dynamics of dengue vector control. This is particularly true in relation to the integration of drone-based surveillance. Semi-structured interviews were conducted to elicit rich, contextual insights from key stakeholders. This approach was selected for its capacity to obtain rich, contextual information from participants with firsthand knowledge of operational systems and community dynamics (Creswell & Poth, 2018). In particular, purposive sampling was utilised to ensure representation from various institutional levels and roles. Five participants were involved in this study. All had at least 5 years of professional experience in vector control, community engagement, and health promotion, providing a diverse range of perspectives relevant to the study's focus. Moreover, participants were selected to ensure institutional diversity and to represent a broad range of experience. Recruitment prioritised unit heads or senior officers; when the primary contact was unavailable, the next-in-command was approached. Interviews continued until thematic saturation was reached, at which point no new categories or concepts emerged.

Content and conduct of the interview: Interviews were conducted on May 20, 2024, via Zoom video conferencing, at the participants' preferred time. The whole session lasted approximately 80 minutes and was conducted in a mix of Bahasa Malaysia and English. All interviews were audio-recorded with the participants' consent, transcribed verbatim, and subsequently translated into English for analysis. A forward-backwards translation process was applied to a subset of transcripts to ensure accuracy, and the research team carefully reviewed all translated transcripts. Despite the virtual format, rapport was readily established, and discussions remained open and detailed throughout the session. To preserve confidentiality, all identifying information was anonymised and securely stored in password-protected folders accessible only to the research team.

Study instrument: A semi-structured interview guide served as the primary data collection instrument and was developed in both English and Bahasa Malaysia. The interview guide was developed based on a thorough literature review of vector control challenges and drone technology acceptance. To ensure validity and clarity, the guide underwent expert review by experienced vector control practitioners, who then pre-tested it with practitioners outside the study sample. Subsequently, feedback from these exercises informed minor adjustments to wording and sequencing. The guide included open-ended questions to elicit participants' views on seven key thematic domains related to the use of drone technology in dengue surveillance. These domains were operational feasibility, public acceptability, community engagement, long-term participation, privacy concerns, legal compliance, and integration with existing systems. Table 3.1 outlined the core themes and corresponding sample questions used to obtain participant insights. The open-ended nature of the guide allowed for flexible follow-up questions, enabling more profound exploration of unanticipated themes as they emerged.

Data Analysis: Thematic analysis was employed using an inductive approach, following Braun and Clarke's (2006) six-phase approach which included familiarization with data, initial coding, theme development, theme review, theme definition, and final reporting. This approach enabled insights to emerge directly from participants' experiences, without reliance on a predetermined theoretical framework. Transcripts were first analysed in their original language to preserve the authenticity and contextual integrity of the data. Initial translations were produced in the target language with attention to relevant cultural and professional terminology. Back-translation of selected excerpts was undertaken to ensure consistency, clarity, and preservation of meaning. Culturally specific phrases and idiomatic expressions were reviewed collaboratively to ensure that the translated content retained the original tone and intent.

Coding was performed using NVivo version 14 software. In the first stage of coding, key phrases and ideas were identified using participants' own words to remain grounded in their perspectives. A preliminary codebook was developed after closely reviewing a subset of transcripts, with emerging codes organized around recurring concepts. The codebook was refined through iterative coding and discussion to improve clarity and consistency. To enhance the reliability of the analysis, a subset of transcripts was independently coded using the same codebook, and discrepancies were discussed and resolved. Intercoder reliability was assessed through comparison of coded segments, with discrepancies resolved through collaborative discussion. Code definitions were subsequently refined to ensure alignment with the data. Themes were developed iteratively and were refined through comparison across participant roles and institutional contexts. The analytic process was documented through NVivo project files, including coded transcripts, evolving code definitions, and analytic notes recorded during coding.

Table 3.1
Initial Domain and Sample Questions for Thematic Analysis

Domain	Questions
Operational and Technical Challenges	What are the potential barriers to using drones and mobile apps for dengue control in Malaysia, and how can they be overcome?
Social Perceptions and Trust	What is the potential reasons drone-based surveillance may not be viewed as acceptable by the local population? What are the best strategies to build trust and make it acceptable to communities?
Community Participation	How can the MOH ensure active community involvement in this study? What are the best strategies to positively impact recruitment and retention over four years?
Ethical and Legal Considerations	What are the potential chances of compromising privacy through drone-based surveillance, and how can these risks be minimised? What Malaysian data protection laws might be violated, and how can the study remain compliant with these laws?
Integration into Public Health System	How can this project help reduce dengue transmission? How can we integrate this new technology with existing surveillance systems?

3.3 Objective 2: To Evaluate the Effectiveness of Drone-Based Imaging in Profiling Potential Breeding Sites of the *Aedes* Mosquito

3.3.1 Study Area

The study was conducted in Section 24, Shah Alam, Selangor, Malaysia (3.069°N, 101.518°E), located approximately 25 km southwest of Kuala Lumpur within the Klang Valley conurbation (Figure 3.2). Note that Selangor is Malaysia's most urbanised and dengue-endemic state, with a warm and humid equatorial climate that supports year-round mosquito breeding. The area experiences mean daily temperatures between 26°C and 32°C and annual rainfall exceeding 2,400 mm, creating ideal environmental conditions for the proliferation of *Aedes* mosquitoes. Section 24 was selected due to its heterogeneous urban morphology and recurring dengue notifications recorded by the Shah Alam City Council. As illustrated in Figure 3.2, the study area comprises four distinct residential typologies: Flat B (high-rise complex, A), Flat H (medium-rise block, B), Teres B (dense terrace housing, C), and Teres D (low-density terrace housing, D). Site A (Flat B) is a compact high-rise apartment complex characterised by limited peridomestic vegetation and extensive impervious surfaces. Meanwhile, Site B (Flat H) comprises medium-rise housing blocks with moderate canopy cover and shaded courtyards. Moreover, Site C (Teres B) is a dense terrace-housing cluster with minimal green space and narrow back lanes. At the same time, Site D (Teres D) consists of low-density terrace housing surrounded by mature trees, open grass areas, and interconnected backyard vegetation. Together, these zones represent varying gradients of built form, vegetation cover, and shading, enabling assessment of how micro-environmental factors influence *Aedes* habitat risk.

The flat complexes are dominated by multi-storey buildings with extensive impervious surfaces, minimal green spaces, and narrow perimeter corridors that generate transient shaded micro-sites but limited organic substrate. In contrast, the terrace zones contain a mixture of single- and double-storey houses surrounded by gardens, boundary hedges, and rear-yard vegetation clusters that trap humidity and reduce solar exposure. Among these, Teres D exhibited the densest vegetation canopy and most persistent shaded areas, forming stable humid niches suitable for oviposition and larval development. The total population of Section 24 is approximately 10,200, unevenly distributed across the residential types. Accordingly, terrace areas accommodate nearly 70% of inhabitants, while the remaining 30% reside in medium- and high-rise flats. Household sizes range from three to six individuals, and many premises feature outdoor water containers, potted plants, and surface drains that can serve as potential breeding substrates for *Ae. aegypti* and *Ae. albopictus*. Field observations confirmed that the area exhibits diverse environmental management practices, including inconsistent vegetation maintenance and drainage upkeep. This contributes to localised differences in mosquito breeding potential. As such, this combination of structural diversity, human density, and microclimatic variability makes Section 24 an ideal urban microcosm for examining fine-scale spatial heterogeneity in *Aedes* ecology. This includes evaluating the role of vegetation-shade interactions in shaping urban vector-borne disease risk.

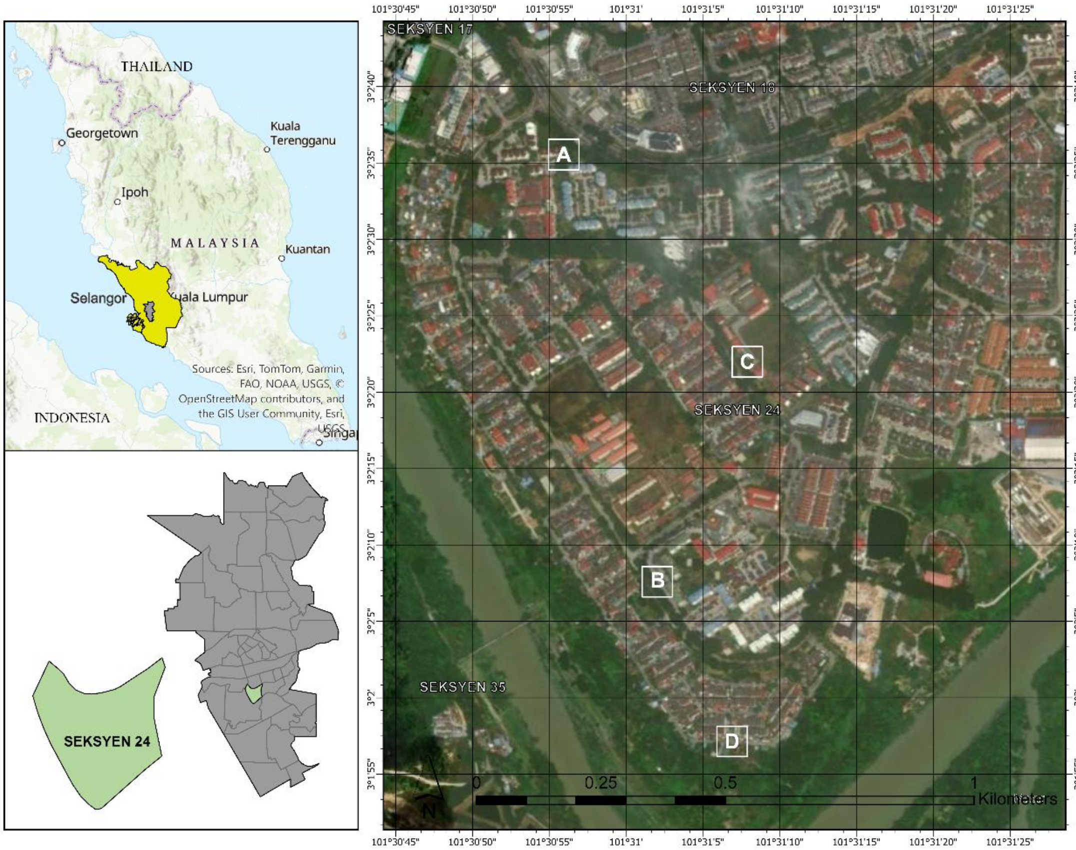


Figure 3.2 Location and Spatial Layout of the Study Area in Section 24, Shah Alam, Selangor, Malaysia

Note: The left panels show the geographic context of the study site within Peninsular Malaysia and the Shah Alam municipal boundary, with section 24 highlighted in green. The right panel presents the high-resolution satellite basemap depicting the four selected residential typologies: A – Flat B (high-rise complex), B – Flat H (medium-rise block), C – Teres B (dense terrace housing), and D – Teres D (low-density terrace housing).

3.3.2 Drone Image Acquisition and Flight Design

High-resolution aerial imagery was acquired using a DJI Phantom 4 Pro Unmanned Aerial Vehicle (UAV) equipped with a 1-inch Complementary Metal-Oxide-Semiconductor (CMOS) sensor (20 MP) and an 8.8 mm focal length lens (Figure 3.3). The drone was operated manually under Visual Line-of-Sight (VLOS) conditions to maintain safe, controlled flight. Flights were conducted between 09:00 and 11:00 a.m., a period selected to minimise solar glare and ensure consistent illumination for vegetation and shade extraction. The missions were performed under clear-sky conditions to reduce atmospheric distortion and shadow fluctuation. Each flight maintained a Ground Sampling Distance (GSD) of 2.5 to 3.0 cm per pixel, with 80% frontal and 75% lateral overlap to ensure orthomosaic continuity. The altitude was standardised at 70 m above ground level, and calibration points were recorded using a

Trimble Geo7X differential Global Positioning System (GPS) for georeferencing accuracy. All operations adhered to the guidelines of the Civil Aviation Authority of Malaysia (CAAM) under Civil Aviation Directive (CAD) 6011, Part XVI (UAS-Malaysia, 2023). The flight preparation workflow included equipment inspection, GPS calibration, and environmental safety checks prior to take-off. During each mission, the UAV was manually launched and landed at a secured open site to prevent interference from surrounding structures or vegetation (Figure 3.3A-C). The process involved using a survey-grade Global Navigation Satellite System (GNSS) pole as a spatial reference. At the same time, the operator maintained real-time telemetry monitoring throughout each flight.

3.3.3 Orthomosaic Reconstruction and Image Pre-Processing

The drone imagery acquired from all four residential typologies was processed using Agisoft Metashape Professional (version 1.8.5) to generate high-resolution, georeferenced orthomosaics suitable for spatial and environmental analysis. Image alignment was conducted in high-accuracy mode with adaptive camera calibration to optimise internal sensor geometry and correct lens distortions. Following alignment, a dense point cloud was generated using depth-map computation to capture acceptable surface variations within the urban landscape. A Digital Surface Model (DSM) was then constructed and orthorectified using Ground Control Points (GCPs) recorded with a Trimble Geo7X differential GPS, providing a horizontal accuracy of less than 5 cm. Subsequently, the final orthomosaic outputs were exported as GeoTIFFs [WGS 84/UTM Zone 47N (EPSG:32647)] at a spatial resolution of 5 cm per pixel. This enables detailed detection of micro-environmental features relevant to *Aedes* breeding site identification.

The processed orthomosaics were subsequently imported into ArcGIS Pro 3.1 (Esri) for raster-based analysis and segmentation. Radiometric corrections were applied to minimise brightness variation across overlapping flight lines and ensure uniform reflectance across the study area. To isolate biologically relevant environmental components, non-vegetated surfaces such as rooftops, pavements, and asphalt roads were masked using reflectance thresholds derived from histogram analysis. This masking process enhanced the precision of vegetation-shade delineation, facilitating accurate extraction of environmental indices for spatial modelling of *Aedes*-prone micro-habitats.

Figure 3.3 Field Operation of Drone-based Aerial Survey in Section 24, Shah Alam. (a) UAV operator performing manual launch sequence under controlled opensite conditions; (b) DJI Phantom 4 Pro deployed on pre-flight calibration ground point; (c) Aerial take-off procedure during vegetation-shade mapping missions. All operations complied with CAAM Regulations and Institutional Ethical Standards

3.3.4 Aim 5: Determine Vegetation-Shade Interactions for *Aedes* Habitat Risk in Urban Areas Using Drone-Based Geospatial Modelling

Data processing and spatial analysis: All orthomosaic datasets were analysed using a multi-step geospatial workflow that integrated vegetation, shading, morphological, and risk modelling processes to identify *Aedes*-prone microhabitats. Table 3.2 summarises the complete analytical framework, including the datasets, analytical methods, software used, and resulting outputs. All analyses were performed using georeferenced orthomosaics captured by a DJI Phantom 4 RTK UAV with a 20 MP RGB camera, providing a GSD of ~2.5 cm/pixel. The outputs from each step were spatially integrated to generate a high-resolution ecological risk map delineating *Aedes*-favourable microhabitats across four residential morphologies in Seksyen 24, Shah Alam, Selangor.

Table 3.2
Summary of Data Processing and Spatial Analysis Workflow for *Aedes* Habitat Risk

Step	**Objective / Parameter**	**Method / Formula**	**Software / Tool**	**Output / Application**
Excess Green Index (ExG)	Quantify/vegetation density and green cover	ExG = 2G − R − B (normalised RGB reflectance)	ArcGIS Pro 3.1 /QGIS 3.34	Classified vegetation map (dense > 30; moderate 10-30; low < 10); % vegetation per morphology
Shade Detection	Identify shaded zones from the brightness layer	Histogram segmentation, threshold < 100 (mean brightness)	ArcGIS Pro/Raster Calculator	Binary shade raster showing canopy/building shadows
Shade-Vegetation Coupling	Map overlap between vegetation and shaded pixels	Raster overlay (ExG > 30 ∩ Brightness < 100)	ArcGIS Pro	Shaded vegetation coupling zones (m^2, %) per site
Composite Ecological Risk Index (CERI)	Integrate vegetation and shading into a continuous risk model	Weighted overlay (equal weight; 0-5 scale via min-max normalisation)	ArcGIS Pro	Composite risk map (0 = low → 5 = high) classified as low, moderate, high
Morphological Correlation	Relate built-form density to vegetation and risk	Digitised building footprint (%), Pearson correlation ($p < 0.05$)	QGIS/IBM SPSS v.29	Correlation matrix (building coverage vs vegetation & risk)
Spatial Hotspot Detection (KDE)	Identify spatial clusters of ecological risk	Kernel Density Estimation; 15 m search radius, quartic kernel	ArcGIS Pro	Hotspot heatmap (yellow-red = high risk)
Directional Shade Gradient Analysis	Examine orientation-driven shade persistence	Solar azimuth & façade direction via DSM; 8 cardinal classes	QGIS Solar Radiation Plugin	Rose diagrams of shade persistence (%) and vegetation adjacency (≤ 5 m)

3.3.5 Aim 6: Evaluate Vegetation-Shade Interactions and Housing Typology Using Drone-Based Microclimate Modelling and a Composite Risk Index

Derivation of environmental indices: Vegetation density was quantified using the Excess Green Index (ExG), a widely adopted RGB-based vegetation index in drone and close-range remote sensing applications. ExG enhances the green spectral component relative to red and blue bands and has been extensively used for vegetation detection and canopy mapping in UAV imagery (De Swaef *et al*., 2021). Higher ExG values indicate greater vegetation cover and canopy density. Surface brightness and relative shade were characterised using a Brightness Index (BI), calculated as the mean reflectance of the red, green, and blue channels. While BI is not a standardised vegetation index, it is commonly used in image processing and remote sensing as a proxy for surface reflectance or luminance, particularly for distinguishing shaded versus sunlit surfaces. In this study, BI was applied as a context-specific metric to capture fine-scale variation in surface brightness and shade persistence relevant to micro-habitat suitability for *Aedes* mosquitoes, rather than as a novel spectral index. Lower BI values correspond to darker, more persistently shaded micro-environments.

To integrate vegetation density and shade into a single environmental suitability metric, a Composite Risk Index (CRI) was developed using a multiplicative interaction between the Excess Green Index (ExG) and the Brightness Index (BI). Prior to integration, both indices were min–max normalised to a common 0–1 scale. Because lower BI values indicate darker, more persistently shaded surfaces, BI was inverted so that higher values corresponded to stronger shading. This interaction-based formulation ensures that CRI values are elevated only where dense vegetation and persistent shade co-occur and remain low where either component is limited. The Composite Risk Index (CRI) is a continuous environmental suitability metric bounded between 0 (lowest risk) and 1 (highest risk). Prior to integration, the contributing indices were min–max normalised to a common 0–1 scale based on their observed minimum and maximum values within each study site. No binary classification or thresholding was applied at this stage, and CRI values were retained as a continuous spatial surface to capture fine-scale variation in micro-habitat suitability. The multiplicative approach was selected to reflect the ecological requirement for vegetation–shade coupling in sustaining *Aedes* breeding micro-habitats, rather than allowing a single factor to dominate independently.

In addition to BI, ExG, and the Composite Risk Index (CRI), several spatial context variables were derived to aid interpretation of high-risk micro-habitats. Impervious surfaces were extracted from the supervised land-cover classification of UAV orthomosaics and represented built-up features such as roofs, paved roads, and concrete surfaces. Edge Distance was calculated as the Euclidean distance from each pixel to the nearest boundary between impervious and vegetated land-cover classes, derived from the classified raster. Shade was characterised indirectly using the inverted Brightness Index ($1 - BI$) and treated as a continuous proxy for relative shading intensity. These variables were not integrated into the CRI formulation or used as predictors in any model but were analysed descriptively to characterise the spatial configuration and environmental context of CRI-identified high-risk zones.

Ground truth validation and urban morphological pattern classification: Urban morphological patterns were classified a priori based on built-environment configuration and orientation observed in UAV-derived orthomosaics, independent of housing typology and environmental indices. Ground validation was conducted concurrently with drone flights to verify classification accuracy and ensure correspondence between aerial and surface conditions. Field teams recorded vegetation type, shade intensity, and potential breeding containers using GPS-tagged photographs and standardized observation sheets. Based on drone imagery and field evidence, microhabitats were grouped into four morphological categories: (i) Building Perimeter Patterns; north/east-facing facades and perimeters influencing shade persistence; (ii) Architectural Interface Patterns; corners and junctions acting as transitional shaded zones; (iii) Organized Vegetation Patterns; linear tree rows along parking areas or road medians; and (iv) Private Realm Patterns; rear-yard vegetation clusters, hedges, and side-boundary trees forming humid micro-environments. These classifications provided a structural and ecological basis for analysing the relationship between built form, vegetation, and shade dynamics influencing *Aedes* breeding risk. Urban morphological pattern classification was conducted independently of environmental indices and CRI values. Patterns were delineated based on built-environment characteristics observable in UAV-derived orthomosaics, including building footprint arrangement, perimeter orientation, yard configuration, and interfaces between built structures and surrounding spaces. Vegetation density (ExG), shade intensity (BI), and CRI were not used as criteria in defining morphological categories.

Spatial and statistical analyses: Raster layers of the BI, ExG, and CRI were analysed in ArcGIS Pro 3.1 to quantify spatial heterogeneity across the four housing typologies. Descriptive statistics were generated, and differences among typologies were tested using violin plots with Tukey's Honestly Significant Difference (HSD) post-hoc comparisons ($\alpha = 0.05$) in GraphPad Prism 10.0. Correlation analyses were performed to examine relationships among environmental variables, including BI, ExG, CRI, Edge Distance (EdgeDist), and impervious surface. Model performance was validated through calibration curve analysis and cumulative gain/lift charts. Hence, to identify statistically significant spatial clusters, Kernel Density Estimation (KDE) and Getis-Ord Gi* hotspot analyses were applied. The resulting high-risk zones were cross-validated with field-observed potential containers to ensure consistency between predicted and actual breeding environments.

Spatial risk modelling and validation framework: Spatial analysis was conducted using a pixel-based environmental risk modelling framework, in which each raster pixel (0.05 m × 0.05 m) represented the fundamental prediction unit. The Composite Risk Index (CRI), standardised between 0 (lowest risk) and 1 (highest risk), was treated as a continuous spatial suitability surface reflecting biologically defined *Aedes*-prone micro-environments, rather than as a regression-based predictive model with fitted coefficients. Model evaluation focused on spatial discrimination and ranking performance rather than binary classification. CRI values were sorted in descending order to prioritise high-risk pixels, and validation metrics were computed based on the proportion of field-validated breeding-prone locations captured within the upper ranks of the CRI distribution. No fixed CRI threshold was imposed, consistent with the continuous nature of environmental risk.

Model calibration was assessed by grouping pixels into equal-frequency CRI bins and comparing the mean CRI value within each bin to the corresponding observed positive rate, defined as the proportion of pixels intersecting ground-validated breeding-prone micro-habitats. Agreement between predicted risk and observed positives was quantified using coefficient of determination (R^2). Ranking performance was further evaluated using cumulative gain analysis, which quantifies the fraction of observed positive pixels captured as the population is progressively sorted by decreasing CRI value. This approach is appropriate for continuous risk surfaces and avoids arbitrary binarisation while enabling operational prioritisation of high-yield intervention zones. To assess the contribution of vegetation alone, a sensitivity analysis was performed in which ExG was evaluated independently using the same spatial ranking and validation framework applied to the CRI. Performance metrics derived from ExG-only rankings were then compared against those obtained using the CRI. All distributional analyses (violin and ridge density plots) were based on pixel-level values extracted from UAV-derived raster layers. The fundamental replication unit was the individual raster pixel, and distributions were generated using all pixels contained within each housing typology polygon. Each housing typology therefore represents a single spatial unit comprising multiple pixel-level observations, rather than multiple independent sites.

3.4 Objective 3: To Evaluate the Accuracy of the ML Algorithm in Classifying Land Cover Types Associated with Potential Mosquito Breeding Sites

High-resolution orthomosaics for four residential sites in Seksyen 24, Shah Alam, Selangor, were classified into land-cover classes using a supervised Random Forest (RF) workflow implemented in Quantum Geographic Information System (QGIS) with the Semi-Automatic Classification Plugin (SCP). RF was selected, as it is a robust ensemble decision-tree algorithm that performs well with high-dimensional, non-normal remote sensing data and has been widely applied to land-cover mapping. All classification and accuracy assessment steps were conducted independently for each of the four sites using an identical set of parameters and class definitions. All processing was conducted in QGIS 3.40 Long-Term Release (LTR) with the SCP, version 8.5. Essentially, SCP is an open-source QGIS extension that provides an integrated environment for preprocessing, supervised classification, and post-processing of remote sensing images. This includes tools for creating training data, RF classification, and accuracy assessment. Furthermore, SCP relies on the Remotior Sensus Python library and standard scientific Python packages for image analysis (Congedo, 2021). For each site, the RGB orthomosaic was loaded into QGIS and added to a single SCP, ensuring consistent band order (Red, Green, Blue) across all sites. However, no additional spectral bands were available. Therefore, the classification relied on these three bands and their combined spectral response.

The classification framework (Table 3.3) was designed to extract environmental proxies directly relevant to *Aedes* mosquito breeding ecology, rather than to perform exhaustive urban land-use mapping. The three selected land-cover classes represent dominant surface types that structure urban *Aedes* habitats. Meanwhile, the built-up class captures residential buildings, paved surfaces, and impervious infrastructure where artificial water-holding containers are commonly found, and human-vector contact is concentrated. Meanwhile, the vegetation class represents shaded environments, including tree canopies, shrubs, and grassed areas, which create favourable microclimatic conditions for adult *Aedes* resting and oviposition. In addition, the soil class encompasses exposed or sparsely vegetated ground surfaces, such as bare earth and unpaved areas. It generally plays a secondary yet occasionally transient role in *Aedes* breeding following rainfall events.

Table 3.3
Land-Cover Classification Framework and Relevance to *Aedes* Breeding Environments

Land-Cover Class	**Urban Surface Characteristics**	**Typical Features Included**	**Spectral Behaviour (RGB)**	**Relevance to *Aedes* Breeding Ecology**	**Rationale for Inclusion**
Built-up	Impervious and semi-impervious residential infrastructure	Roofs, paved roads, parking areas, walkways, courtyards, and building façades	Generally higher reflectance in the red band; variable green response depending on material and shading	Strongly associated with artificial water-holding containers (e.g., gutters, containers, drains) and high human-vector contact	Represents core peridomestic environments where *Ae. aegypti* breeding and dengue transmission are concentrated
Vegetation	Shaded natural or managed green surfaces	Tree canopies, shrubs, grassed areas, roadside vegetation, and landscaped spaces	Pronounced green-band peak with lower red reflectance	Provides shaded, humid microclimates favourable for adult resting, oviposition, and survival	Acts as a stable proxy for microhabitat suitability and mosquito persistence

Land-Cover Class	Urban Surface Characteristics	Typical Features Included	Spectral Behaviour (RGB)	Relevance to *Aedes* Breeding Ecology	Rationale for Inclusion
Soil	Exposed or sparsely vegetated ground surfaces	Bare earth, unpaved clearings, disturbed ground, construction patches	Intermediate spectral response; gradual increase from blue to red bands	Generally low and transient breeding relevance, except after rainfall or where containers accumulate	Included to differentiate exposed ground from built-up and vegetated areas and avoid overestimation of risk

Note: The classification framework focuses on environmental proxies rather than direct identification of breeding containers. The selected classes capture spatial features that repeatedly co-occur with *Aedes* breeding habitats in urban settings and provide a scalable basis for neighbourhood-level risk characterisation.

3.4.1 Aim 7: Evaluate ML-Based Classification of Potential *Aedes* Breeding Habitats Using RGB Drone Imagery

Training data: Supervised classification training data were digitised manually using Region of Interest (ROI) tools in the SCP in QGIS. Training ROIs were delineated as small, homogeneous polygons, visually interpreted from the orthomosaics. Accordingly, ROIs were placed to capture the spectral variability within each class. For each polygon, all enclosed pixels were used as training samples for the RF classifier. The classification (Table 3.4) focused on surface characteristics relevant to *Aedes* breeding environments in urban areas.

Table 3.4
Classification of the ROI for Training Data

Class	**Polygon Digitisation**	**Areas Included**	**Notes**
Built-up	Digitised over homogeneous roof surfaces, colours, and paved areas	Roads, parking lots,	Avoided shadows and mixed pixels along edges
Vegetation	Drawn over tree canopies, shrubs, and grassed areas	Lawns, small parks, and roadside vegetation	Training polygons on both dark tree crowns and brighter grass to capture within-class variability
Soil	Drawn over exposed or sparsely vegetated ground	Bare earth, disturbed ground, unpaved clearings	Avoided mixture with vegetation or concrete

Across each site, training ROIs were distributed to cover the full spatial extent and the range of spectral variation within each class, including different roof colours and varying soil brightness. This spatially stratified approach reduces over-fitting to a single part of the class. It is consistent with best practice for supervised land-cover mapping. Within SCP, each ROI polygon was assigned to the appropriate class ID and stored in the training file. Concurrently, ROIs were inspected and edited iteratively to remove polygons that intersected shadows, contained obvious mixed pixels, or had data gaps. The final training set for each site comprised multiple polygons per land-cover class, yielding several thousand mapped pixels per class. The mapped pixels for each class and site are the total number of classified pixels, which is proportional to the mapped area of that class.

Spectral signature and scatterplot analysis: Prior to executing the classification process, the spectral characteristics and distinctness of the three land-cover categories were systematically examined using spectral signature plots and band-to-band scatterplots generated from the training samples. Visual inspection of spectral signatures is a common step in supervised classification. It helps confirm that the defined classes are spectrally meaningful and distinguishable in the available bands. For each site, the ROIs stored in the SCP training file were used to compute mean spectral signatures for each class. Using the SCP, the mean Digital Numbers (DNs) for each class were plotted against the three image bands (Blue ≈ 475 nm, Green ≈ 550 nm, Red ≈ 650 nm). These plots provide an initial qualitative assessment of class separability in spectral space.

In addition, scatterplots of band values for the training pixels were generated to examine the distribution of classes in Two-Dimensional (2D) feature space. Each land-cover class was displayed with a different symbol colour. Distinct clusters in these scatterplots indicated where classes were well separated, while overlapping clusters highlighted potential confusion areas, particularly between built-up and soil. Thus, by incorporating this exploratory spectral analysis, the final training data set for all study sites was limited to ROIs that were both visually and spectrally consistent. This ultimately improves the reliability of the subsequent RF classification.

RF algorithm and model configuration: An RF classifier was used to perform per-pixel supervised classification of each orthomosaic. RF is an ensemble method that builds a large number of decision trees using bootstrapped samples and random subsets of predictor variables. Class predictions are made by majority vote across the trees (Figure 3.4). RF is robust to noisy training data, can oversee non-linear class boundaries and interactions among spectral bands, and has been demonstrated to outperform many traditional parametric classifiers for land cover mapping (Belgiu & Drăguţ, 2016). Within the SCP, supervised land-cover classification was performed using the "Band Processing" and "Classification" modules. Band set one (RGB orthomosaic) was specified as the input feature set, and "Class ID" was used as the training source to ensure that the model learned from integer-encoded land-cover labels.

An RF classifier with 100 trees was employed to achieve stable ensemble predictions at a reasonable computational cost. The minimum samples per split was set to 2, following the default setting to allow fine partitioning of the feature space. Conversely, class weights were set to "balanced" to compensate for class imbalance in the training data and reduce bias toward majority classes. For each site, the trained model generated a classified raster in which each pixel was assigned to one of three land-cover classes: built-up, vegetation, or soil. The same classifier configuration and class schema were applied across all four sites to ensure methodological consistency and enable robust morphological comparisons between flat and terrace housing typologies.

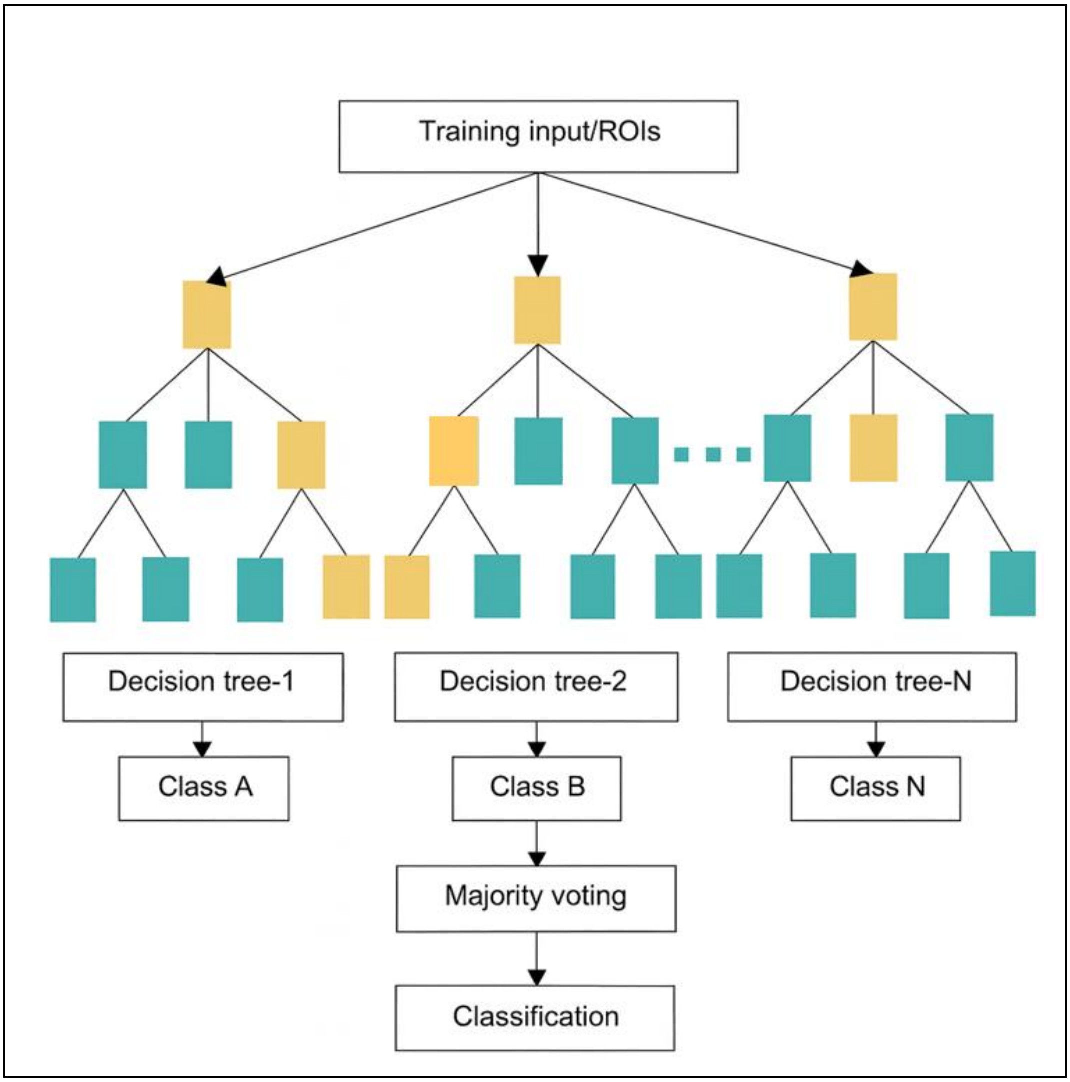


Figure 3.4 Implementation of Generalised RF Decision Tree Models on the Training Datasets (Source: Tempa & Aryal, 2022)

Validation data: Independent validation data were generated to evaluate accuracy and avoid bias in classification performance estimates. For each site, a new point vector layer was created in QGIS with one attribute field, ref_class, storing the reference class code (2 = Built-up, 3 = Vegetation, 4 = Soil). Correspondingly, points were digitised manually by visual interpretation of the orthomosaic, aided by field notes and very-high-resolution basemaps. Validation points were placed only in locations that were clearly interpretable and not inside training ROIs, to ensure independence between calibration and assessment samples. For each class, approximately 30 validation points were collected, spread across the site to represent spatial and intra-class variability. As the accuracy module operates on raster data, validation points were buffered into circular polygons (radius < 0.5 m) while preserving the ref_class attribute.

Accuracy assessment and statistical metrics: For each site, the RF classification output raster served as the classification map, and buffered validation polygons with ref_class as the reference label field served as the ground-truth data. The tool performs a pixel-wise comparison between the predicted class of each raster cell and the reference label of the polygon it falls within. It returns both a pixel-count error confusion matrix and an area-adjusted error matrix consistent with design-based accuracy assessment. For thematic map accuracy assessment, the confusion matrix, Overall Accuracy (OA), Producer's Accuracy (PA), User's Accuracy (UA), and the Kappa (κ) coefficient were computed (Table 3.5) (Cohen, 1960; Stehman, 1997; Congalton, 1991; Congalton & Green, 2019).

Table 3.5
Accuracy Assessment Metrics Used in the Study

Metric	**Description**
Overall Accuracy (OA)	Proportion of correctly classified pixels across all classes.
Producer's Accuracy (PA)	For each class, the probability that a reference pixel of that class is correctly labelled in the map.
User's Accuracy (UA)	For each class, the probability that a pixel labelled as that class in the map truly belongs to it.
Kappa coefficient (K)	An index of agreement between the classification and reference data corrected for chance, reported both overall and per class.

OA is the proportion of all samples that are correctly classified:

$$\mathrm{OA} = \frac{\sum_{i=1}^{K} n_{ii}}{N} , \tag{3.1}$$

where the numerator (n_{ii}) is the sum of the main diagonal of the confusion matrix (correct classifications), and N is the total number of validation samples. OA provides a single summary measure of agreement between the RF map and the reference data (Congalton, 1991).

For each reference class (j), the PA is the probability that a sample that truly belongs to class (j) is correctly labelled on the map:

$$\mathrm{PA}_j = \frac{n_{jj}}{n_{+j}} , \tag{3.2}$$

where n_{jj} is the number of correctly classified samples for class (j) (diagonal element), and n_{+j} is the column total. PA, therefore, measures omission error, that is, the fraction of the reference class (j) that has been omitted and misclassified as other map classes (Congalton & Green, 2019; Stehman, 1997).

For each mapped class (i), the UA is the probability that a sample labelled as class (i) on the map truly belongs to that class in the reference data:

$$\mathrm{UA}_i = \frac{n_{ii}}{n_{i+}} , \tag{3.3}$$

where n_{ii} is the number of correctly classified samples for class i (diagonal element), and n_{i+} is the row total. UA is related to commission error, that is, the fraction of pixels mapped as class (i) that belong to other classes (Congalton, 1991; Stehman, 1997).

In addition to OA, the κ coefficient was used as a chance-corrected measure of agreement between the RF classification and the reference data (Cohen, 1960; Congalton & Green, 2019). Where p_0 is the observed agreement, which is equivalent to OA in proportion form, and p_e is the agreement expected by chance. The κ coefficient is:

$$p_o = \sum_{i=1}^{K} p_{ii} \quad , \tag{3.4}$$

$$p_e = \sum_{i=1}^{K} p_{i+}\, p_{+i} \quad , \tag{3.5}$$

$$\kappa = \frac{p_o - p_e}{1 - p_e} \quad . \tag{3.6}$$

Values of κ close to 1 indicate strong agreement beyond chance, values around 0 indicate agreement no better than random, and negative values indicate systematic disagreement (Cohen, 1960; Congalton & Green, 2019).

Random forest model transferability between sites: To assess the transferability of RF land-cover classifiers across residential areas, a systematic cross-site validation framework was implemented. It uses four study sites representing two distinct housing typologies: flat residential areas (Flat B and Flat H) and terraced housing developments (Teres B and Teres D). The classification schema comprised three land-cover classes (built-up, vegetation, and soil) consistent with the primary classification protocol employed in this study.

The experimental design adopted a reciprocal training-testing approach within each housing typology. For flat residential areas, two model transfer scenarios were evaluated: (i) an RF classifier trained on Flat H and applied to Flat B, and (ii) an RF classifier trained on Flat B and applied to Flat H. Similarly, for terraced housing, the transferability studies involved (i) training on Teres D and testing on Teres B, and (ii) training on Teres B and testing on Teres D. Across all four experiments, RF hyperparameters were held constant at values established during within-site analyses, with no site-specific recalibration performed on test sites. This methodological constraint ensured that accuracy metrics reflected genuine model generalisability rather than site-specific optimisation. Finally, comprehensive accuracy metrics were extracted, including OA, κ, and class-specific PA and UA for each land-cover class.

3.5 Ethical Considerations

3.5.1 Survey Distribution and Participation

This study was conducted in full compliance with ethical guidelines for human research and was approved by the Universiti Teknologi MARA (UiTM) Research Ethics Committee (Reference No. REC/07/2023 (ST/MR/183) (Appendix 7). Ethical approval ensured that the study adhered to internationally recognised standards, including the Declaration of Helsinki and Malaysia's Personal Data Protection Act (PDPA), safeguarding participant rights, confidentiality, and data security. Prior to participation, informed consent was obtained from all respondents, emphasising the voluntary nature of the study, the right to withdraw at any stage without consequences, and the assurance of data confidentiality. Furthermore, participants were provided with a detailed information sheet outlining the study objectives, potential risks and benefits, and data-use policies to ensure fully informed decision-making prior to consent was granted. All collected data were fully anonymised and de-identified to prevent any potential identification of respondents. Note that no Personally Identifiable Information (PII) was recorded, and all responses were securely stored in encrypted, password-protected databases accessible only to the research team. Additionally, data handling and storage protocols complied with institutional and national research integrity guidelines, ensuring confidentiality and responsible data management.

3.5.2 Semi-structured Interview

The study received approval from the Medical Research and Ethics Committee (MREC) of the MOH Malaysia (NMRR ID-24-00374-8SP (IIR), approved on March 25, 2024) (Appendix 8). Written informed consent was obtained from all participants prior to data collection. Participants were fully informed of their rights, including the right to withdraw at any time without consequence and the measures in place to ensure confidentiality. Concurrently, anonymity was preserved by removing identifying information from transcripts, and all data were stored securely in accordance with applicable national data protection standards.

3.5.3 Drone Flight Operation

This study was conducted in strict accordance with the ethical standards and institutional regulations of UiTM and complied with national and international research integrity frameworks governing remote sensing and environmental surveillance. Note that the project involved only the acquisition and analysis of aerial imagery of public spaces for ecological and environmental assessment. Hence, no human participants, personal identifiers, or private residential data were collected. All datasets were anonymised and georeferenced solely for scientific use, with all data stored in secure institutional storage.

Drone flight operations strictly adhered to the CAD 6011 Part XVI (Unmanned Aircraft Systems - Malaysia, 2023). Prior to the commencement of drone operations, comprehensive regulatory approvals were obtained to ensure full compliance with Malaysian aviation regulations and local government ordinances. Moreover, flight authorisation was secured from the CAAM (Reference No.: CAAM/BOP/ATF/P2024/09/2481) under the provisions of the Malaysian Civil Aviation Regulations. It governs the operation of remotely piloted aircraft systems in Malaysian airspace. Additional clearance was obtained from the Department of Survey and Mapping Malaysia (Reference No.: JUPEM.BGSP.2024. 2444.UDARA) for aerial surveying and mapping activities within controlled zones. Local operational permission was granted by Majlis Bandaraya Shah Alam (Reference No.: MBSA.LSN.700-3/36/10), the municipal authority responsible for the governance of the study area, authorising drone flights over residential neighbourhoods.

All flight operations were conducted in strict accordance with regulatory height restrictions, no-fly zone boundaries, and privacy protection guidelines for operations above populated residential areas. Additionally, appropriate measures were taken to respect resident privacy by conducting flights during daylight hours and maintaining an appropriate altitude to prevent the identification of individuals or activities on private property (Appendix 9-12).

CHAPTER 4
RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents and critically discusses the study's findings in relation to the seven aims derived from the three specific research objectives. The results are first organised with community and expert perspectives on drone-assisted dengue prevention (Aims 1-4). This is followed by the spatial and environmental profiling of potential *Aedes* breeding habitats using drone-based imaging and modelling (Aims 5-6), and concluding with the evaluation of Machine Learning (ML) approaches for land classification (Aim 7). For each aim, the empirical results are first described, along with an integrated discussion that incorporates the findings within the existing literature and the broader context of dengue prevention and technological adoption. The first part of this chapter addresses Aim 1, which examines sociodemographic determinants of public perception and engagement in drone-assisted dengue surveillance; Aim 2, which investigates sociodemographic determinants of willingness to adopt surveillance technology and mosquito control training; Aim 3, which evaluates community knowledge and practices on mosquito control at state and urban-rural levels for sustainable dengue prevention; and Aim 4, which explores expert perspectives on drone-based surveillance of mosquito breeding sites. Together, these aims provide a comprehensive understanding of how households and experts perceive, accept, and are prepared to engage with drone technology as part of dengue control strategies.

The subsequent part presents the findings for Aim 5. It determines vegetation-shade interactions for *Aedes* habitat risk in urban areas using drone-based geospatial modelling, and Aim 6. This then evaluates vegetation-shade interactions and housing typology using drone-based microclimate modelling and a Composite Risk Index (CRI). Notably, these aims translate the environmental characteristics captured by drones into indicators of potential *Aedes* breeding sites. The final part of the chapter focuses on Aim 7, which evaluates ML-based classification of potential *Aedes* breeding sites using RGB drone imagery. This, in turn, assesses the approach's accuracy and practical utility. In essence, the integrated results and discussion presented for Aims 1 to 7 illustrate how social acceptance, environmental risk assessment, and ML classification together contribute to evaluating the feasibility, optimisation, and scalability of drone-assisted dengue prevention strategies.

4.2 Aim 1: Sociodemographic Determinants of Public Perception and Engagement in Drone-Assisted Dengue Surveillance in Malaysia[4]

Dengue fever remains a critical public health concern in Malaysia, driven by its endemic nature and cyclical outbreaks (Selvarajoo *et al.*, 2020). The disease, caused by the Dengue Virus (DENV) and transmitted by *Aedes* mosquitoes, has seen a steady rise in incidence, exacerbated by urbanisation, climate change, and inadequate vector control measures. According to the World Health Organisation (WHO), Malaysia reported 112,833 dengue cases as of Week 45 in 2024, a 9.2% increase from the previous year (WHO, 2024). This upsurge aligns with global trends, where dengue cases have surged due to rapid population growth, increased human mobility, and urban environmental changes (Abdullah *et al.*, 2025). Despite extensive control programmes, vector resistance to insecticides, socio-environmental factors, and public non-compliance with preventive measures continue to pose significant barriers to sustainable dengue management (Abubakar *et al.*, 2025).

Traditional dengue vector control strategies in Malaysia rely on a combination of source reduction, larviciding, space spraying, and biological interventions (Salleh *et al.*, 2022). While these methods have been widely implemented, insecticide resistance in *Aedes* mosquitoes and challenges in detecting hidden breeding sites have rendered them only partially effective. Moreover, current surveillance systems predominantly depend on manual inspections and reactive responses, often failing to provide real-time data for pre-emptive interventions (Aira *et al.*, 2023). To address these limitations, integrating emerging technologies into dengue control programmes is crucial. Geographic Information Systems (GIS), ML models, and remote sensing have enhanced disease mapping and early warning systems (Xu *et al.*, 2024; Curtis *et al.*, 2020). However, drone-assisted surveillance has emerged as a promising alternative, offering high-resolution aerial mapping, rapid identification of mosquito breeding sites, and cost-effective surveillance of inaccessible areas (Carrasco-Escobar *et al.*, 2022; Valdez-

[4] Zulfadli Mahfodz, Nazri Che Dom, Rahmat Dapari, Siti Aekbal Salleh, Siti Nazrina Camalxaman (2025). Sociodemographic Determinants of Public Perception and Engagement in Drone-Assisted Dengue Surveillance in Malaysia. *PLOS One* (Submitted March 2025:*Under review*)

Delgado *et al.*, 2023). Although various pilot studies have demonstrated the feasibility of drones in vector surveillance, community perceptions, technological readiness, and privacy concerns remain critical factors influencing large-scale adoption (Gonzalez *et al.*, 2023; Valdez-Delgado *et al.*, 2023).

Drones, equipped with multispectral imaging and Artificial Intelligence (AI)-driven analysis, enable precise detection of stagnant water bodies, a primary habitat for *Aedes* mosquitoes (Minakshi *et al.*, 2020; Mahfodz *et al.*, 2024). Unlike conventional vector control methods, drones facilitate automated identification of high-risk areas, providing spatially accurate data for targeted interventions. In regions with persistent dengue outbreaks, drones have been successfully integrated into urban and peri-urban vector control programmes. This demonstrates significant improvements in surveillance efficiency and intervention outcomes (Carrasco-Escobar *et al.*, 2022; Mahfodz *et al.*, 2024). Nevertheless, despite their technological potential, public scepticism surrounding privacy, ethical concerns, and operational safety persists (Shapira & Cauchard, 2022). Hence, understanding community perspectives on drone-assisted mosquito control is imperative to ensure public acceptance and policy feasibility. Additionally, disparities in digital literacy and access to technology may further influence the adoption of drone-based interventions, particularly in rural communities.

Given these challenges, this study aims to evaluate the technological readiness and community acceptance of drone-based dengue surveillance in Malaysia. In particular, understanding how various population segments perceive and adopt this technology is critical for developing effective, community-driven interventions. In addition to acceptance, sociodemographic factors such as age, gender, area of residence, and housing type may influence public attitudes toward drone-assisted mosquito control. Thus, by examining these variables, this study seeks to identify key determinants of community willingness to engage with drone surveillance programmes and how these perceptions differ between urban and rural populations.

Furthermore, this study explores the role of digital platforms and social media in shaping public awareness and engagement in dengue prevention. With over 88% of Malaysians having daily internet access and high social media penetration, digital tools offer a powerful means to disseminate public health information and promote community participation in vector control initiatives. Nonetheless, while awareness of dengue prevention is high, there remains a significant gap between knowledge and actual preventive behaviour. Therefore, addressing this knowledge-practice gap is crucial to enhancing the effectiveness of community-led mosquito control efforts. By focusing on these objectives, this study contributes to the scientific discourse on digital transformation in vector control. It also offers empirical insights into the integration of drone technology within Malaysia's national dengue surveillance framework. The findings will also provide policy recommendations for health authorities, ensuring that technological innovations are practical and socially acceptable and scalable in high-burden dengue-endemic regions. Note that this research aligns with global efforts to modernise vector surveillance through data-driven, technology-enhanced approaches. This ultimately supports more proactive and sustainable dengue control strategies.

4.2.1 Sociodemographic Characteristics of the Study Population

The analysis of the heatmaps reveals notable variations in sociodemographic characteristics across different states in Malaysia (Figure 4.1). The gender distribution indicates that male representation is highest in Perlis (50.0%) and Terengganu (48.9%), whereas Melaka (100.0%) and Pulau Pinang (94.4%) have the highest proportions of females. This suggests potential gender disparities in either population composition or survey response rates, possibly influenced by demographic trends, workforce distribution, or cultural factors in each state. In terms of residence type, a stark contrast is observed between urbanised and rural states. Wilayah Persekutuan (100.0%), Selangor (92.0%), and Johor (44.1%) exhibit predominantly urban populations, consistent with their status as economic hubs. Conversely, Terengganu (97.9%), Kelantan (95.9%), and Kedah (89.5%) have overwhelmingly rural populations, reflecting traditional settlement patterns and lower urban development in these regions. These differences could influence policy decisions related to urban planning, infrastructure development, and resource allocation.

Examining age-group distribution, younger individuals aged 18 to 30 years are highly concentrated in Pulau Pinang (94.4%) and Melaka (87.5%). This suggests either a higher influx of students and early-career professionals or a trend toward younger demographics in these states. Meanwhile, the 31 to 40 years age group is most prominent in Pahang (54.8%), whereas middle-aged individuals (41 to 50 years) are more prevalent in Terengganu (36.2%). Moreover, the elderly population (> 61 years) is notably higher in Terengganu (12.8%) and Kelantan (9.5%). This possibly indicates that ageing communities in these states are due to lower migration outflows and traditional settlement retention. Following this, the ethnic composition follows Malaysia's national trend, with Malays making up the majority in all states, exceeding 90% in most regions. However, Chinese representation is notable in Pulau Pinang (11.1%) and Melaka (25.0%), reflecting their historical presence in these states. Indian representation remains minimal, with the highest concentration in Wilayah Persekutuan (1.1%) and Terengganu (4.3%). The "Others" category remains relatively insignificant, underscoring the country's major ethnic makeup. These findings may have implications for cultural and community-based policies, as well as for economic activities tied to ethnic composition across regions.

The duration of residence indicates that states with high urbanisation, such as Wilayah Persekutuan (21.6%) and Kelantan (21.6%), have the highest percentage of short-term residents (< 6 months, 6 months to 1 year). This suggests a higher rate of population mobility due to employment, education, or migration factors. Conversely, states such as Selangor (87.6%), Perak (82.6%), and Pulau Pinang (83.3%) have a significant proportion of long-term residents (> 3 years), reflecting a stable population base. Note that this distribution may influence housing policies and social infrastructure planning, particularly in high-mobility states. Lastly, housing type preferences vary significantly by state. Flats and apartments are predominantly observed in Wilayah Persekutuan (46.0%), reflecting the density of urban housing. In comparison, terrace houses are most common in Selangor (53.2%) and Perak (63.6%). By contrast, bungalows and semi-detached houses are more prevalent in Kelantan (23.0%) and Kedah (30.0%), indicating a preference for landed properties in rural regions. Other types of housing, such as traditional wooden houses, are significantly found in Kelantan (28.4%) and Perlis (70.0%). This reflects rural architectural traditions and lower urban penetration. These trends provide insights for housing development strategies tailored to different state demographics.

Overall, the observed patterns suggest that urbanisation, economic factors, and cultural demographics play a critical role in shaping population distributions across states. Nonetheless, these findings have implications for policymakers, urban planners, and public health officials, particularly in addressing housing needs, resource distribution, and social development strategies aligned with each state's demographic profile.

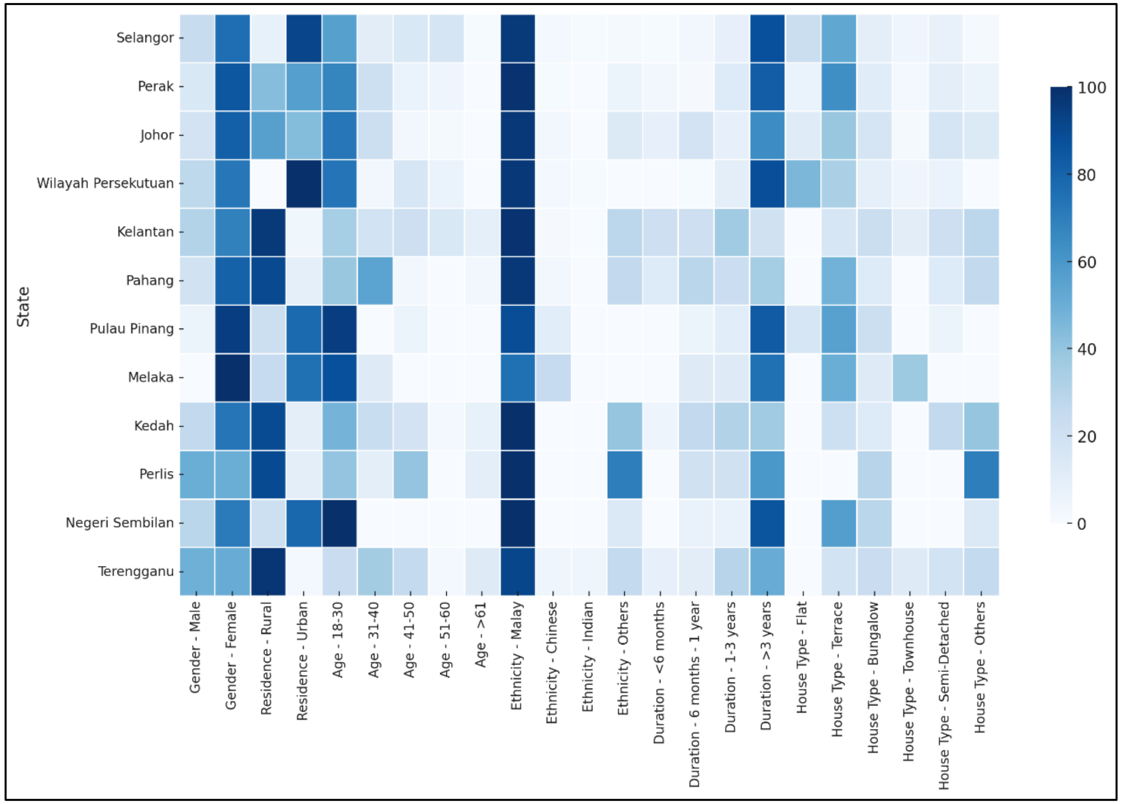


Figure 4.1 Heatmap of Sociodemographic Characteristics by State in Malaysia

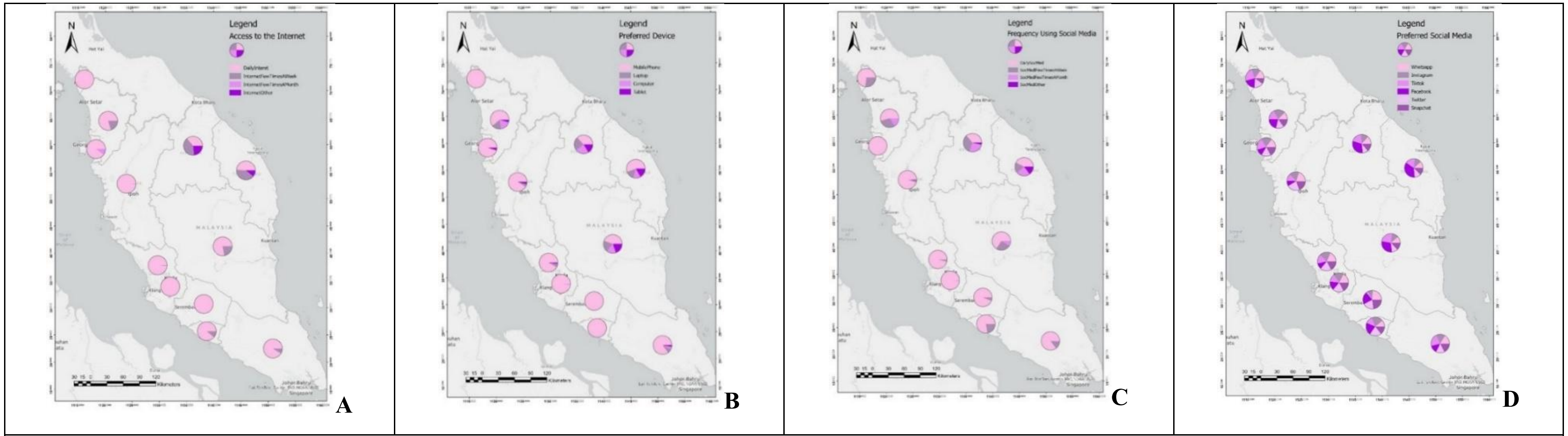
Note: Darker shades of blue indicate higher percentages, while lighter shades represent lower percentages across various demographic attributes such as gender, residence, age groups, ethnicity, duration of living in the area, and house type.

Furthermore, the spatial distribution of internet access frequency across dengue hotspot communities in Peninsular Malaysia highlights a significant digital divide between urban and rural states. In particular, Selangor (39.8%), Wilayah Persekutuan (10.0%), and Johor (6.2%) exhibit the highest proportion of daily internet users, as illustrated by the larger pie charts with dominant pink sections (Figure 4.2A). These states, characterised by high urbanisation and improved infrastructure, facilitate frequent digital engagement. This enables efficient online communication and information dissemination. Conversely, Kelantan (3.1%), Pahang (2.8%), and Terengganu (2.7%) highlight a notable proportion of infrequent internet users, with higher weekly internet access rates (Kelantan: 3.5%; Terengganu: 2.2%). These findings suggest that rural states experience limitations in broadband connectivity, socioeconomic constraints, and lower digital literacy rates. Consequently, this may reduce the effectiveness of internet-based public health interventions, including dengue awareness campaigns and early warning systems.

Across all dengue hotspots, mobile phones dominate as the primary device for internet access, particularly in Selangor (37.0%), Wilayah Persekutuan (9.8%), and Johor (5.8%) (Figure 4.2B). This trend reflects Malaysia's high mobile penetration rate, enabling individuals in both urban and rural areas to remain digitally connected despite infrastructure limitations. Nevertheless, a notable disparity in device usage exists between urbanised and rural states. While Selangor (2.2%), Kelantan (2.0%), and Wilayah Persekutuan (0.0%) exhibit some preference for laptops and computers, Kelantan (3.2%), Pahang (1.6%), and Terengganu (3.0%) remain heavily reliant on mobile-only access. This reinforces the need for mobile-optimised health communication strategies in rural areas. However, the absence of laptops and desktops in several states suggests potential challenges in accessing web-based resources, digital literacy programmes, and telemedicine services. This emphasises the significance of mobile-friendly public health interventions for dengue prevention.

A strong daily social media usage trend is evident in urban and semi-urban states, particularly in Selangor (38.7%), Wilayah Persekutuan (9.9%), and Johor (5.8%), as presented by the larger pie charts indicating a high proportion of daily engagement (Figure 4.2C). These states, with higher digital connectivity and greater integration of social media into daily life, offer opportunities for real-time public health messaging, dengue awareness programmes, and community engagement strategies through digital platforms. In contrast, Kelantan (3.1%), Pahang (2.3%), and Terengganu (2.3%) exhibit a higher proportion of users who access social media only a few times a week or a month, with Kelantan's weekly usage at 2.8% and Terengganu's at 1.0%. This pattern suggests that while social media adoption exists, engagement levels remain lower due to cultural, infrastructural, or digital literacy factors. Therefore, a blended communication approach integrating social media with traditional media such as radio and community outreach programmes may enhance awareness of dengue prevention in these areas.

Figure 4.2D indicates that WhatsApp is the dominant social media platform across all states, highlighting high reliance on direct messaging for communication. For example, Selangor (42.5%), Wilayah Persekutuan (10.4%), and Johor (7.5%) demonstrate the highest preference for WhatsApp. This renders it the most effective platform for public health engagement. Meanwhile, Instagram (43.1% in Selangor, 10.0% in Wilayah Persekutuan, and 7.4% in Johor) and TikTok (36.6% in Selangor, 8.1% in Wilayah Persekutuan, and 10.2% in Johor) are more popular in urbanised states, where visual content and short-form videos drive higher engagement. In contrast, Facebook is more prevalent in semi-urban and rural areas, particularly in Kelantan (19.5%), Pahang (9.1%), and Terengganu (12.8%). This makes it a suitable platform for community-based engagement and long-form information dissemination. Although Twitter usage remains lower overall, Selangor (43.2%) and Johor (7.0%) present relatively higher engagement. This suggests potential use for real-time outbreak updates and public health announcements. Snapchat, on the other hand, displays minimal engagement across all states, making it a less effective platform for health interventions.



Variables		States, n (%)												
		Selangor	Perak	Johor	Wilayah Persekutuan	Kelantan	Pahang	Pulau Pinang	Melaka	Kedah	Perlis	Negeri Sembilan	Terengganu	Total
Access to the internet	Daily	345 (39.8)	131 (15.1)	54 (6.2)	87 (10.0)	27 (3.1)	24 (2.8)	16 (1.8)	7 (0.8)	30 (3.5)	10 (1.2)	14 (1.6)	23 (2.7)	768 (88.7)
	A few times a week	3 (0.3)	1 (0.1)	5 (0.6)	0 (0.0)	30 (3.5)	7 (0.8)	0 (0.0)	1 (0.1)	8 (0.9)	0 (0.0)	0 (0.0)	19 (2.2)	74 (8.5)
	A few times a month	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	2 (0.2)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	2 (0.2)
	Other	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	17 (2.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	5 (0.6)	22 (2.5)
Preferred device to access internet	Mobile phone	320 (37.0)	121 (14.0)	50 (5.8)	85 (9.8)	28 (3.2)	14 (1.6)	17 (2.0)	8 (0.9)	23 (2.7)	10 (1.2)	14 (1.6)	26 (3.0)	716 (82.7)
	Laptop	19 (2.2)	6 (0.7)	4 (0.5)	0 (0.0)	17 (2.0)	6 (0.7)	0 (0.0)	0 (0.0)	6 (0.7)	0 (0.0)	0 (0.0)	7 (0.8)	65 (7.5)
	Computer	2 (0.2)	0 (0.0)	3 (0.3)	2 (0.2)	17 (2.0)	5 (0.6)	0 (0.0)	0 (0.0)	7 (0.8)	0 (0.0)	0 (0.0)	6 (0.7)	42 (4.8)
	Tablet	7 (0.8)	5 (0.6)	2 (0.2)	0 (0.0)	12 (1.4)	6 (0.7)	1 (0.1)	0 (0.0)	2 (0.2)	0 (0.0)	0 (0.0)	8 (0.9)	43 (5.0)
Frequency of using social media	Daily	335 (38.7)	126 (14.5)	50 (5.8)	86 (9.9)	27 (3.1)	20 (2.3)	18 (2.1)	6 (0.7)	21 (2.4)	7 (0.8)	13 (1.5)	20 (2.3)	729 (84.2)
	A few times a week	13 (1.5)	4 (0.5)	8 (0.9)	1 (0.1)	24 (2.8)	8 (0.9)	0 (0.0)	2 (0.2)	11 (1.3)	3 (0.3)	1 (0.1)	9 (1.0)	84 (9.7)
	A few times a month	0 (0.0)	0 (0.0)	1 (0.1)	0 (0.0)	20 (2.3)	3 (0.3)	0 (0.0)	0 (0.0)	6 (0.7)	0 (0.0)	0 (0.0)	11 (1.3)	41 (4.7)
	Other	0 (0.0)	2 (0.2)	0 (0.0)	0 (0.0)	3 (0.3)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	7 (0.8)	12 (1.4)
Preferred social media	Whatsapp	283 (42.5)	99 (14.9)	50 (7.5)	69 (10.4)	55 (8.3)	23 (3.5)	15 (2.3)	4 (0.6)	22 (3.3)	6 (0.9)	13 (2.0)	27 (4.1)	755 (87.2)
	Instagram	232 (43.1)	69 (12.8)	40 (7.4)	54 (10.0)	43 (8.0)	19 (3.5)	15 (2.8)	6 (1.1)	29 (5.4)	5 (0.9)	4 (0.7)	22 (4.1)	666 (76.9)
	Tiktok	108 (36.6)	28 (9.5)	30 (10.2)	24 (8.1)	35 (11.9)	22 (7.5)	9 (3.1)	2 (0.7)	14 (4.7)	4 (1.4)	1 (0.3)	18 (6.1)	620 (71.6)
	Facebook	40 (24.4)	12 (7.3)	10 (6.1)	15 (9.1)	32 (19.5)	15 (9.1)	3 (1.8)	2 (1.2)	9 (5.5)	2 (1.2)	3 (1.8)	21 (12.8)	538 (62.1)
	Twitter	326 (43.2)	125 (16.6)	53 (7.0)	82 (10.9)	43 (5.7)	24 (3.2)	18 (2.4)	8 (1.1)	28 (3.7)	7 (0.9)	12 (1.6)	29 (3.8)	295 (34.1)
	Snapchat	246 (39.7)	91 (14.7)	50 (8.1)	65 (10.5)	54 (8.7)	24 (3.9)	16 (2.6)	5 (0.8)	25 (4.0)	4 (0.6)	12 (1.9)	28 (4.5)	164 (18.9)

Figure 4.2 Different Variables Related to Technology and Internet Access Among Dengue Hotspot Communities Across Peninsular Malaysia. The Map Illustrates: (A) Access to the Internet, (B) Preferred Device for Internet Access, (C) Frequency of Social Media Usage, and (D) Preferred Social Media Platforms

4.2.2 Sociodemographic Influences on Public Perception and Engagement with Drone-Based Dengue Surveillance

The results highlight significant sociodemographic factors influencing public perceptions and engagement with drone-based dengue surveillance and intervention strategies. Gender, area, age, duration of stay, type of house, ethnicity, and state all exhibited varying levels of statistical significance ($p < 0.05$) in shaping attitudes toward drone-related activities (Figure 4.3). Meanwhile, negative perceptions about drones were significantly associated with gender ($p = 0.001$), ethnicity ($p = 0.091$), and state ($p = 0.001$). This indicates that cultural and regional differences influence acceptance levels. Similarly, concerns regarding drones flying near homes were more pronounced among individuals based on area ($p = 0.001$) and duration of stay ($p = 0.122$), suggesting that urban versus rural settings shape public apprehension toward drone surveillance. Regarding privacy concerns about drones capturing images, significant associations were found with age ($p = 0.010$), and state ($p = 0.001$), suggesting that privacy anxieties may vary by demographic and geographic factors. In essence, this suggests that younger populations and individuals from certain states may express heightened concerns over drone-related data collection.

In terms of technology adoption, willingness to download a drone-related app was significantly linked to area ($p = 0.220$), age ($p = 0.085$), type of house ($p = 0.053$), ethnicity ($p = 0.070$), and state ($p = 0.082$). These findings suggest that younger individuals, those from urbanised areas, and specific ethnic groups may be more inclined to adopt mobile-based dengue monitoring solutions. When analysing comfort in participating in drone-assisted cleanup activities, gender ($p = 0.489$), area ($p = 0.002$), age ($p = 0.001$), duration of stay ($p = 0.001$), type of house ($p = 0.033$), and state ($p = 0.001$) were all significant. This implies that long-term residents and those with greater community attachment may be more willing to engage in physical cleanup efforts. In a similar note, willingness to travel for cleanup efforts was associated with gender ($p = 0.048$), area ($p = 0.003$), age ($p = 0.001$), and ethnicity ($p = 0.459$). This underscores the significance of considering demographic-specific motivators for volunteerism in dengue prevention efforts.

For training participation, significant associations were observed across multiple factors, including gender (p = 0.001), area (p = 0.001), age (p = 0.014), duration of stay (p = 0.001), type of house (p = 0.001), and ethnicity (p = 0.699). These findings suggest that digital literacy and community involvement may influence the likelihood of individuals engaging in drone-related training programmes. Lastly, comfort in sharing drone-based dengue data on social media was significantly associated with gender (p = 0.017), area (p = 0.001), age (p = 0.005), duration of stay (p = 0.001), type of house (p = 0.001), ethnicity (p = 0.052), and state (p = 0.001). This indicates that privacy concerns and digital engagement levels shape public willingness to disseminate health-related drone data online. Overall, the results emphasise the need for targeted communication strategies, culturally adaptive outreach, and digital literacy initiatives to ensure the successful implementation of drone-based dengue prevention efforts. By addressing demographic-specific concerns and engagement barriers, policymakers can enhance public trust, increase participation, and optimise vector control strategies using drone technology.

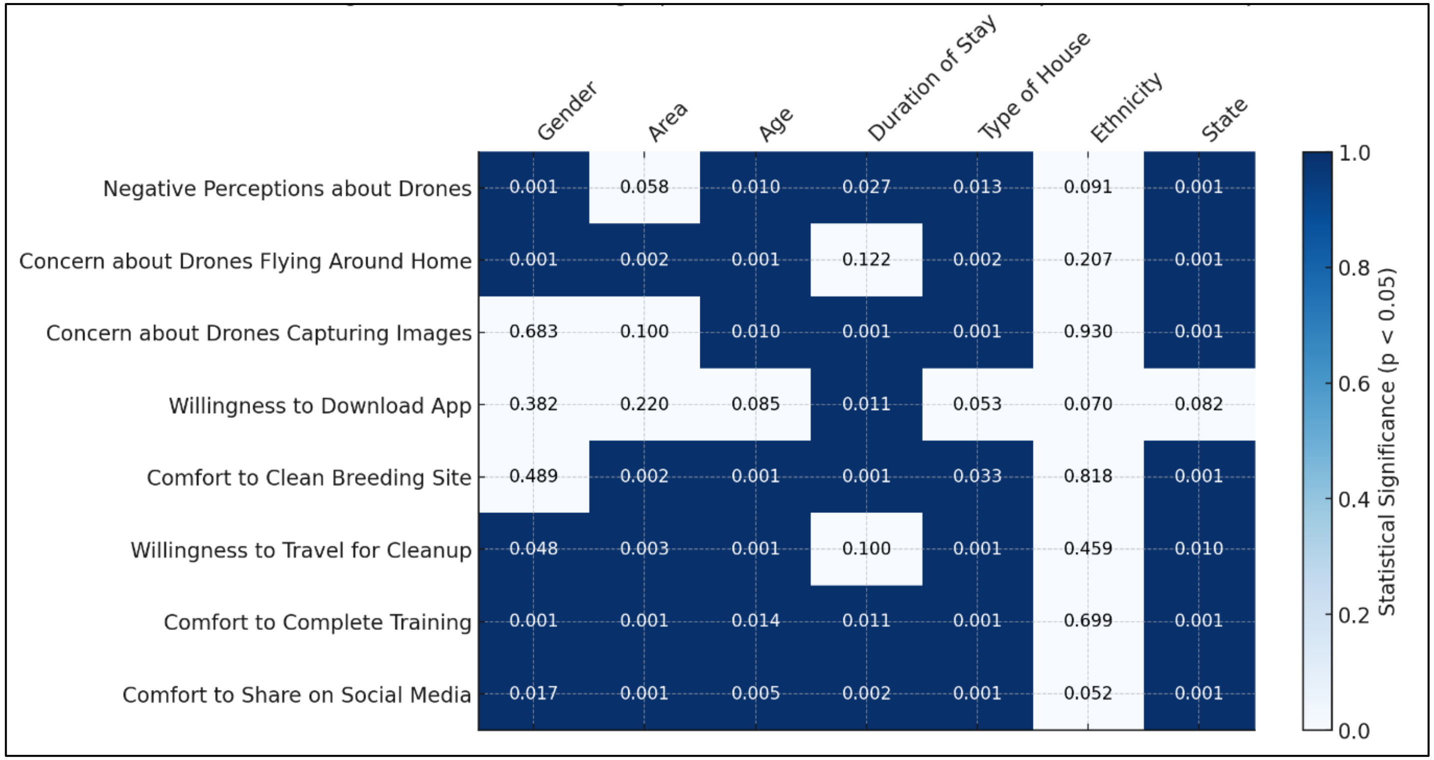


Figure 4.3 Heatmap of Statistical Significance (p-values) for Sociodemographic Factors Influencing Public Perception and Engagement with Drone-based Dengue Surveillance

Note: Darker shades represent higher statistical significance ($p < 0.05$), indicating strong associations between sociodemographic characteristics (e.g., gender, age, ethnicity, residence) and key behavioural and attitudinal variables related to drone technology. White and lighter shades indicate weaker or non-significant relationships ($p > 0.05$).

4.2.3 Discussion

The findings of this study provide crucial insights into the sociodemographic influences on public perception and engagement with drone-based dengue surveillance in Malaysia. Furthermore, the results highlight the complexities of integrating emerging technologies into vector control programmes, emphasising the need for a nuanced understanding of community acceptance and participation.

The study identified significant variations in public perception based on sociodemographic characteristics, with gender, age, ethnicity, and geographic location emerging as key determinants. Urban populations demonstrated greater acceptance and willingness to participate in drone-assisted mosquito control activities than their rural counterparts. This disparity is likely attributed to greater exposure to technology, higher digital literacy, and better internet infrastructure in urban settings. In addition, these findings align with previous research indicating that urban dwellers are more inclined to adopt digital health interventions due to their frequent use of technology-driven services (Ausserhofer *et al.*, 2024; Rosenlund *et al.*, 2023; Sapienza *et al.*, 2022). Conversely, privacy concerns related to drone surveillance were more pronounced in rural populations, particularly among older individuals. Following this, the hesitancy towards drone-based monitoring may stem from limited familiarity with Unmanned Aerial Vehicles (UAVs), cultural apprehensions, and a lack of targeted public awareness campaigns. Previous studies have suggested that distrust in technology often correlates with lower levels of education and limited digital exposure. This reinforces the need for tailored communication strategies to address these concerns (Ezeudoka & Fan, 2024; Yu et al., 2024; Wang *et al.*, 2025).

A notable finding of this study is the significant association between sociodemographic factors and willingness to participate in drone-assisted cleanup efforts and training programmes. Accordingly, younger individuals and long-term residents demonstrated higher engagement levels. This suggests that community attachment and digital familiarity enhance participation in technology-driven public health initiatives. Remarkably, these results corroborate findings from other studies that highlight the role of community involvement in the success of vector control programmes (Nguyen-Tien *et al.*, 2019; Wilson *et al.*, 2020; Toledo *et al*, 2007). Gender differences also played a critical role in public engagement, with male respondents exhibiting a greater willingness to participate in drone-assisted interventions than female respondents. This gender disparity could be influenced by traditional societal roles and perceptions of risk associated with technological engagement (Wang & Degol, 2017; Wolf & Moser, 2011). Hence, addressing these disparities requires gender-sensitive outreach programmes that emphasise the accessibility and safety of drone-based dengue surveillance activities (Manyazewal *et al.*, 2024).

The results indicate a significant digital divide between urban and rural states, impacting technology adoption and public engagement with drone-based vector control. Specifically, internet access frequency and social media usage were significantly lower in rural areas, limiting the potential reach of digital health interventions (Rousseau & Susanth, 2024). While WhatsApp and Facebook were the most preferred platforms for disseminating dengue-related information, rural populations had lower engagement rates than their urban counterparts. This finding underscores the significance of integrating traditional media and community-based approaches alongside digital platforms to enhance awareness and participation. Moreover, the study noted that the willingness to download a mobile application for drone-assisted mosquito control was significantly associated with age, ethnicity, and urbanisation level. In line with this, younger and urban populations were more inclined to adopt mobile-based dengue surveillance solutions. At the same time, older individuals and rural dwellers demonstrated resistance. Essentially, these findings suggest that targeted digital literacy initiatives and community education programmes are necessary to bridge the technology adoption gap and maximise the effectiveness of drone-based interventions (Vanderburg *et al.*, 2023).

The integration of drone technology into Malaysia's national dengue control programme offers a promising approach to enhancing surveillance and intervention efficiency. However, addressing public concerns regarding privacy, safety, and digital accessibility is crucial for successful implementation (Vitak & Shilton, 2020). The study's findings provide several policy recommendations. Correspondingly, public health authorities should implement community-centred education campaigns to address privacy concerns and enhance understanding of the benefits of drone-assisted vector control. Consistent with this, these campaigns should be tailored to different demographic groups, using culturally appropriate messaging and accessible communication channels. Additionally, expanding internet infrastructure and digital literacy programmes in rural areas can enhance engagement with technology-driven public health interventions. At the same time, collaborations with local community leaders and grassroots organisations can facilitate knowledge-sharing and build public trust in drone technology.

In addition, policymakers should incorporate gender-sensitive approaches in drone-assisted mosquito control programmes. For example, encouraging female participation through inclusive training workshops and community-led initiatives can improve overall engagement and acceptance. Building on this, establishing clear guidelines on data privacy, ethical drone usage, and community consent mechanisms is essential to addressing public apprehensions. Subsequently, transparency in data collection and usage policies can enhance trust and cooperation among the population. Given the variations in digital engagement levels across demographic groups, a blended approach combining digital platforms with conventional media such as radio, television, and community outreach is necessary for effective information dissemination. Overall, these strategies will ensure that information reaches all population segments, particularly those with limited internet access.

4.2.4 Conclusion

This study highlights the critical role of sociodemographic factors in shaping public perceptions and engagement with drone-based dengue surveillance. While the adoption of UAV technology presents a transformative opportunity for vector control, addressing barriers related to privacy, digital accessibility, and community trust is essential for large-scale implementation. Thus, by leveraging targeted public education, bridging the digital divide, and establishing robust regulatory frameworks, policymakers can enhance the effectiveness of drone-assisted dengue control programmes. This ultimately contributes to a more sustainable and technologically integrated public health response.

4.3 Aim 2: Sociodemographic Determinants of Willingness to Adopt Surveillance Technology and Mosquito Control Training for Dengue in Malaysia[5]

Dengue fever remains one of the most pressing public health challenges globally, particularly in tropical and subtropical regions where rapid urbanisation, climate variability, and ineffective vector control contribute to persistent outbreaks (Malavige *et al.*, 2023; Sarker *et al.*, 2024). In Malaysia, the dengue burden has escalated in recent years, with *Aedes* mosquitoes, primarily *Aedes aegypti* and *Aedes albopictus,* thriving in densely populated urban and peri-urban environments (Hii *et al.*, 2016; Yenamandra *et al.*, 2024). Despite ongoing efforts through conventional strategies such as fogging, larviciding, and environmental sanitation, the effectiveness of these approaches has been hindered by insecticide resistance. This includes low community participation and weak behavioural adherence to preventive measures (Packierisamy *et al.*, 2015; Dambach *et al.*, 2024). In response, these limitations underscore the need for integrated, innovative approaches that combine technological advancements with sustained community engagement.

Recent developments in digital public health have introduced novel tools such as drone surveillance for mosquito habitat identification and mobile applications for real-time vector alerts (Mahfodz *et al.*, 2024; Mahotra *et al.*, 2024). These technologies hold promise for enhancing surveillance coverage and promoting community-driven responses. For instance, drone-based monitoring enables precise mapping of breeding hotspots. Meanwhile, mobile apps can facilitate rapid dissemination of risk information and encourage timely preventive actions (Valdez-Delgado *et al.*, 2021). Still, the successful implementation of these tools hinges on public acceptance, which is often shaped by sociodemographic characteristics such as age, gender, education, and digital literacy. Simultaneously, community-based training programmes remain a critical pillar of vector control, offering hands-on education on mosquito prevention practices. Nonetheless, participation in such programmes is equally influenced by sociodemographic factors and localised perceptions of disease risk (Onen *et al.*, 2023; Vigodny *et al.*, 2023; Chen *et al.*, 2023; Perez-Guerra *et al.*, 2024; Oliveira *et al.*, 2024).

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[5] Mahfodz, Z., Dapari, R., Salleh, S.A., Camalxaman, S.N., Aljaafre, A.F. & Dom, N.C. (2026). Sociodemographic determinants of willingness to adopt surveillance technology and mosquito control training for dengue in Malaysia. *Sci Rep* 16, 3069.

While previous research has addressed either technology adoption or community engagement independently, few studies have comprehensively explored the intersection of sociodemographic determinants, digital surveillance adoption, and willingness to participate in mosquito control training. For this reason, this study addresses this gap by investigating how demographic profiles influence public receptivity toward both technology-based and traditional dengue prevention strategies. By examining these dual pathways of engagement, the study provides novel insights into designing targeted, context-sensitive interventions that align with the preferences and behaviours of different population subgroups. In addition, to further strengthen the study's conceptual grounding, the researchers draw on two complementary frameworks: the Technology Acceptance Model (TAM) and the Health Belief Model (HBM). Accordingly, TAM explains how perceived usefulness and ease of use affect individuals' willingness to adopt digital tools, such as mobile health applications.

Meanwhile, HBM provides a lens for understanding how perceived susceptibility, severity, benefits, and barriers influence engagement in health-related behaviours, including participation in community training. These frameworks guide our interpretation of how sociodemographic attributes mediate public responses to dengue control interventions in the Malaysian context. Therefore, the objective of this study is to assess the sociodemographic determinants influencing (i) the willingness to adopt a dengue surveillance mobile application and (ii) the willingness to participate in mosquito control training programmes. By identifying key predictors and potential barriers, the findings aim to inform more inclusive and effective vector control strategies that integrate technological innovation with grassroots participation.

4.3.1 Sociodemographic Determinants of Willingness to Engage in Vector Control

Table 4.1 presents the sociodemographic profiles of 866 respondents across Peninsular Malaysia, highlighting key factors such as gender, area of residence, age, ethnicity, housing type, and household size. These characteristics play a crucial role in shaping attitudes toward technological interventions in vector control. This is particularly true in determining the willingness to download a drone surveillance application and to participate in mosquito control training sessions.

Females constituted the majority of respondents (75.8%), and previous studies suggest that women often demonstrated greater concern for household health and environmental safety. This may translate into a greater willingness to adopt community-driven mosquito control measures. Notably, the high proportion of female respondents in urban areas, where technology adoption is more prevalent, suggests a potentially positive attitude toward mobile-based surveillance applications. On the contrary, males, who represent only 24.2% of the sample, may be more willing to participate in hands-on mosquito control training, as they engage more in outdoor activities.

A significant urban dominance (63.6%) suggests that a substantial portion of the study population has higher digital literacy and access to mobile applications, which may enhance their willingness to download a drone-based mosquito surveillance app. Conversely, rural respondents (36.4%), particularly those in Kelantan (95.9%) and Terengganu (97.9%), may exhibit lower technological engagement. However, they have a higher interest in participatory mosquito control training, given their greater exposure to mosquito-breeding environments.

The predominance of younger respondents (18-30 years: 57.9%) suggests a favourable environment for mobile application adoption, as younger populations are generally more tech-savvy and receptive to digital interventions. In contrast, older respondents (31-50 years: 29.7%, > 51 years: 12.4%) may be less inclined toward technology-based solutions, though they are more open to traditional vector control training sessions. This highlights the need for dual engagement strategies: younger respondents are targeted through app-based solutions. At the same time, older demographics are engaged through in-person educational programmes. The study sample is overwhelmingly Malay (96.4%), with minimal representation from other ethnic groups. This demographic composition suggests that vector control campaigns should be tailored to align with Malay cultural and community values, leveraging existing kampung-based networks for training initiatives. Educational level was also captured, with the majority of respondents holding at least a diploma or university degree. Concurrently, higher educational attainment was associated with increased willingness to download the dengue surveillance app. Despite this, this variable was not included in the final regression model to minimise multicollinearity with age and digital access.

Table 4.1
Sociodemographic Characteristics of Respondents and Their Potential Influence on Vector Control Engagement in Peninsular Malaysia

Characteristics		**States, n (%)**												**Total**
		Selangor	**Perak**	**Johor**	**K. Lumpur**	**Kelantan**	**Pahang**	**Penang**	**Melaka**	**Kedah**	**Perlis**	**N. Sembilan**	**T'ganu**	
Gender	Male	83 (23.9)	20 (15.2)	11 (18.6)	24 (27.6)	23 (31.1)	6 (19.4)	1 (5.6)	0 (0.0)	10 (26.3)	5 (50.0)	4 (28.6)	23 (48.9)	210 (24.2)
	Female	265 (76.1)	112 (84.8)	48 (81.4)	63 (72.4)	51 (68.9)	25 (80.6)	17 (94.4)	8 (100)	28 (73.3)	5 (50.0)	10 (71.4)	24 (51.1)	656 (75.8)
Area of residence	Rural	28 (8.0)	57 (43.2)	33 (55.9)	0 (0.0)	71 (95.9)	28 (90.3)	4 (22.2)	2 (25.0)	34 (89.5)	9 (90.0)	3 (21.4)	46 (97.9)	315 (36.4)
	Urban	320 (92.0)	75 (56.8)	26 (44.1)	87 (100)	3 (4.1)	3 (9.7)	14 (77.8)	6 (75.0)	4 (10.5)	1 (10.0)	11 (78.6)	1 (2.1)	551 (63.6)
Age Group (years old)	18-30	196 (56.3)	89 (67.4)	43 (72.9)	64 (73.6)	26 (35.1)	12 (38.7)	17 (94.4)	7 (87.5)	18 (47.4)	4 (40.0)	14 (100)	11 (23.4)	501 (57.9)
	31-40	37 (10.6)	28 (21.2)	13 (22.0)	3 (3.4)	14 (18.9)	17 (54.8)	0 (0.0)	1 (12.5)	9 (23.7)	1 (10.0)	0 (0.0)	17 (36.2)	140 (16.1)
	41-50	52 (14.9)	9 (6.8)	2 (3.4)	14 (16.1)	16 (21.6)	1 (3.2)	1 (5.6)	0 (0.0)	7 (18.4)	4 (40.0)	0 (0.0)	12 (25.5)	118 (13.6)
	51-60	60 (17.2)	6 (4.5)	1 (1.7)	6 (6.9)	11 (14.9)	0 (0.0)	0 (0.0)	0 (0.0)	1 (2.6)	0 (0.0)	0 (0.0)	1 (2.1)	86 (10.0)
	>61	3 (0.9)	0 (0.0)	0 (0.0)	0 (0.0)	7 (9.5)	1 (3.2)	0 (0.0)	0 (0.0)	3 (7.9)	1 (10.0)	0 (0.0)	6 (12.8)	21 (2.4)
Ethnicity	Malay	334 (96.0)	130 (98.5)	57 (96.6)	84 (96.6)	73 (98.6)	30 (96.8)	16 (88.9)	6 (75.0)	38 (100)	10 (100.)	14 (100)	43 (91.5)	835 (96.4)
	Chinse	9 (2.6)	1 (0.8)	2 (3.4)	2 (2.3)	1 (1.4)	1 (3.2)	2 (11.1)	2 (25.0)	0 (0.0)	0 (0.0)	0 (0.0)	2 (4.3)	22 (2.5)
	Indian	3 (0.9)	0 (0.0)	0 (0.0)	1 (1.1)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	2 (4.3)	6 (0.7)
	Others	2 (0.6)	1 (0.8)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	3 (0.4)

Characteristics		States, n (%)												Total
		Selangor	Perak	Johor	K. Lumpur	Kelantan	Pahang	Penang	Melaka	Kedah	Perlis	N. Sembilan	T'ganu	
Duration of living in the area	<6 months	3 (0.9)	4 (3.0)	5 (8.5)	0 (0.0)	16 (21.6)	4 (12.9)	0 (0.0)	0 (0.0)	2 (5.3)	0 (0.0)	0 (0.0)	4 (8.5)	38 (4.4)
	6 months to 1 year	11 (3.2)	2 (1.5)	11 (18.6)	1 (1.1)	16 (21.6)	9 (29.0)	1 (5.6)	1 (12.5)	10 (26.3)	2 (20.0)	1 (7.1)	5 (10.6)	70 (8.1)
	1-3 years	29 (8.3)	17 (12.9)	5 (8.5)	9 (10.3)	27 (36.5)	7 (22.6)	2 (11.1)	1 (12.5)	12 (31.6)	2 (20.0)	1 (7.1)	14 (29.8)	126 (14.5)
	>3 years	305 (87.6)	109 (82.6)	38 (64.4)	77 (88.5)	15 (20.3)	11 (35.5)	15 (83.3)	6 (75.0)	14 (36.8)	6 (60.0)	12 (85.7)	24 (51.1)	632 (73.0)
Type of House	Flat/Apartment	79 (22.7)	9 (6.8)	7 (11.9)	40 (46.0)	0 (0.0)	0 (0.0)	3 (16.7)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	138 (15.9)
	Terrace	185 (53.2)	84 (63.6)	23 (39.0)	29 (33.3)	12 (16.2)	15 (48.4)	10 (55.6)	4 (50.0)	8 (21.1)	0 (0.0)	8 (57.1)	9 (19.1)	387 (44.7)
	Bungalow	34 (9.8)	15 (11.4)	10 (16.9)	8 (9.2)	17 (23.0)	4 (12.9)	4 (22.2)	1 (12.5)	5 (13.2)	3 (30.0)	4 (28.6)	11 (23.4)	116 (13.4)
	Townhouse	17 (4.9)	3 (2.3)	1 (1.7)	4 (4.6)	8 (10.8)	0 (0.0)	0 (0.0)	3 (37.5)	0 (0.0)	0 (0.0)	0 (0.0)	6 (12.8)	42 (4.8)
	Semi-Detached	27 (7.8)	13 (9.8)	10 (16.9)	6 (6.9)	16 (21.6)	4 (12.9)	1 (5.6)	0 (0.0)	10 (26.3)	0 (0.0)	0 (0.0)	9 (19.1)	96 (11.1)
	Others	6 (1.7)	8 (6.1)	8 (13.6)	0 (0.0)	21 (28.4)	8 (25.8)	0 (0.0)	0 (0.0)	15 (39.5)	7 (70.0)	2 (14.3)	12 (25.5)	87 (10.1)
Number of Households	1	4 (1.1)	2 (1.5)	2 (3.4)	0 (0.0)	8 (10.8)	1 (3.2)	1 (5.6)	0 (0.0)	1 (2.6)	0 (0.0)	0 (0.0)	4 (8.5)	23 (2.7)
	2	18 (5.2)	12 (9.1)	10 (16.9)	0 (0.0)	22 (29.7)	8 (25.8)	0 (0.0)	0 (0.0)	3 (7.9)	2 (20.0)	0 (0.0)	5 (10.6)	80 (9.2)
	3	36 (10.3)	15 (11.4)	7 (11.9)	10 (11.5)	18 (24.3)	5 (16.1)	0 (0.0)	0 (0.0)	14 (36.8)	1 (10.0)	2 (14.3)	10 (21.3)	118 (13.6)
	4	68 (19.5)	42 (31.8)	22 (37.3)	13 (14.9)	12 (16.2)	9 (29.0)	4 (22.2)	2 (25.0)	10 (26.3)	3 (30.0)	1 (7.1)	17 (36.2)	203 (23.4)
	5 or more	222 (63.8)	61 (46.2)	18 (30.5)	64 (73.6)	14 (18.9)	8 (25.8)	13 (72.2)	6 (75.0)	10 (26.3)	4 (40.0)	11 (78.6)	11 (23.4)	442 (51.0)
Total		**348 (40.2)**	**132 (15.2)**	**59 (6.8)**	**87 (10.0)**	**74 (8.6)**	**31 (3.6)**	**18 (2.1)**	**8 (0.9)**	**38 (4.4)**	**10 (1.2)**	**14 (1.6)**	**47 (5.4)**	**866 (100)**

4.3.2 Sociodemographic Factors Influencing Willingness to Download a Dengue Application

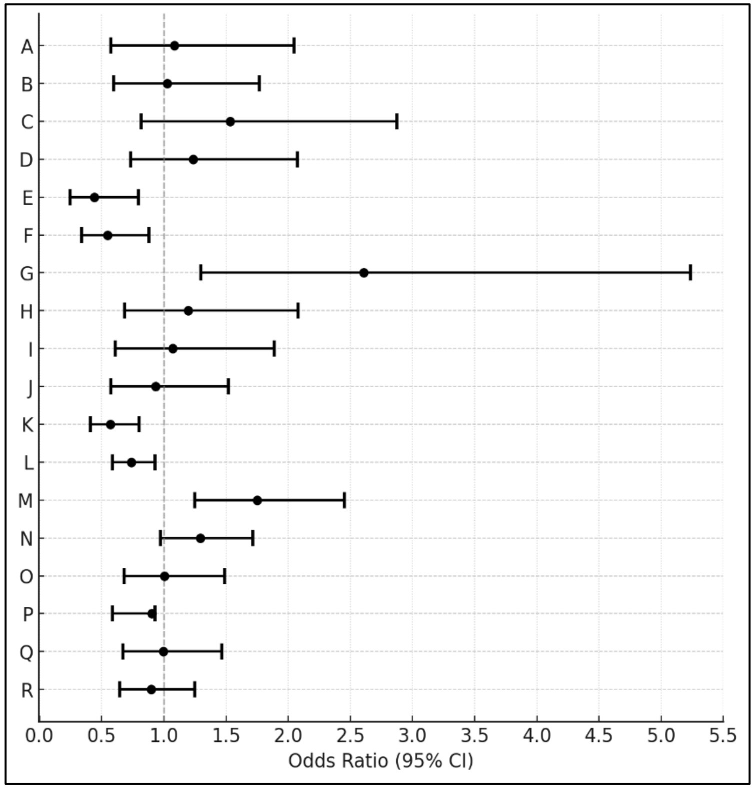
Table 4.2 presents the results of the multinomial logistic regression analysis examining sociodemographic and perceptual factors influencing willingness to download a dengue surveillance application. One of the most significant predictors of technology adoption was age: respondents under 40 were significantly more likely to express interest in downloading the application than those over 40. Specifically, respondents under 40 had Odds Ratios (ORs) of 0.441 (95% CI: 0.244-0.796; $p = 0.007$) for "Maybe" responses and 0.545 (95% CI: 0.338-0.879; $p = 0.013$) for "Yes" responses. Residential stability also emerged as a significant determinant. Those residing in their area for more than 3 years were 2.607 times more likely (95% CI: 1.298-5.238; $p = 0.007$) to consider downloading the app than those with shorter residency. This suggests that long-term residents may feel more invested in community health and thus be more receptive to adopting surveillance tools.

Perceptions of drone technology significantly influenced app adoption, as detailed in Table 4.2. Respondents who had negative perceptions of drones, as measured using Likert-scale items related to concerns regarding privacy invasion, misuse of aerial footage, and distrust in government surveillance practices, were significantly less likely to consider or commit to downloading the app. Specifically, negative perception was associated with a reduced likelihood for both "Maybe" (OR = 0.571, $p = 0.001$) and "Yes" (OR = 0.738, $p = 0.009$) responses compared to "No." Moreover, these concerns reflect apprehension around data security, potential infringement of personal space, and uncertainty concerning the effectiveness of drones in accurately identifying breeding sites. In addition, the survey included items such as "I am concerned that drone surveillance invades my privacy" and "I doubt drones are effective in detecting mosquito breeding sites," rated on a 5-point agreement scale. Responses were categorised into "Yes" (positive perception), "No" (negative perception), and "Unsure," with "No" respondents indicating statistically significantly lower willingness to adopt the app. Interestingly, those who were "Unsure" exhibited higher openness to "Maybe" responses (OR = 1.752; $p = 0.001$), suggesting that improved communication and education could potentially shift them toward adoption.

Contrary to expectations, urban-rural residence, gender, and housing type were not statistically significant predictors of willingness to adopt the app ($p > 0.05$ across all comparisons). This implies that perceptions and individual attitudes, particularly toward drone surveillance, may override structural or environmental factors in shaping app adoption behaviour.

Table 4.2
Multinomial Regression Analysis of Factors Influencing Willingness to Download a Dengue Application

Independent Variables	Predictors	Willingness to Download the Dengue Application		
		p-value	OR	95% CI
Area of residence				
Rural vs Urban	A. Maybe vs No	0.799	1.086	0.576, 2.048
	B. Yes vs No	0.922	1.027	0.597, 1.767
Gender				
Male vs Female	C. Maybe vs No	0.184	1.531	0.817, 2.872
	D. Yes vs No	0.427	1.234	0.735, 2.073
Age				
< 40 years vs > 40 years	E. Maybe vs No	0.007	0.441	0.244, 0.796
	F. Yes vs No	0.013	0.545	0.338, 0.879
Duration of living in the area				
> 3 years vs < 3 years	G. Maybe vs No	0.007	2.607	1.298, 5.238
	H. Yes vs No	0.526	1.196	0.687, 2.081
Type of house				
Terrace vs Others	I. Maybe vs No	0.812	1.071	0.609, 1.886
	J. Yes vs No	0.786	0.935	0.576, 1.519
Negative perceptions about drone use				
No vs Yes	K. Maybe vs No	0.001	0.571	0.408, 0.800
	L. Yes vs No	0.009	0.738	0.587, 0.928
Unsure vs Yes	M. Maybe vs No	0.001	1.752	1.250, 2.454
	N. Yes vs No	0.074	1.293	0.975, 1.713
Concern about drone use				
No vs Yes	O. Maybe vs No	0.975	1.006	0.681, 1.487
	P. Yes vs No	0.439	0.903	0.587, 0.928
Unsure vs Yes	Q. Maybe vs No	0.975	0.994	0.673, 1.468
	R. Yes vs No	0.521	0.897	0.644, 1.250



Note: The table presents ORs, 95% Confidence Intervals (CIs), and p-values for key sociodemographic variables, housing type, and perceptions of drone use, categorised by responses ("No," "Maybe," and "Yes"). Significant associations are highlighted to identify potential predictors of app adoption.

4.3.3 Factors Influencing Willingness to Participate in Dengue Prevention Training Programmes

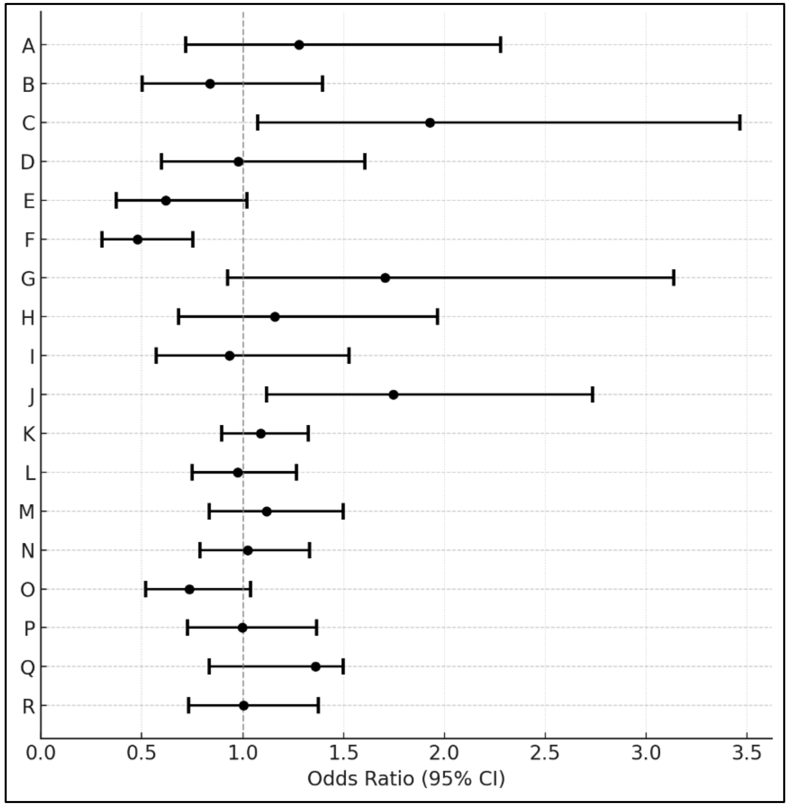
Table 4.3 summarises the multinomial logistic regression findings on willingness to engage in mosquito control training programmes. In particular, gender emerged as a significant factor: males were 1.929 times more likely (95% CI: 1.074-3.467; $p = 0.028$) to consider participating in training compared to females, though the effect was significant only at the “Maybe” level. Meanwhile, age was inversely associated with training participation. Respondents under 40 were significantly less likely to indicate definite willingness to join training ($p = 0.001$), with an OR of 0.478 (95% CI: 0.304-0.753). This suggests that younger individuals, while more open to digital solutions, may be less motivated to attend structured, in-person programmes, highlighting a need for hybrid or gamified training formats for this demographic. Housing type was another significant predictor. Residents in terrace houses were 1.747 times more likely (95% CI: 1.117-2.734; $p = 0.015$) to express definite interest in training compared to those in other housing types. This may be due to higher perceived exposure to mosquito breeding in such residential environments. In contrast to app adoption, perceptions of drone surveillance did not significantly influence training participation ($p > 0.05$ for all comparisons). This further supports the notion that public scepticism toward drone technology is specific to digital interventions and does not extend to traditional health education activities.

Overall, the findings indicate that gender, age, and housing type are the primary sociodemographic drivers of willingness to participate in dengue prevention training programmes. While males and older individuals exhibit greater engagement, younger populations may require alternative outreach strategies, such as digital learning modules or gamified training, to increase participation. Additionally, the strong association between housing type and willingness to train suggests that community-based interventions may benefit from tailoring recruitment efforts to specific residential environments. Thus, by understanding these factors, public health initiatives can be better structured to maximise engagement and effectiveness in dengue prevention efforts.

Table 4.3

Multinomial Regression Analysis of Factors Influencing Willingness to Participate in Dengue Prevention Training Programmes

Independent Variables	**Predictors**	**Willingness to be Trained for Dengue Prevention**		
		p-value	**OR**	**95% CI**
Area of residence				
Rural vs Urban	A. Maybe vs No	0.403	1.279	0.718, 2.278
	B. Yes vs No	0.498	0.838	0.502, 1.397
Gender				
Male vs Female	C. Maybe vs No	0.028	1.929	1.074, 3.467
	D. Yes vs No	0.932	0.979	0.597, 1.606
Age				
< 40 years vs > 40 years	E. Maybe vs No	0.060	0.618	0.374, 1.021
	F. Yes vs No	0.001	0.478	0.304, 0.753
Duration of living in the area				
>3 years vs <3 years	G. Maybe vs No	0.086	1.705	0.926, 3.139
	H. Yes vs No	0.585	1.159	0.683, 1.965
Type of house				
Terrace vs Others	I. Maybe vs No	0.787	0.934	0.571, 1.529
	J. Yes vs No	0.015	1.747	1.117, 2.734
Negative perceptions about drone use				
No vs Yes	K. Maybe vs No	0.387	1.090	0.897, 1.325
	L. Yes vs No	0.851	0.975	0.750, 1.268
Unsure vs Yes	M. Maybe vs No	0.455	1.118	0.835, 1.497
	N. Yes vs No	0.851	1.025	0.789, 1.333
Concern about drone use				
No vs Yes	O. Maybe vs No	0.080	0.734	0.519, 1.038
	P. Yes vs No	0.984	0.997	0.728, 1.366
Unsure vs Yes	Q. Maybe vs No	0.080	1.362	0.835, 1.497
	R. Yes vs No	0.984	1.003	0.732, 1.375



Note: The table presents ORs, 95% CIs, and p-values for key sociodemographic variables, housing type, and perceptions of drone use, categorised by responses ("No," "Maybe," and "Yes"). Significant associations are highlighted to identify potential predictors of app adoption.

4.3.4 Discussion

This study provides important insights into the sociodemographic determinants influencing willingness to engage in dengue vector control strategies. This is specifically evident in the adoption of a dengue surveillance mobile application and participation in mosquito control training sessions. In line with this, the findings highlight key demographic patterns that shape public engagement with technology-based interventions and community-driven vector control programmes. This underscores the need for targeted, evidence-based public health strategies.

One of the most significant findings of this study is that age plays a crucial role in influencing willingness to adopt drone-based mosquito surveillance applications. Younger respondents (18 to 30 years) were significantly more likely to consider downloading the application than older respondents. This finding aligns with previous research from Brazil, Thailand, and Nepal. The studies observed that younger populations demonstrated greater receptivity to digital health interventions due to their familiarity with mobile technologies and greater trust in app-based surveillance systems (Partridge *et al.*, 2018; Aschbrenner *et al.*, 2019; Ferretti *et al.*, 2023). Nonetheless, a study in Puerto Rico noted that even among younger users, privacy and trust concerns reduced adoption rates. This is particularly true when public health surveillance tools were not accompanied by transparent communication strategies (Perez-Guerra *et al.*, 2024). In contrast, older individuals may exhibit lower digital literacy and greater scepticism toward technology-driven vector control measures, which could explain their lower adoption rates (Oh *et al.*, 2021; Chan *et al.*, 2024).

Additionally, a longer duration of residence in a particular area was positively associated with willingness to use the application. Residents who had lived in their neighbourhoods for more than three years were significantly more likely to consider adopting the technology. This could be attributed to greater awareness of local dengue risks, higher levels of community engagement, and a stronger sense of responsibility toward vector control efforts. Similar findings were observed in studies conducted in Singapore and Mexico, where long-term residents presented greater participation in both digital and community-led vector control activities (Harris *et al.*, 2018; Haldane *et al.*, 2019). Interestingly, urban-rural differences were not significant predictors of application adoption. However, this finding contrasts with several studies from India and Indonesia, where urban populations typically exhibited higher digital health adoption due to better infrastructure and access (Hanjahanja-Phiri *et al.*, 2024; Shapira & Cauchard, 2022). Our results suggest that in the Malaysian context, factors such as individual awareness, digital literacy, and perceived usefulness may outweigh geographic location. This underscores the need for tailored health communication strategies that cut across urban-rural boundaries.

A critical barrier to technology adoption in our study was negative perceptions of drone surveillance. Respondents who expressed concerns about privacy, data security, and government surveillance were significantly less likely to download the dengue application. These concerns mirror findings from a multisite study in Malaysia, Turkey, and Mexico, where fear of being monitored and uncertainty about drone accuracy limited public trust in UAV-based surveillance (Annan *et al.*, 2022). Therefore, addressing these concerns through community engagement, transparent data governance, and clear messaging about the public health benefits of drone usage will be essential to promote adoption. In contrast to technology adoption, willingness to participate in mosquito control training sessions was significantly influenced by gender and housing type. Accordingly, male respondents were nearly twice as likely to express interest in training programmes compared to female participants. This finding echo reports from vector control studies in India and sub-Saharan Africa. It was noted that men were more involved in field-based vector control activities, while women focused on household-level interventions (Gunn *et al.*, 2018; Hayden *et al.*, 2018; Wenham *et al.*, 2020). Still, women's central role in maintaining household hygiene and water storage practices should not be overlooked. In essence, gender-inclusive programme design remains vital for achieving equitable and effective dengue prevention (De-menezes *et al.*, 2022).

Another significant predictor of training participation was housing type. Terrace house residents were more likely to participate in training programmes, likely due to higher mosquito exposure in these built environments. This is consistent with findings from Thailand and the Philippines. Notably, residents in high-density housing reported greater participation in mosquito control due to increased perceived vulnerability (Connel, 1999). Age, again, influenced engagement, with younger respondents indicating less interest in training. This supports the dual-intervention concept of technology-driven tools for digitally literate youth and community-based education for older or less tech-savvy populations.

The dual-intervention model explored in this study, combining mobile surveillance technology with community-based training, has strong potential for operational integration into Malaysia's existing dengue control framework. The Ministry of Health's (MOH) Communication for Behavioural Impact (COMBI) programme, for example, could be augmented with mobile reporting tools to enhance community monitoring and early outbreak alerts. Similarly, public health campaigns and school-based vector control education could incorporate app usage and training modules, fostering multisectoral engagement. The scalability of this approach is supported by growing smartphone penetration in both urban and rural areas. Hence, future implementations should also align the model with other preventive strategies. This includes source-reduction campaigns, larvicide distribution, and routine fogging, to maximise community impact.

While the findings are rooted in the Malaysian context, the study offers important insights for other dengue-endemic Low- and Middle-Income Countries (LMICs) with similar urbanisation patterns, community health structures, and mobile technology uptake. For instance, countries across Southeast Asia, Latin America, and parts of Africa face comparable challenges in engaging diverse communities in vector control. The framework assessed here targeted app-based surveillance, and age-tailored engagement could be adapted to such settings with contextual modifications. As such, negative perceptions of drones, particularly concerns about surveillance and privacy, emerged as significant barriers to app adoption. These concerns mirror findings in other public health and disaster response contexts, where drones are often associated with intrusive government oversight or unfamiliar technology (Dom *et al.*, 2025). In response, public health messaging should proactively address these fears by highlighting the community-led nature of drone operations. They could also clarify data privacy protections and showcase success stories from similar deployments. Consistent with this, integrating participatory design or community co-creation sessions may also improve trust and perceived legitimacy.

To support policymakers, several actionable strategies can be considered to enhance the practical implementation of the dual-intervention model proposed in this study. First, bilingual, age-targeted awareness campaigns should be developed to differentiate engagement strategies for mobile app users and those who prefer in-person training, ensuring inclusivity across digital literacy levels. Second, drone education and privacy assurance modules can be embedded within existing COMBI and dengue outreach programmes to address public scepticism and build trust in emerging technologies. Third, leveraging community influencers such as local leaders and health volunteers can play a vital role in promoting community participation and dispelling misconceptions about technology use in vector control. Finally, pilot-testing the intervention across diverse epidemiological zones would allow for its evaluation of adaptability and inform scale-up strategies. These context-specific approaches strengthen the translational potential of our findings and offer a viable path forward for integrated, technology-supported community-based dengue prevention.

This study has several limitations that must be acknowledged. First, data were collected using self-reported measures, which may introduce social desirability bias, particularly for questions on preventive behaviour and willingness to participate. Second, there was an overrepresentation of female respondents (75.8%) and urban residents (63.6%), which may limit the generalisability of the findings to male and rural populations. This imbalance may have skewed the results, particularly for gender- or location-specific predictors. Hence, future studies should consider quota sampling or oversampling underrepresented groups to improve representativeness. Moreover, although perceptions of drones were assessed using structured questions, in-depth qualitative methods (e.g., interviews or focus groups) could provide richer insights into the reasons behind distrust or reluctance. These would help refine intervention designs.

An additional limitation of this study is the exclusion of educational attainment, which is known to influence digital health adoption and public health engagement. While age and internet usage were used as proxies for digital literacy, the absence of formal education data limits our ability to analyse the independent effect of formal education on willingness to adopt surveillance technologies or to participate in training. Finally, although the survey was stratified by state, the researcher did not examine whether regional dengue burden influenced response rates or engagement outcomes. As such, integrating dengue incidence data in future studies could provide valuable context for interpreting regional variations in willingness to participate.

4.3.5 Conclusion

This study underscores the critical role of sociodemographic factors in shaping public engagement with dengue vector control initiatives. Younger populations are more willing to adopt technology-driven solutions, whereas older individuals prefer traditional community-based interventions. Gender and housing type further influence engagement patterns, underscoring the need for tailored public health interventions. Importantly, this study offers a novel contribution by simultaneously examining the intersection of sociodemographic variables, perceptions of drone technology, and dual engagement pathways. It is an area that remains underexplored in current dengue control literature. Thus, by integrating the TAM and the HBM, this research provides a theoretically grounded, context-specific understanding of public readiness for both digital and grassroots interventions.

For policymakers and public health planners, the findings suggest actionable strategies: deploy mobile-based tools to engage tech-savvy youth while reinforcing community training for older and high-risk populations. Following this, existing programmes such as COMBI or digital platforms, including MySejahtera, could be leveraged to operationalise this dual-intervention model. Moreover, future research should explore the long-term behavioural impact of such dual interventions and incorporate qualitative methods to understand perceptions of emerging technologies. Expanding representative sampling, especially among underrepresented rural and male populations, will also enhance the generalisability of findings. By leveraging both technology-based and traditional vector control approaches, Malaysia and similar dengue-endemic countries can optimise prevention strategies, reduce disease transmission, and enhance community resilience against mosquito-borne infections.

4.4 Aim 3: Community Knowledge and Practices on Mosquito Control in Malaysia Reveal State-Level and Urban-Rural Disparities for Sustainable Dengue Prevention[6]

Mosquito-borne diseases, particularly dengue, represent one of the most urgent challenges for sustainable cities and societies in tropical and subtropical regions (Naik *et al.*, 2023; Zhang *et al.*, 2024). Globally, dengue incidence has increased by more than eightfold over the past two decades, placing nearly half of the world's population at risk (Yang *et al.*, 2021). In Malaysia, dengue is hyperendemic, with recurrent outbreaks causing significant morbidity, mortality, and economic burden (Ng *et al.*, 2023). Despite decades of intensive vector control programmes, including fogging, larviciding, and environmental sanitation, sustained reductions in *Aedes* mosquito populations remain elusive. Note that this persistent failure highlights the limitations of reactive, top-down interventions. It emphasises the need for proactive, community-driven prevention strategies embedded within sustainable urban and rural systems. A critical barrier is the long-recognised knowledge-practice gap, in which communities may have strong awareness of dengue risks yet fail to translate this knowledge into preventive action consistently.

Studies in Southeast Asia repeatedly indicate that while individuals understand mosquito breeding sites and transmission pathways, preventive behaviours such as container cleaning, larval control, and waste management are inconsistently practised (Selvarajoo *et al.*, 2020; Shafie *et al.*, 2023; Crowley *et al.*, 2025). Following this, contributing factors include behavioural fatigue, socio-economic pressures, and reliance on government-led fogging operations (Abdullah *et al.*, 2024). Such gaps undermine the sustainability of vector control and hinder resilience building in cities and communities. In Malaysia, most dengue Knowledge, Attitude, and Practice (KAP) studies have been conducted at the district or city level, limiting their generalisability and obscuring broader socio-ecological disparities (Selvarajoo *et al.*, 2020; Elia-Amira *et al.*, 2023).

Nevertheless, the burden of dengue is spatially uneven: highly urbanised states such as Selangor and Kuala Lumpur consistently report the highest case numbers.

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[6] Mahfodz, Z., Dapari, R., Salleh, S.A., Camalxaman, S.N., Yusop, M.M. & Dom, N. C. (2026). Uneven Mosquito Control Knowledge, Attitudes, and Practices in Malaysia Shape Sustainable Dengue Prevention Across Urban and Rural Settings. *Sci Rep. (Accepted May 2026).*

Meanwhile, rural states such as Kelantan and Terengganu remain vulnerable due to weaker infrastructure and limited community engagement (Hadi *et al.*, 2025). These disparities are shaped by rapid urbanisation, high housing density, migration patterns, and differential access to health services and environmental management systems (Dom *et al.*, 2025). Hence, understanding these variations is essential for disease prevention and for advancing Sustainable Development Goals (SDGs) related to health (SDG 3), sustainable cities and communities (SDG 11), and climate action (SDG 13).

Against this backdrop, the present study was designed to examine state-level and urban-rural variation in community knowledge and practices on mosquito control across Peninsular Malaysia. Specifically, it aimed to: (i) analyse sociodemographic determinants of mosquito control behaviours; (ii) compare knowledge and practices across states; (iii) evaluate the extent of the knowledge-practice gap; and (iv) assess urban-rural differences in mosquito control behaviours. Furthermore, by generating robust comparative evidence, this study contributes to understanding how local socio-ecological contexts shape community engagement in vector control. Ultimately, the findings aim to inform the design of state-tailored, context-specific, and community-centred strategies that integrate public health with urban planning and environmental management. This advances more sustainable and resilient approaches to dengue prevention in Malaysia.

4.4.1 Sociodemographic Characteristics of Respondents

A total of 866 respondents participated in the survey (Table 4.4). The majority were female (75.8%), with males accounting for 24.2%. Most respondents resided in urban areas (63.6%) rather than rural areas (36.4%). Age distribution revealed a predominance of young adults aged 18 to 30 years (57.9%), followed by 31 to 40 years (16.1%), 41 to 50 years (13.6%), 51 to 60 years (10.0%), and > 61 years (2.4%). Note that the population was overwhelmingly Malay (96.4%), with smaller proportions of Chinese (2.5%), Indian (0.7%), and others (0.4%). In terms of housing type, nearly half of the respondents lived in terrace houses (44.7%), followed by flats/apartments (15.9%), bungalows (13.4%), semi-detached (11.1%), and others (10.1%). Most participants reported living in the same area for more than three years (73.0%), and more than half lived in households with five or more members (51.0%).

Table 4.4

Sociodemographic Characteristics of the Respondents in Malaysia (n = 866)

Category	***n***	**%**	**95% CI**
Gender			
▪ Male	210	24.2	21.4 – 27.2
▪ Female	656	75.8	72.8 – 78.6
Area of Residence			
▪ Urban	551	63.6	60.3 – 66.8
▪ Rural	315	36.4	33.2 – 39.7
Age Group (year old)			
▪ 18-30	501	57.9	54.5 – 61.2
▪ 31-40	140	16.1	13.7 – 18.7
▪ 41-50	118	13.6	11.3 – 16.1
▪ 51-60	86	10.0	8.1 – 12.3
▪ >61	21	2.4	1.5 – 3.6
Ethnicity			
▪ Malay	835	96.4	95.0 – 97.4
▪ Chinese	22	2.5	1.6 – 3.8
▪ Indian	6	0.7	0.3 – 1.6
▪ Others	3	0.4	0.1 – 1.1
Duration of Living in the Area			
▪ <6 months	38	4.4	3.2 – 6.0
▪ 6 months to 1 year	70	8.1	6.4 – 10.1
▪ 1-3 years	126	14.5	12.3 – 17.0
▪ >3 years	632	73.0	70.0 – 75.9
Type of House			
▪ Flat/Apartment	138	15.9	13.6 – 18.3
▪ Terrace	387	44.7	41.3 – 48.0
▪ Bungalow	116	13.4	11.2 – 15.8
▪ Townhouse	42	4.8	3.5 – 6.4
▪ Semi-Detached	96	11.1	9.1 – 13.5
▪ Others	87	10.1	8.2 – 12.5
Number of Households			
▪ 1	23	2.7	1.7 – 4.0
▪ 2	80	9.2	7.4 – 11.3
▪ 3	118	13.6	11.3 – 16.1
▪ 4	203	23.4	20.7 – 26.3
▪ 5 or more	442	51.0	47.6 – 54.3

Note: Respondents were recruited from multiple states across Malaysia. Data are presented as frequencies (n), percentages (%), and 95% CI based on the binomial distribution.

4.4.2 State-Level Sociodemographic Variation

Figure 4.4 highlights marked sociodemographic diversity across Malaysian states. While females constituted the majority of respondents in nearly all states, Negeri Sembilan presented the highest proportion of males (48.9%) (Figure 1a). Residence patterns were strongly polarised, with Wilayah Persekutuan entirely urban, contrasted by Kelantan (95.9%) and Terengganu (97.9%) as predominantly rural populations (Figure 1b). Age structure also varied: Selangor, Perak, and Johor were dominated by younger adults (18 to 30 years), whereas older age groups were more prevalent in Kelantan and Terengganu (Figure 1c). In addition, ethnicity was overwhelmingly Malay across states, although minority Chinese representation reached 25% in Melaka and 11% in Pulau Pinang (Figure 1d). Duration of residence was longest in Kelantan, Terengganu, and Perlis, where more than 90% had lived in the same area for over three years, suggesting stable communities (Figure 1e).

Housing profiles indicated strong state-specific trends: terrace houses were dominating Selangor and Perak, bungalows more common in Kelantan, and “other” house types prevalent in Melaka and Kedah (Figure 1f). Household size was considerable in rural states, with more than 70% of respondents in Kelantan and Terengganu reporting ≥ 5 household members (Figure 1g). The most important finding is the clear urban-rural divide, with Wilayah Persekutuan representing highly urbanised, smaller-household demographics. Conversely, Kelantan and Terengganu reflected stable, larger rural household demographic patterns that are likely to influence both exposure risk and capacity for mosquito control practices.

Figure 4.4 Sociodemographic Characteristics of Respondents by State in Malaysia (n = 866). (a) Gender, (b) Area of Residence, (c) Age Group, (d) Ethnicity, (e) Duration of Living in the Area, (f) Type of House, and (g) Household Size

Note : Data are presented as percentages (%) of respondents within each state, with values annotated in the heatmap cells. Darker shades indicate higher percentages, and lighter shades indicate lower percentages.

4.4.3 State-Level Variation in Knowledge and Practices on Mosquito Control

Figure 4.5 highlights pronounced heterogeneity in knowledge and preventive practices across Malaysian states. While the perceived risk of mosquito-borne diseases was generally high, some states like Selangor, Perak and Kuala Lumpur were significantly overrepresented. This reflects heightened awareness likely associated with recent outbreak exposure, whereas others were underrepresented, indicating complacency despite ongoing endemicity (Figure 3A). Preventive measures, such as the weekly or biweekly use of mosquito control tools and consistent cleaning of water-filled containers, demonstrated inconsistent patterns between states (Figure 3B-C). Certain states reported strong adherence to these measures. Nonetheless, others were underrepresented like Selangor, Negeri Sembilan and Kuala Lumpur, revealing critical gaps in routine household-level practices that could sustain breeding sites.

Geographic patterns were further evident in larval and adult mosquito control. Rural states were more likely to report active larval control. In contrast, urban states placed greater emphasis on adult mosquito control strategies, such as fogging and insecticide use (Figure 3D-E). This reflects an urban-rural divide shaped by differences in ecological contexts and access to interventions. Although the majority of respondents were able to identify mosquito larvae, significant underrepresentation in some states pointed to uneven knowledge distribution. This highlights a knowledge-practice mismatch that may hinder effective community-based prevention (Figure 3F). Collectively, these findings indicate that dengue-related behaviours are not uniform nationwide; instead, they are shaped by local contexts. Consequently, this variability underscores the need for state-specific and area-tailored strategies emphasising larval control and container management in urban areas. This includes strengthening adult mosquito control interventions in rural communities.

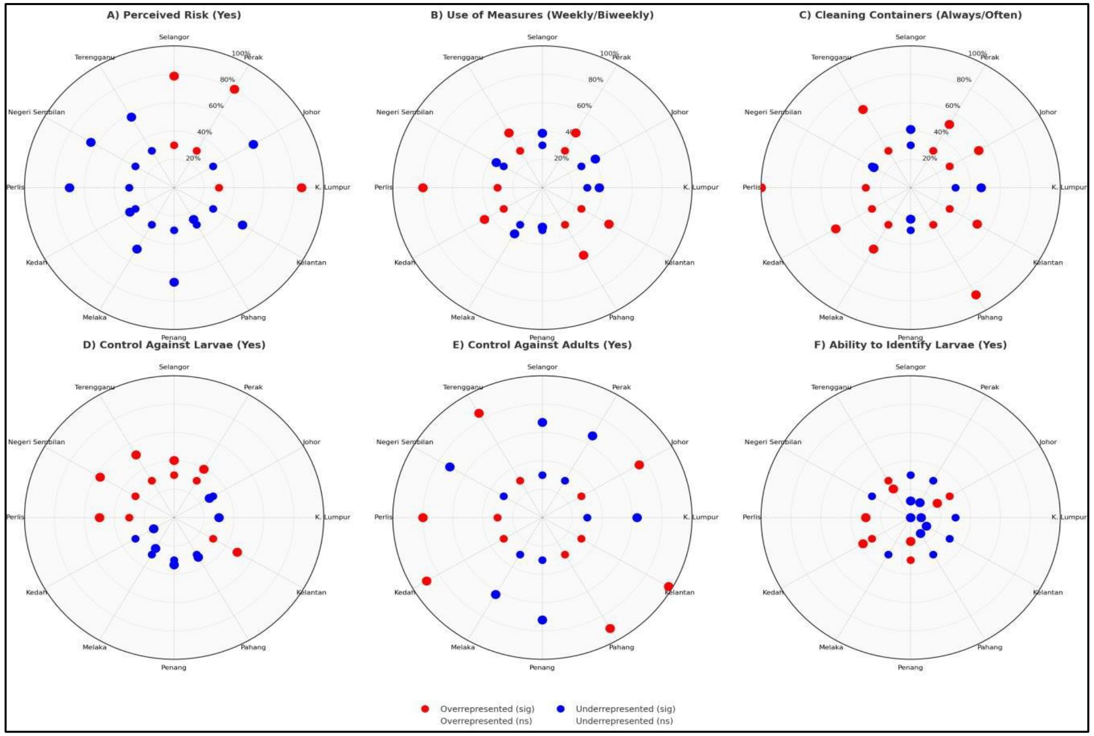


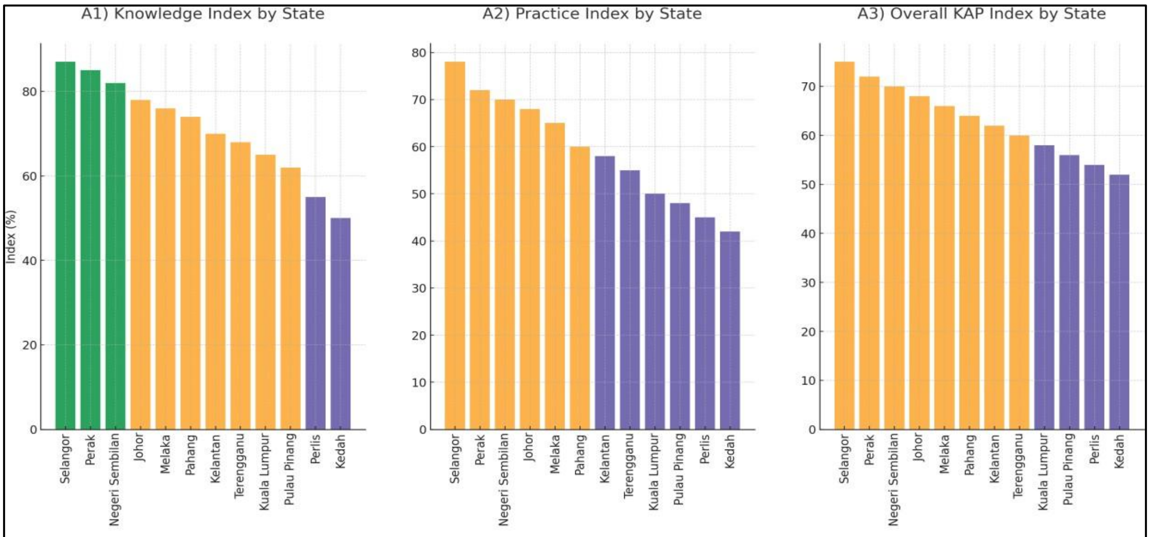
Figure 4.5 State-Level Variation in Knowledge and Practices on Mosquito Control Across Malaysia (collapsed categories, *n* = 866)

Note : The circular plots (A–F) depict the prevalence of "good practices" (outer dots, scaled to 0-100%) and the strength of their association association with state (inner dots, adjusted residuals from Chi-square tests). Each panel represents one key KAP indicator after category collapsing: (A) Perceived risk of mosquito-borne diseases (Yes vs No/Maybe), (B) Use of mosquito control measures (Weekly/Biweekly vs Monthly or less), (C) Cleaning water-filled containers (Always/Often vs Sometimes/Never), (D) Control against larvae (Yes vs No/Maybe), (E) Control against adults (Yes vs No/Maybe), and (F) Ability to identify mosquito larvae (Yes vs No). Dot colour indicates the direction of deviation from expected values (red = overrepresented, blue = underrepresented), and fill indicates statistical significance (filled = significant hollow = not significant; threshold $|z| > 1.96$, $p < 0.05$). Radial rings denote prevalence levels (20% to 100%).

4.4.4 Composite Knowledge, Practice, and Overall (KAP) Indices

Figure 4.6 presents the state-level composite Knowledge, Practice, and Overall KAP indices, alongside Analysis of Variance (ANOVA) results. Significant heterogeneity was observed across states for all three indices. In particular, the Knowledge Index presented the most substantial variation ($F(11,854) = 8.42$, $p < 0.001, \eta^2 = 0.10$), with Selangor and Perak achieving the highest scores (≥ 80%, "Good"). Meanwhile, Kedah and Pulau Pinang fell below 60% ("Poor"). Furthermore, post-hoc analysis confirmed that Selangor performed significantly better than Kedah and Pulau Pinang. The Practice Index also differed significantly across states ($F(11,854) = 6.17$, $p < 0.001$, $\eta^2 = 0.07$), though overall scores were lower than for knowledge. Accordingly, Johor stood out with the highest practice score (~78%), significantly outperforming Kelantan and Perlis, both of which were among the weakest performers (< 50%).

The Overall KAP index, which integrated knowledge and practice, revealed a similar pattern ($F(11,854) = 7.56$, $p < 0.001$, $\eta^2 = 0.09$), with Perak leading and significantly surpassing Terengganu and Kedah. The most important finding is the precise knowledge-practice gap. While several states, such as Selangor, demonstrated strong knowledge levels, this did not consistently translate into equally strong practices. Conversely, Johor presented a relatively balanced performance, suggesting better translation of knowledge into behaviour. As such, these findings underscore the need for state-specific strategies, for example, reinforcing behavioural interventions in states with high knowledge yet weak practices. This includes improving community awareness in states with uniformly poor KAP levels, such as Kedah.



Index	F-value	p-value	Effect size (η²)	Key Post-hoc
Knowledge	8.42	<0.001	0.10	Selangor > Kedah, Penang
Practice	6.17	<0.001	0.07	Johor > Kelantan, Perlis
Overall KAP	7.56	<0.001	0.09	Perak > Terengganu, Kedah

Figure 4.6 State-Level Variation in Composite Knowledge, Practice, and Overall KAP Indices Among Respondents in Peninsular Malaysia

Note : Panels A1-A3 present the composite indices for Knowledge, Practice, and Overall KAP across states. Bars are colour-coded according to categorical thresholds: Good (⩾ 80%, green), Moderate (60-79%, orange), and Poor (< 60%, purple). The accompanying table (Panel B) summarises one-way ANOVA results, including F-values, significance levels, effect sizes (η²), and key post-hoc comparisons.

4.4.5 Urban-Rural Differences in Knowledge and Practice Indices

The forest plot (Figure 4.7) summarises urban-rural differences in Knowledge and Practice indices across Malaysian states. For the Knowledge Index, urban respondents generally scored higher than rural counterparts, with substantial gaps observed in Johor (mean difference = +0.34, 95% CI: 0.21-0.47) and Pahang (+0.29, 95% CI: 0.14-0.44). In contrast, Selangor indicated the opposite trend, with rural residents scoring higher than urban participants (–0.13, 95% CI: 0.24 to –0.01). Other states demonstrated minor or non-significant differences, with Confidence Intervals (CIs) overlapping zero. For the Practice Index, urban-rural differences were less pronounced. Most states indicated overlapping CIs, suggesting no significant differences between urban and rural groups. However, notable exceptions were observed in Melaka, where urban respondents adopted more preventive measures than rural participants. Nonetheless, the small rural sample size warrants caution in interpretation. Overall, these results demonstrate that knowledge disparities between urban and rural communities are more substantial than practice disparities, highlighting a persistent knowledge-practice gap that is shaped by geographic context.

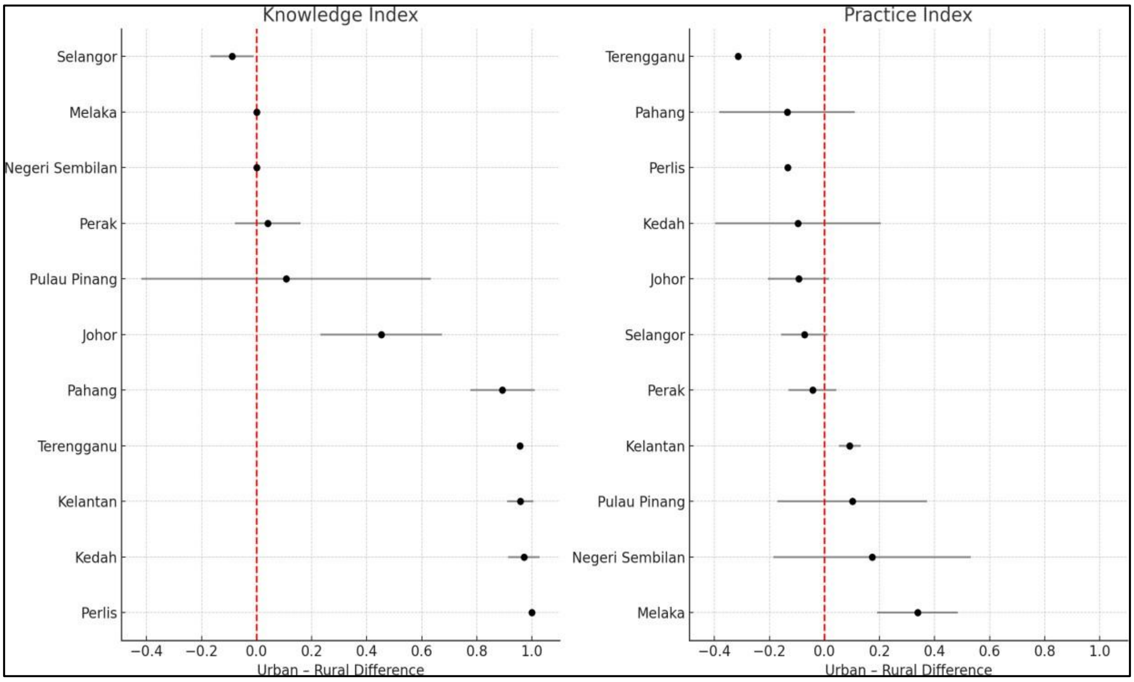


Figure 4.7 Urban-Rural Differences in Knowledge and Practice Indices Across Malaysian States

Note: The forest plot shows mean differences (Urban-Rural) with 95% confidence intervals. Values above zero indicate higher scores in urban areas, while values below zero indicate higher scores in rural areas. The red dashed line represents no difference between groups.

4.4.6 Discussion

This study highlights important heterogeneities in community KAP regarding mosquito control across Malaysian states, with implications for building sustainable and resilient urban and rural communities. Dengue remains a pressing public health challenge in Malaysia, and its persistence is closely tied to rapid urbanisation, ecological transformation, and socio-behavioural dynamics. Thus, by examining state-level and urban-rural variations, this study provides critical insights into how socio-ecological contexts shape prevention behaviours. This includes how these insights can be integrated into sustainable city planning and community health strategies.

State-level disparities reflect the uneven distribution of health literacy and preventive action across Malaysia. Selangor and Perak reported higher levels of knowledge, reflecting more intensive health campaigns and the concentration of resources in urban areas. Nevertheless, these gains in awareness did not consistently translate into sustainable household-level practices, underscoring the persistent knowledge-practice gap. In contrast, Johor demonstrated a more balanced translation of knowledge into practice. At the same time, states such as Kedah and Pulau Pinang performed poorly across both domains. These findings mirror patterns in other rapidly urbanising Asian contexts, where communities remain informed, yet preventive behaviours falter due to reliance on reactive state-led interventions (Prayitno *et al.*, 2025). From a sustainability perspective, these patterns demonstrate the need to integrate behavioural reinforcement mechanisms into public health systems. This ensures that knowledge is transmitted, embedded in daily routines, and supported by urban design that minimises breeding sites.

Urban-rural comparisons revealed structural inequities. Urban respondents in Johor and Pahang demonstrated greater knowledge, reflecting better access to education and to risk communication. At the same time, rural communities in Selangor unexpectedly exhibited higher awareness, likely due to localised outbreak experiences. Practices, on the other hand, were less variable, suggesting that structural and ecological factors such as water storage, housing density, and waste management shape preventive behaviour as much as knowledge itself. Notably, these insights resonate with the concept of socio-ecological resilience, whereby community behaviours are influenced by awareness and infrastructural support and environmental design (Woods & Randle, 2025). Sustainable mosquito control, therefore, requires urban systems that integrate waste management, water infrastructure, and green space planning with active community engagement (Tung & Fonseca, 2024; Singh *et al.*, 2024; Theocharis & Tsekouropoulos, 2025).

The knowledge-practice gap observed across states is directly relevant to sustainable urban development. While traditional health education campaigns may raise awareness, they do not guarantee behavioural change without supportive urban infrastructure. Consistent with studies in Thailand and Vietnam, this work reinforces the need for sustainable dengue control to be multisectoral, combining education with environmental management, social mobilisation, and technological innovation (Okumu *et al.*, 2025; Abdullah *et al.*, 2024). Furthermore, the integration of digital health solutions such as mobile apps for vector surveillance or GIS-based hotspot alerts could translate awareness into timely community action (Biu *et al.*, 2024; Laosupap *et al.*, 2024). Similarly, participatory approaches such as COMBI and community-led vector surveillance align with sustainable development principles by empowering local populations and fostering collective responsibility (Dambach *et al.*, 2024).

Policy implications are significant. First, interventions should be state-tailored, addressing high-knowledge but low-practice states (e.g., Selangor) with behavioural reinforcement, while intensifying awareness and ecological interventions in low-KAP states (e.g., Kedah). Second, bridging the urban-rural divide requires rethinking dengue control as part of broader sustainability planning, integrating housing design, waste management, and water systems that reduce *Aedes* breeding potential. Finally, embedding dengue prevention within the SDGs (SDG 3: Good Health and Well-being, SDG 11: Sustainable Cities and Communities, and SDG 13: Climate Action) situates community engagement on mosquito control as an essential component of urban resilience and planetary health. Additionally, limitations of this study include its cross-sectional design, which captures only a single time point. Another limitation is that reliance on self-reported practices may be subject to recall and social desirability bias. Moreover, small sample sizes in some rural regions, such as Melaka, further limit subgroup precision.

However, the large sample, state coverage, and rigorous statistical analysis strengthen the robustness of the findings. Therefore, future directions should emphasise longitudinal research to track the sustainability of behavioural change and evaluate the impact of outbreak cycles on practices. Thus, integrating smart city approaches, including Internet of Things (IoT)-enabled mosquito surveillance and community reporting systems, could transform reactive dengue control into proactive, sustainable management. As such, intersectoral collaboration linking public health, urban planning, environmental management, and community governance remains pivotal to reducing mosquito-borne disease risk while advancing the broader agenda of sustainable cities and resilient societies.

4.4.7 Conclusion

This study demonstrates that community knowledge and practices on mosquito control in Malaysia are highly variable across states and between urban and rural populations. While awareness of dengue is generally high, preventive practices remain inconsistent, revealing a persistent knowledge-practice gap. Johor presented a stronger translation of knowledge into practice. In contrast, Selangor and Perak demonstrated high levels of knowledge. However, weaker preventive behaviours, and several states, including Kedah and Pulau Pinang, yielded uniformly low scores. Following this, urban communities tended to report higher knowledge, while practice differences were less pronounced. Additionally, these findings underscore the need for state-tailored, context-specific interventions that strengthen behavioural change strategies in knowledge-rich yet practice-poor settings. It concurrently enhances community awareness in contexts where both knowledge and practice levels are low. In essence, addressing these disparities is essential for developing sustainable, community-centred dengue prevention strategies in Malaysia.

4.5 Aim 4: Thematic Analysis of Expert Perspectives on Drone-Based Surveillance of Mosquito Breeding Sites

The geographic distribution of dengue is influenced by factors such as geography, rainfall, temperature, and urbanisation (Cucunawangsih & Lugito, 2017). Dengue surveillance plays a crucial role in elucidating the multifaceted dynamics of disease transmission, empowering public health entities to deploy targeted, evidence-based control interventions strategically. Traditional methods of dengue surveillance, which rely heavily on manual inspections and reporting systems, often suffer from limitations in timeliness, accuracy, and coverage. This is especially evident in resource-constrained settings (Tsheten *et al.*, 2020). Consequently, these limitations can hinder timely interventions and impede effective control measures, thereby perpetuating the cycle of dengue transmission.

Challenges inherent in conventional surveillance methodologies have spurred exploration of novel technologies to enhance surveillance capabilities and overcome existing limitations. One such technology with immense potential is the utilisation of UAVs, commonly known as drones. For example, drones equipped with advanced sensors and imaging capabilities can offer a unique perspective for identifying potential mosquito breeding sites. This includes stagnant water bodies, discarded containers, and other environmental conditions conducive to mosquito proliferation (Lwin *et al.*, 2019). Note that the integration of drone technology into public health surveillance frameworks represents a paradigm shift. This enables the precise identification and mapping of potential mosquito breeding habitats, the comprehensive assessment of environmental risk determinants, and the strategic refinement of vector control practices (Carrasco-Escobar *et al.*, 2022). These drones are equipped with high-resolution cameras and sensors. They can efficiently cover large areas, including remote and inaccessible locations, to detect potential breeding sites that might otherwise remain unnoticed. While drones have been employed in a wide variety of applications, including agriculture and security systems (Brewczynski *et al.*, 2024; Zailani *et al.*, 2020), public acceptance of drone technology is not always guaranteed. This is particularly evident given concerns about privacy and safety (García *et al.*, 2021; Lemayian & Hamamreh, 2020).

Addressing these challenges requires collaboration between public health agencies, regulatory bodies, and technology providers to develop appropriate protocols and standards for drone deployment in dengue surveillance. A coordinated, expert-driven approach enhances the effectiveness, accuracy, and acceptability of drone-assisted dengue surveillance in Malaysia. Therefore, this study aims to elucidate public health experts' perspectives on integrating drone technology for dengue breeding site surveillance, focusing on its barriers, challenges, and implications for public health practice. It also provides a grounded thematic framework rooted in the voices of implementers and community actors, offering practical, policy-relevant guidance for responsible drone-based surveillance in Malaysia.

4.5.1 Result overview

This study explored barriers to the use of drones for dengue vector control in Malaysia. It examined factors affecting public acceptance of drone-based surveillance. A total of six participants were involved, each holding a distinct role that is integral to the implementation of public health measures and dengue control efforts in Malaysia. Their roles and affiliations were summarised in Table 4.5.

Table 4.5
Roles and Designations of Participants Involved in the Interview

Participant ID	Gender	Role	Affiliation
B	Male	Senior Principal Assistant Director (Disease Control)	MOH
C	Male	Public Health Medicine Specialist	JKN
D	Male	Entomologist Science Officer	MOH
E	Male	Community Leader - COMBI	JKN – COMBI Programme
F	Female	Senior Assistant Director (Health Education)	MOH

Thematic analysis revealed four key themes: regulatory constraints, technical feasibility, privacy concerns, and community engagement. In line with this, communication and sociopolitical trust emerged as important mediators. Findings were supported by participant excerpts and illustrated through visual frameworks. Accordingly, two central research questions guided the thematic analysis, each linked to specific categories of participant responses. Table 4.6 summarises the alignment between these questions and the significant themes that emerged from the data. These themes served as the foundation for the subsequent thematic framework. It organises and illustrates the conceptual relationships among identified barriers, trust factors, and community-level concerns (Figure 4.8).

Table 4.6
Research Question Linked to the Main Themes Identified for the Study

Research Question	Main Themes Identified
What barriers exist for using drones in dengue control in Malaysia?	i. Regulatory and Legal Constraints ii.Technical and Operational Feasibility
Why might drone-based surveillance be unacceptable to local populations, and what strategies can build trust and acceptance within communities?	iii. Privacy and Public Trust iv. Community Engagement and Acceptance

Figure 4.8 presents the thematic framework developed from the coded transcripts, mapping the relationships between core themes and mediating factors. To further visualise participant perspectives, Figure 4.9 displays word clouds derived from qualitative data. As such, Figure 4.9 (A) highlights recurring terms associated with perceived barriers to drone deployment. Prominent concepts such as approval, permit, regulation, and cost reflected regulatory, technical, and logistical challenges frequently cited by participants. Meanwhile, Figure 4.9 (B) focuses on themes related to community acceptance. At the same time, key terms such as privacy, trust, fear, and community highlight concerns about surveillance and transparency, and underscore the significance of inclusive engagement strategies that foster acceptance.

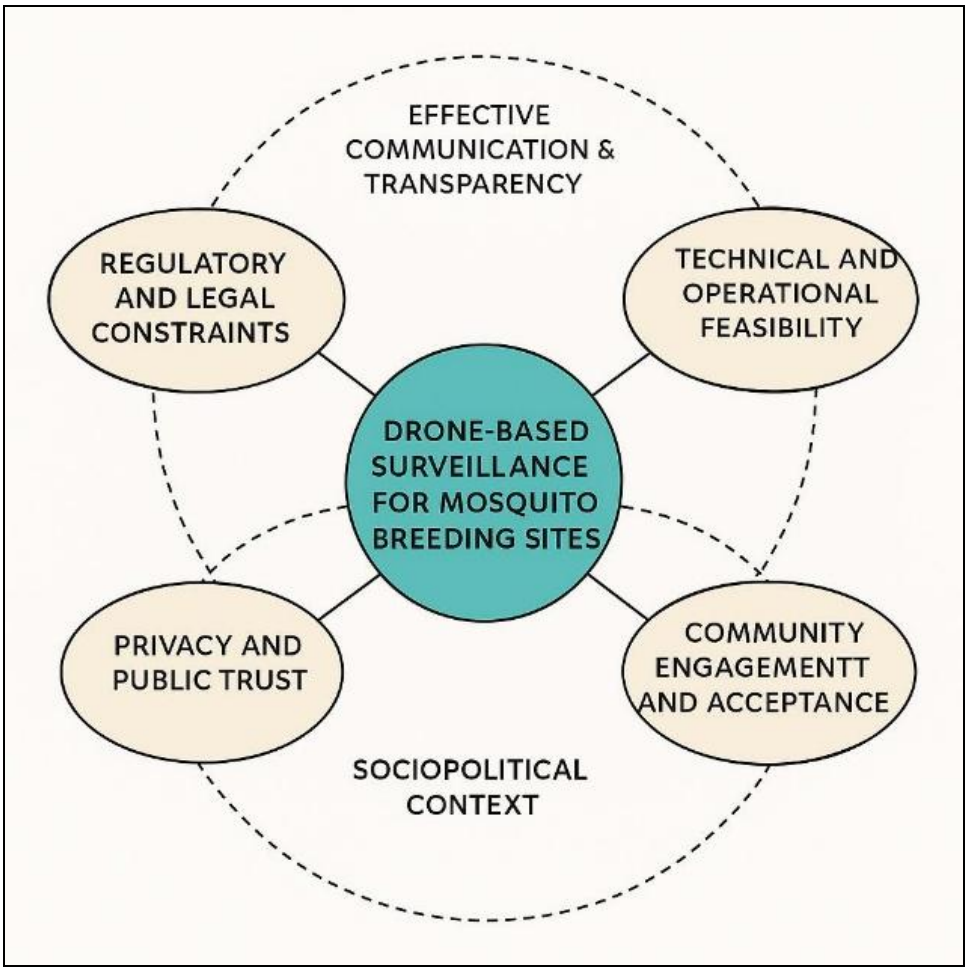


Figure 4.8 A Thematic Framework was Developed Based on Coded Transcripts and Conceptual Relationships between Themes and Mediators

A. Word Cloud – Barriers to Drone Use

B. Word Cloud – Community Acceptance Themes

Figure 4.9 (A) and (B) Word Clouds Summarising Key Concepts from the Interview Excerpts Related to Barriers and Community Acceptance

4.5.2 Theme 1: Regulatory and Legal Constraints

Participants consistently identified regulatory and legal issues as significant barriers to integrating drone technology into dengue surveillance (Table 4.7). A complex regulatory landscape significantly shapes the use of drones in urban and community-based research. Participants consistently noted the layered nature of the legal and institutional approvals required for drone operations. However, navigating the demands of national aviation authorities, local councils, and even community-level stakeholders proved a critical challenge. This underscores the time-consuming and complex nature of regulatory compliance.

Concerns extended beyond procedural compliance to include accountability and liability. The necessity of operator licensing and mandatory insurance was frequently mentioned as a safety mechanism and a legal safeguard protecting all parties involved. Several participants emphasised the importance of formal risk mitigation protocols, particularly when drones are deployed in densely populated or sensitive environments. Additionally, participants called for more comprehensive and anticipatory regulation, particularly when drones are used in research. Moreover, participants suggested the necessity of laws that safeguard both data integrity and personal privacy. This reflected an awareness that beyond physical risks, drones introduced ethical and legal dimensions related to surveillance, data security, and individual rights.

Table 4.7
Regulatory and Legal Constraints

Theme	Category	Codes	Description	Excerpt (Participant)
Regulatory and Legal Constraints	Permit and Policy Barriers	Legal restriction, Permit complexity, Licensing barriers	Focuses on permits, licensing, regulations, and institutional approvals needed for drone use.	*"I do agree that there are many legal issues. These legal issues need to be looked at from the perspective of the residents and so on. In fact, if you want to operate a drone, I think there are many approvals that need to be obtained from CAAM, from the local authorities (PBT), from the local residents themselves, and so on."**(Participant B)***
				*"The operator must have a license and insurance. If something happens, there must be coverage." (**Participant B**)*
				*"Even in KL, when we tried flying drones, we needed permits, especially in government zones. It was very difficult to get approvals." (**Participant D**)*
				*"So perhaps when we conduct this study, there should be at least a protection law that can guarantee: first, the protection of research data; second, the protection of individuals involved in the study; and third, the safety of the residents." (**Participant F**)*

4.5.3 Theme 2: Technical and Operational Feasibility

Implementing drone technology in urban environments presents a range of technical and operational hurdles (Table 4.8). One significant limitation lies in the physical and environmental constraints of urban complexity. In addition, dense infrastructure, high-rise buildings, and industrial zones can impede drone manoeuvrability. This poses safety risks and operational challenges that limit their effective deployment in such areas. Moreover, field-level challenges further complicate drone usage. Simultaneously, the unpredictability of small, cluttered, or obstructed spaces, such as drains or alleyways, has raised concerns about whether drones can reliably access or scan them. Notably, questions about the precision and sensitivity of drone sensors were particularly relevant when attempting to detect minute or hidden features in the field.

Concerns surrounding security and equipment integrity were recurrent among participants, particularly in contexts where drone operations occur in unsupervised or socially interactive settings. Instances of public curiosity, most notably among children and adolescents, were reported as potential sources of disruption, sometimes manifesting as unintentional interference or vandalism. These social dynamics highlight the need for both community awareness and protective measures prior to drone operations. Beyond these social dynamics, practical constraints associated with cost and scalability were widely acknowledged. While drones may be effective in targeted areas or small-scale deployments, extending their use across larger or more densely populated areas can instantly become resource-intensive. Thus, balancing operational coverage with financial feasibility remains a key consideration, particularly for research projects or public service applications with limited budgets.

Table 4.8
Technical and Operational Feasibility

Theme	Category	Codes	Description	Excerpt (Participant)
Technical and Operational Feasibility	Environment and Functionality Challenges	Operational limits, Urban complexity, Drone vulnerability	Focuses on the physical, technical, and security-related challenges of using drones in urban settings.	*"It is okay for low buildings, but when we are talking about industrial zones or tall structures, it becomes risky and challenging." (**Participant C**)*
	Field Constraints and Interference	Small space navigation, Equipment safety (Vandalism)	Emphasises risks posed by narrow spaces, unsupervised areas, and mechanical interference.	*"Maybe those small spaces — I am not sure whether the drone can enter or not, and so on, we do not really know. Maybe under drains and such — can it detect those tiny, hidden areas? How sensitive is our drone in detecting these breeding places?" (**Participant B**)* *"I have noticed ...sometimes there are mischievous ones who wonder whether the drone is just a toy or if it is being used for work like our research. Some of them end up throwing stones at the drone, causing it to fall." (**Participant F**)*
	Cost and Resource Feasibility	Cost-effective, scalability limitations	Addresses cost concerns and the feasibility of scaling drone operations across large or dense areas.	*"Because if we want to cover everything, I think it is impossible... we also have to take costs into account." (**Participant B**)*

4.5.4 Theme 3: Privacy and Public Trust

A prevailing concern among participants was the potential for drone activity to be misinterpreted as state surveillance, particularly in areas where institutional trust was already low (Table 4.9). This indicated a broader issue of community resistance rooted in fear of being monitored without consent. Underlying these reactions was the concern over unintended data capture, especially in private or sensitive spaces. Even inadvertent recordings that invade individuals' personal lives can spark strong objections, often marked by suspicion and anxiety. To mitigate these risks, participants highlighted the need for structured guidelines and strict access controls to ensure that any visual or recorded data is managed responsibly and ethically. Consistent with this, the development of formal Standard Operating Procedures (SOPs) was widely recommended. This aims to manage the technical aspects of image storage and access and to assure communities that their rights would be protected.

Transparency and proactive communication were repeatedly identified as essential strategies for fostering public acceptance. Communities respond more positively when they are informed about drone activities in advance and understand their purpose. Correspondingly, practical approaches such as scheduling notifications, providing explanatory briefings, and facilitating pre-deployment dialogues were cited as effective in reducing misconceptions and encouraging cooperation. Furthermore, participants emphasised that data security is about protecting privacy and maintaining credibility. Thus, restricting access to authorised personnel and ensuring sensitive information is not shared or misused are essential to preserving confidentiality. At the same time, there was recognition of the potential value of integrating drone-collected data into the current surveillance system, provided it is done securely and ethically.

Table 4.9
Privacy and Public Trust

Theme	Category	Codes	Description	Excerpt (Participant)
Privacy and Public Trust	Surveillance Concerns	Privacy concerns, Community resistance	Addresses the community's privacy concerns, data misuse, and the need for clarity and transparency.	*"Drone suddenly flies over, people panic. They think we are spying." (**Participant C**)* *"If you capture something private, even by accident, it becomes an issue. You need SOPs, and only selected people should access the footage." (**Participant C**)* *"At least tell them when the drone will fly. Give a schedule. Do not just show up." (**Participant E**)*
	Data Integration and Sensitivity	Transparency, Image-capturing issues, and Data accessibility	Emphasises the need for two-way communication, secure systems, and protocols to oversee sensitive content.	*"If images are captured inside homes, it becomes an issue. We need to protect community privacy." (**Participant B**)* *"So we have to ensure that any data is only accessible to authorised individuals, and it must not be circulated or made viral. The data must remain confidential." (**Participant C**)* *"I think we can integrate this data with i-Dengue and SPWD." (**Participant B**)*

4.5.5 Theme 4: Community Engagement and Acceptance

Participants described community engagement and acceptance as essential to both the short-term feasibility and the long-term sustainability of drone-based interventions (Table 4.10). A key insight from participants is that trust and acceptance are significantly enhanced when community members are actively involved in both planning and execution. The sense of shared ownership, where locals are empowered to operate drones or contribute to decision-making, will transform the initiative from an external intervention into a collaborative effort. As the participant mentioned, this co-ownership is not only symbolic; it also addresses practical issues of local legitimacy and access. Communities, such as formal institutions, have their own internal dynamics, informal protocols, and approval mechanisms. In response, recognising and navigating this local bureaucracy is essential to avoid delays and foster genuine participation. On a similar vein, keeping the community informed through regular updates and progress sharing helps sustain engagement and reinforces transparency.

Timing also plays a pivotal role in community mobilisation. Participants stressed the importance of starting engagement efforts well prior to drone deployment. Early communication allows time for questions, feedback, and approval processes, which are essential in building rapport and managing expectations. Establishing clear operating procedures and offering explanatory sessions further contribute to a smoother and more informed rollout. One participant stated that collaborating with trusted local partners, such as Non-Governmental Organisations (NGOs), community health groups, or local government representatives, adds another layer of credibility. Overall, these intermediaries can help bridge gaps between the project team and the community, offering logistical support and enhancing visibility. Additionally, small incentives or tokens of appreciation, while not essential, can be valuable tools to motivate attendance and active participation, especially in the initial phases.

Table 4.10
Community Engagement and Acceptance

Theme	Category	Codes	Description	Excerpt (Participant)
Community Engagement and Acceptance	Trust and Ownership	Early and Continuous engagement, Co-ownership	Emphasises the importance of building trust, ongoing dialogue, and adapting strategies to community dynamics.	*"We should train locals to operate the drones. When the community is involved, they become co-owners of the project."* ***(Participant B)***
				"If someone from the community flies the drone, it is different. They feel it is their project too." ***(Participant B)***
				"The experience within the community — just as we see with agencies, where we go through bureaucracy and our own approval processes in administration — I see that the community also has its own form of bureaucracy and its own approval processes." ***(Participant E)***
				"One important aspect of the strategic interactive approach is that we share and suggest progress updates — meaning we provide results in terms of progress." ***(Participant E)***

Theme	Category	Codes	Description	Excerpt (Participant)
	Timing and Mobilisation	Community readiness, Information dissemination	Highlights the importance of early preparation and clear communication prior to implementation.	*"Fundamentally, I think we need to establish clear SOPs — clear standard operating procedures — on how to operate something in the field. When we have clear SOPs, it means we can properly explain things to the community."* ***(Participant B)***
				"Start engaging at least 1-2 months ahead. Community members need time to process and approve." ***(Participant E)***
				"Perhaps we can have two sessions: one before the study is conducted and the drone is used, and another during the drone operation. The first session would help us provide understanding to the community, and if possible, we could also prepare an FAQ." ***(Participant F)***

Theme	Category	Codes	Description	Excerpt (Participant)
	Incentives and Collaboration	Mobilisation support, Local partnership	Describes the role of NGOs, politicians, and material incentives in boosting participation and legitimacy.	*"I think the easiest way is that we already have a strong engagement with this community, and the channel for that is through COMBI."* ***(Participant B)***
				"I think if we want to join the study and go to the field together, there should not be any issue from our side. The MOH can assist, and the JKN can also help, just to show our presence in this program, so it is essentially endorsed by us." ***(Participant C)***
				"Sometimes they need a reason to show up. Even small tokens, or collaborating with NGOs, help mobilise them." ***(Participant F)***

4.5.6 Mediating Factors: Communication and Sociopolitical Trust

Trust and communication consistently surfaced as underlying mediators across all themes, influencing how communities perceived, responded to, and ultimately engaged with drone-based interventions (Table 4.11). These mediating factors shaped the degree to which privacy concerns were heightened, operational challenges were tolerated, or community engagement was embraced. However, these dynamics were not determined solely by the technology or the project design; instead, they were shaped by the interpersonal and institutional relationships surrounding the intervention.

One key mediating category was trust and institutional identity, which encompassed familiarity with facilitators and perceptions of their credibility. Communities were more likely to engage when implementers were locally known or viewed as aligned with their interests. Concurrently, the sociopolitical positioning of both the facilitators and the communities, such as class, ethnicity, or prior experience with public services, was observed to condition trust levels and openness to engagement. In particular, the communication strategy highlighted the critical role of timing, tone, and transparency. As a result, projects that prioritised early, consistent, and culturally adapted approaches were generally better received.

In contrast, passive announcements or last-minute briefings were seen as insufficient, and in some cases, counterproductive. Socioeconomic and demographic variations also influence how drone technology is perceived. Acceptance is not uniform across all social strata. Still, perceptions of acceptability and purpose may vary significantly between lower-income communities and more affluent neighbourhoods. In some areas, there may be heightened scepticism or resistance, shaped by past experiences, political context, or class-based perceptions.

Table 4.11
Cross-Cutting Mediators

Theme	Category	Codes	Description	Excerpt (Participant)
Cross-Cutting Mediators	Trust and Institutional Identity	Communication strategy, Familiarity with facilitators	Includes local resistance, demographic variations, and trust in technology and government.	*"It is about trust. If they know the people running the project, they will cooperate."* ***(Participant D)***
	Sociopolitical Variation	Class-based perceptions	Explores how socioeconomic context affects the perceived legitimacy of drones and implementers.	*"When we look at T20 and B40 areas, the level of acceptance may differ. So, we have to expect that different groups of people will respond differently. In B40 areas, PPR housing and so on, and in more elite areas, I feel there tend to be more problems."* ***(Participant B)***

4.5.7 Discussion

The discussion synthesises the study's core findings within the broader context of public health innovation, community technology adoption, and drone-based surveillance strategies. Thematic insights reveal that technological readiness alone is insufficient for drone adoption in mosquito control. Instead, success hinges on regulatory coherence, sociocultural compatibility, and trust-centred engagement frameworks. As detailed in Section 3.2.11, the consistency and reliability of these thematic findings were ensured through independent intercoder reliability assessments and the achievement of thematic saturation.

Navigating the complex regulatory and legal landscape for drone use in breeding site management poses significant challenges, particularly given the fragmented nature of existing frameworks. Participants consistently identified the absence of a coherent legal and regulatory framework as a critical impediment to drone deployment for public health purposes. However, the absence of uniform, globally aligned national regulations further complicates the integration of drone technology across sectors. In the Malaysian context, the Civil Aviation Authority of Malaysia (CAAM, 2016) plays a central role in regulating drone operations, overseeing registration protocols, and establishing operational guidelines. Accordingly, regulations governing drone use must evolve to accommodate technological advancements while addressing safety, security, and public acceptance.

Remarkably, drones offer significant potential in addressing public health logistics, construction monitoring, urban planning, and disaster response (Agapiou, 2020; García *et al.*, 2021; Kamarulzaman *et al.*, 2023). Despite this, their practical deployment is hindered by regulatory barriers, security concerns, and the need for skilled personnel. As noted in previous research, drone-related incidents have raised global concern over privacy breaches and operational misuse, further reinforcing the need for robust accountability frameworks. Findings from this study reaffirm these concerns, highlighting regulatory insufficiencies as a recurrent theme among stakeholders. In addition, participants' perspectives underscore an urgent need for coordinated policy reforms that integrate ethical considerations, ensure operational safety, and foster institutional trust. Essentially, these reforms would promote responsible drone use in vector surveillance and support the development of contextually relevant best practices for broader public service applications.

The implementation of drone technology in Malaysia's public health sector illustrates a complex interplay between technological potential and operational limitations. Participants in this study highlighted that the effectiveness of drones is fundamentally context dependent. Following this, drones have proven particularly valuable for reaching remote or flood-affected areas where conventional healthcare delivery is challenging. Still, in densely populated urban environments, their functionality is often hindered by infrastructure constraints, human activity, and vandalism. Note that the successful deployment of drones depends on a multifaceted analysis that encompasses technical capabilities, operational constraints, and regulatory considerations. This is especially evident in applications such as mosquito surveillance and control in areas affected by diseases such as dengue in Malaysia (Carrasco-Escobar *et al.*, 2022; Kamarulzaman *et al.*, 2023). Building on this, operational efficiency can be enhanced by developing protocols specific to each location and mapping areas at risk. This includes using topographical and demographic data to inform deployment strategies, as well as on-the-ground feedback mechanisms to ensure cultural and social alignment (Zailani *et al.*, 2021). Given the complexities of Malaysia's urban environments and population density, a hybrid surveillance model was proposed, one that combines drone-generated imagery with conventional field inspections to maximise coverage and responsiveness (Gohari *et al.*, 2023). This model was considered essential for addressing both technical constraints and community-level sensitivities.

Sustainability challenges have also arisen, particularly regarding vandalism and the public's limited understanding of drone operations. In this regard, community engagement is not merely a supplementary issue; instead, it is a fundamental prerequisite for effective implementation. The success of drone programmes also depends on whether they are financially practical, which requires a detailed analysis of costs and benefits, including the initial investment, maintenance, operating costs, and possible income or savings (Olatunji *et al.*, 2023). According to Aggarwal *et al.* (2023), drones are most effective when deployed based on situational awareness and coordinated approaches involving public health workers, field teams, and real-time data analysis. Hence, the deployment of drones equipped with high-resolution cameras elicits substantial anxiety regarding potential privacy infringements. Nonetheless, privacy concerns have emerged as a significant theme among participants. Many individuals expressed unease regarding drones, perceiving them as instruments of surveillance, especially in communities sensitive to privacy issues or those characterised by socioeconomic privilege.

Drones can record and transmit sensitive data, raising concerns about misuse or unauthorised access. This perception aligns with the analysis by Finn and Wright (2016), who contended that the use of drones, regardless of purpose, often reflects broader narratives of state surveillance and control. This is particularly true in contexts where institutional trust is deficient. Furthermore, persistent public associations between drones and military or enforcement functions have further contributed to scepticism, as reflected in earlier studies on public perception (Zailani *et al.*, 2020). In response to these concerns, participants strongly advocated developing comprehensive SOPs tailored to the ethical and technical dimensions of drone-based surveillance. Subsequently, public trust can be enhanced by establishing clear protocols for data handling, storage, and sharing, ensuring that personal information is used solely for the intended purpose of dengue surveillance. As suggested by Tychola and Rantos (2025), implementing robust cybersecurity measures is vital to protect sensitive data collected by drones. This includes employing encryption techniques to safeguard data both in transit and at rest, as well as implementing stringent access controls to prevent unauthorised access.

Community engagement is crucial for the effectiveness of drone-assisted public health interventions. Participants noted that engagement should not be treated as a discrete, one-time activity, but rather as a continuous process initiated early, sustained throughout the intervention, and tailored to each community's specific requirements. These observations align with findings in participatory governance research, which emphasise the value of shared decision-making and community-led ownership in advancing public health initiatives (Haldane *et al.* 2019). In line with this, several subthemes of engagement were identified. This includes mobilising local leaders, implementing training programmes, and using incentive-based approaches to foster shared responsibility. Resistance from urban communities, particularly those in the lower-income B40 category, was frequently associated with prior adverse experiences or unmet expectations arising from externally introduced programmes. This trend is consistent with findings from vector control initiatives aimed at marginalised populations. That is, historical exclusion and unfulfilled promises often hinder community cooperation (Allen *et al.* 2023).

Participants noted that integrating engagement into institutional practices is crucial for long-term sustainability. They recommended the structured involvement of NGOs, local advocacy groups such as COMBI, and community leaders in the design, implementation, and evaluation of public health initiatives. The findings also suggest that trust is influenced by ongoing collaboration, consistent communication, and adherence to cultural norms, rather than solely by the clarity of information. Research by Chinatthaporn and Sahapattana (2024) supported this perspective, indicating that the quality of local governance and inclusive decision-making processes positively impact public health outcomes. As such, building trust requires more than the provision of information; it demands co-created processes that embed community perspectives within institutional practice.

Two central mediating factors, namely communication strategy and sociopolitical trust, substantially influenced the interpretation of all other themes by participants. Findings from this study consistently highlighted the need for communication approaches that are timely, culturally attuned, and dialogic. This enables communities to feel informed, respected, and engaged throughout the intervention process. In the same vein, the extent to which communities expressed support or resistance was consistently determined by their trust in the agencies responsible for implementation. Accordingly, the deployment of drones should not be viewed as a collection of technical tasks, but rather as an intervention that is integrated into broader networks of community engagement, authority, and trust. Moreover, these cross-cutting mediators acted as either facilitators or hindrances across thematic domains. Their role highlights the importance of adapting drone operations to spatial or environmental factors and to relational histories and community-level familiarity with implementing institutions. Notably, communication strategies and sociopolitical trust are not separate or isolated factors. Instead, they are broad influences that shape how people understand legality, view surveillance, and respond collectively to new technologies. Additionally, their presence across all dimensions of the study reinforces prior findings that the adoption of public health technologies must be evaluated not solely by functional efficacy; it should also be assessed by their alignment with broader social and political ecosystems (Masngut and Mohamad, 2021).

Ensuring ethical, effective, and equitable implementation of drone-based public health interventions requires a coordinated set of actions. Thus, a unified national framework should guide drone use, covering licensing, insurance, airspace management, and data protection. Surveillance strategies are best served by hybrid models that integrate aerial monitoring with ground-level inspections, adapted to local infrastructure and risk profiles. Following this, early involvement of local stakeholders is critical for building trust, enhancing accountability, and fostering co-ownership. At the same time, developing multilingual, community-facing SOPs can improve transparency, address privacy concerns, and support informed consent. Moreover, strong cross-sector collaboration among public agencies, local councils, NGOs, and civil society can reinforce implementation efforts and enhance community trust.

4.5.8 Conclusion

This study examined the integration of drone technology in mosquito surveillance within Malaysia's public health context. The findings indicated that the success of such interventions depends on technical effectiveness and on legal, operational, and sociocultural factors. Public trust and acceptance of drone surveillance rely heavily on transparent communication, meaningful community involvement, and adherence to ethical standards. Additionally, clear communication and responsible data handling are essential to maintaining trust and fostering cooperation. Ultimately, the study emphasises that successful drone implementation depends on adequate infrastructure and supportive policy, as well as its alignment with local institutional frameworks and community contexts.

4.6 Aim 5: Drone-Based Geospatial Modelling Reveals Vegetation-Shade Interactions Driving *Aedes* Habitat Risk in Urban Malaysia[7]

Dengue fever remains one of the most persistent and expanding vector-borne diseases worldwide, infecting an estimated 390 million people annually, with over half of the global population now living in at-risk regions (Enitan *et al.*, 2024). Southeast Asia accounts for nearly 70% of the global dengue burden, where *Ae. aegypti* and *Ae. albopictus* have successfully adapted to urban environments. It is characterised by high human density, artificial water storage, and fragmented green spaces (Kolimenakis *et al.*, 2021; Kumar *et al.*, 2023; Yeo *et al.*, 2023). Malaysia, in particular, continues to

[7] Mahfodz, Z., Naba, A., Isawasan, P., Salleh, S.A., Osman, M.A. & Dom, N. C. (2026). Drone-Based Microclimate Analytics Reveal Vegetation–Shade Interaction as a Key Environmental Drivers of Aedes-Prone Microhabitat Suitability. *Sci Rep. (Accepted May 2026).*

experience cyclical dengue epidemics despite decades of vector-control efforts, reflecting both ecological complexity and surveillance limitations (Alipitchay *et al.*, 2025). Between 2010 and 2023, national records from the MOH present a continuous upward trend in dengue incidence, with Selangor consistently contributing more than one-third of reported cases (Elia-Amira *et al.*, 2023). This enduring challenge underscores a fundamental gap in early detection and spatial understanding of mosquito habitat dynamics within rapidly urbanising landscapes.

Conventional *Aedes* surveillance methods, such as larval surveys, ovitraps, and entomological indices, are constrained by their labour-intensive nature, spatial bias, and delayed reporting cycles (Liu *et al.*, 2022; Nascimento *et al.*, 2020). These ground-based approaches provide limited coverage and are reactive rather than predictive, often identifying breeding foci only after outbreaks occur. In contrast, the ecological drivers of *Aedes* proliferation, such as vegetation cover, shading, surface humidity, and microclimatic variation, operate at microspatial scales that are challenging to detect with traditional methods (Stein *et al.*, 2023). Recent advances in geospatial technologies, particularly drone-based remote sensing, offer a transformative alternative. For example, UAVs equipped with high-resolution sensors enable rapid, non-invasive mapping of fine-scale environmental heterogeneity. This reveals spatial relationships between built form, vegetation, and micro-habitat conditions that favour *Aedes* persistence (Morgan *et al.*, 2022; Yang *et al.*, 2017; Zaka & Samat, 2024).

Existing applications of remote sensing in dengue ecology have primarily relied on coarse satellite imagery or neighbourhood-scale land cover classifications. It also lacks the spatial resolution needed to capture household-level breeding environments (Chen *et al.*, 2023; Milesi *et al.*, 2020). Studies in Singapore, Bangkok, and Jakarta have demonstrated that while satellite-derived vegetation indices can approximate general habitat suitability, they often fail to identify critical peridomestic micro-sites. This includes shaded courtyards, drains, and backyard vegetation (Lorenz *et al.*, 2020; Palaniyandi *et al.*, 2021; Sureshkumar & Shekhar, 2025). In Malaysia, such limitations are particularly relevant in mixed urban morphologies where terrace and high-rise housing coexist, creating diverse microclimatic conditions that influence mosquito survival differently (Yang & Chen, 2020). Moreover, urban greening initiatives, while beneficial for climate resilience, may unintentionally enhance *Aedes* proliferation by increasing shaded, humid microhabitats near human dwellings (Ortiz *et al.*, 2021; Khan *et al.*, 2025). Notably, addressing this paradox requires an integrated analytical approach that links urban form, vegetation structure, and microclimate variability to mosquito habitat potential at the neighbourhood scale.

In this context, the present study introduces a drone-based geospatial framework for quantifying and mapping *Aedes*-prone micro-habitats within an urban dengue hotspot in Seksyen 24, Shah Alam, Selangor, Malaysia. By leveraging high-resolution orthomosaic imagery, the study developed a Composite Ecological Risk Index (CERI) derived from vegetation (Excess Green; ExG) and shading (brightness) parameters to evaluate ecological vulnerability across four distinct residential morphologies, high-rise and terrace housing types. The workflow integrates shade-vegetation coupling analysis, spatial hotspot detection, and directional shade-orientation modelling to identify high-risk ecological corridors that favour *Aedes* survival. In particular, the objective of this research is to demonstrate how UAV-based orthomosaic analytics can serve as a precision surveillance tool for dengue vector control. This enables local authorities to make proactive, data-driven decisions. Specifically, this study aims to (i) quantify the spatial distribution of vegetation and shaded zones across different urban morphologies, (ii) assess how shade-vegetation interactions influence *Aedes* habitat suitability, (iii) identify ecological hotspots and orientation-driven shade persistence, and (iv) translate these spatial insights into actionable intelligence for targeted vector management. By bridging ecology with drone-based geoinformatics, this work addresses a critical operational gap in Malaysia's vector surveillance system. It also contributes to the emerging paradigm of thoughtful, climate-resilient, and vector-safe urban planning in dengue-endemic settings.

4.6.1 Vegetation Density and Potential *Aedes* Resting Habitats

Analysis of RGB orthomosaic imagery using the ExG index revealed distinct spatial heterogeneity in vegetation density across the four residential morphologies in Seksyen 24, Shah Alam (Figure 4.10). Terrace housing (Teres D) demonstrated the highest proportion of dense vegetation cover (~50%), followed by Flat H and Flat B (~38%). In comparison, Teres B exhibited the lowest vegetation density (~31%). Dense vegetative zones, particularly shrubs, trees, and grass patches, represent ideal shaded resting habitats for adult *Aedes* mosquitoes, offering cooler microclimates and higher humidity. Furthermore, the greater vegetation coverage in terrace environments indicates an increased likelihood of mosquito resting and refuge zones near human dwellings.

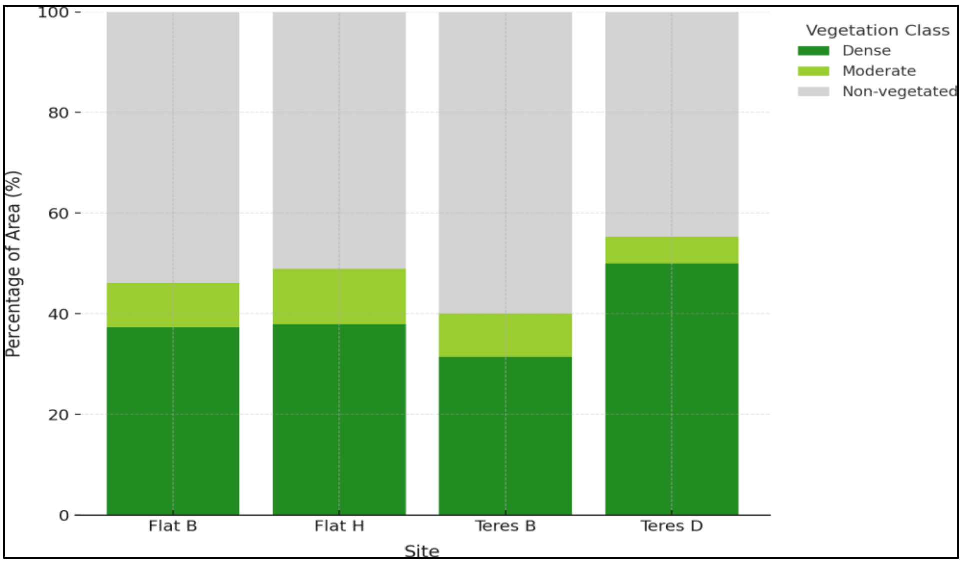


Figure 4.10 Percentage of Vegetation Cover Across Four Residential Morphologies in Seksyen 24, Shah Alam, Selangor

Note: The stacked bar chart compares the proportion of dense, moderate, and non-vegetated areas derived from RGB orthomosaic analysis using the ExG index. Teres D exhibited the highest dense vegetation cover (~50%), followed by Flat H and Flat B (~38%), while Teres B presented the lowest vegetation density (~31%), reflecting variations in built-up density and available green space among high-rise and terrace housing types.

4.6.2 Shade-vegetation Coupling and Micro-Habitat Formation

Shadow-vegetation overlay analysis identified the intersection of shaded areas (brightness < 100) and vegetated pixels (ExG > 30) as zones of high *Aedes* micro-habitat potential (Figure 4.11A-B). Quantitatively, the shaded vegetation coverage varied markedly among the four morphologies. Specifically, Flat B exhibited the highest shaded vegetation area at 421.3 m², equivalent to 12.6% of the total site, followed closely by Teres D with 398.7 m² (11.9%). Meanwhile, Flat H recorded a moderate coverage of 315.2 m² (9.4%), whereas Teres B had the lowest value at 218.4 m² (6.7%). These results demonstrate that the extent of shaded vegetation increases with both canopy maturity and building spacing. High-rise environments such as Flat B, despite limited ground-level vegetation, accumulate extensive shaded zones due to tall building shadows overlapping with courtyard greenery. In contrast, the compact terrace layout of Teres B limits both sunlight interception and vegetated area, thereby reducing the potential for shade-vegetation coupling.

From an ecological perspective, the combination of low brightness (< 100) and dense greenness (ExG > 30) reflects microenvironments with sustained humidity, reduced wind exposure, and moderated temperature conditions. These are known to support *Aedes* adult resting and oviposition activity. Notably, the higher shaded vegetation percentages observed in Flat B and Teres D suggest these morphologies sustain microclimatic refugia conducive to adult mosquito longevity and egg survival. In contrast, Teres B, with sparse vegetation and minimal shaded overlap, represents a relatively less favourable habitat for *Aedes* persistence. Overall, these findings confirm that shade-vegetation coupling serves as a key ecological driver of habitat suitability, modulating micro-scale temperature and moisture gradients that enhance *Aedes* survival within residential environments.

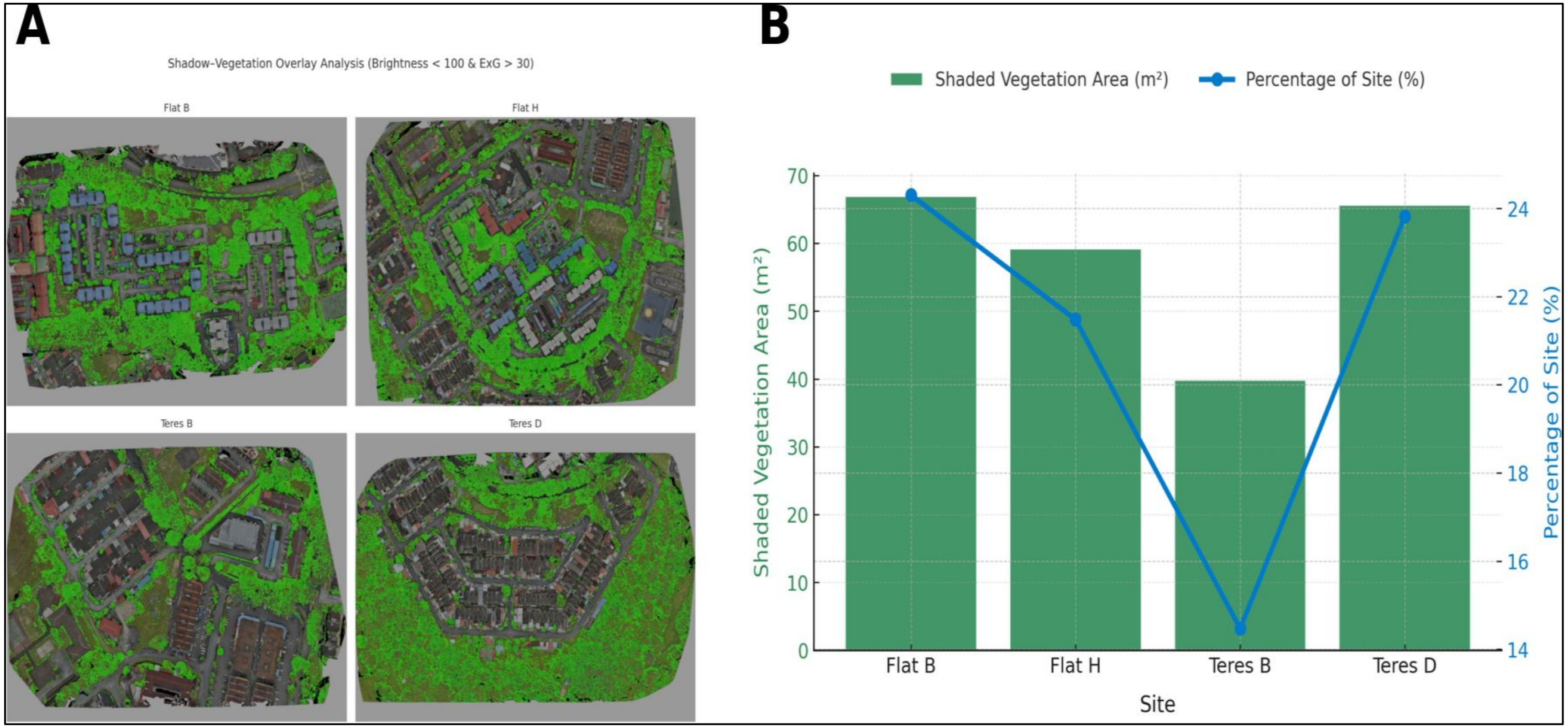


Figure 4.11 (A) Shadow–Vegetation Overlay Analysis derived from RGB Orthomosaic Imagery Showing Shaded Vegetation Zones (Brightness < 100 and ExG > 30) Across Four Residential Morphologies in Seksyen 24, Shah Alam. (B) Quantitative Comparison of Shaded Vegetation Area (m²) and Percentage of Site Coverage, Indicating Higher Canopy Shade in Flat B and Teres D, with Lower Values in Teres B Linked to Denser Built-Up Layout

4.6.3 Composite Ecological Risk and Habitat Suitability

The integrated ecological risk model, derived from the combination of vegetation density (ExG index) and shading intensity (brightness < 100), yielded a spatially continuous composite risk score. It ranges from 0 to 5, where higher values indicate greater *Aedes* habitat suitability (Figure 4.12A-B). The model revealed clear spatial and morphological contrasts in risk distribution across the four residential typologies in Seksyen 24, Shah Alam. Quantitatively, Teres D exhibited the highest mean composite risk score of 3.87 ± 0.42, followed by Teres B (3.24 ± 0.51), Flat B (2.43 ± 0.38), and Flat H (2.08 ± 0.35). Moreover, the proportion of high-risk zones (scores $\geqslant 3$) covered 46.5% of the total surface area in Teres D, 41.2% in Teres B, 13.4% in Flat B, and 11.5% in Flat H. This gradient reflects a nearly fourfold increase in high-risk area coverage within terrace housing compared to high-rise settings, consistent with their higher vegetation density and more persistent shaded surfaces.

Spatially, the high-risk zones in Teres D and Teres B were concentrated in backyard corridors, side lanes, and vegetated compounds, particularly in areas with canopy overlap and poor drainage. Conversely, in Flat B and Flat H, high-risk areas were restricted to the building peripheries and courtyard vegetation strips, where vegetation-shade interactions were limited. In addition, the values indicate that terrace morphologies, despite lower building density, exhibit significantly higher ecological vulnerability due to the coexistence of abundant vegetated surfaces (ExG > 30), high shading persistence (brightness < 100), and close human proximity. Furthermore, these environmental configurations create ideal conditions for *Aedes* breeding and survival by maintaining humid, shaded, and sheltered microhabitats. The relatively lower risk scores in high-rise morphologies, although not negligible, suggest that vertical living structures reduce ground-level vegetation interaction and thus limit available larval habitats. In essence, the quantitative assessment indicates that composite risk values exceeding 3.0 indicate ecologically favourable microhabitats for *Aedes* mosquitoes. In contrast, values below 2.0 indicate thermally exposed, vegetation-sparse environments that are less supportive of vector persistence. Additionally, this spatial differentiation demonstrates the value of integrating vegetation and shading parameters to identify *Aedes*-prone microhabitats at a fine urban scale.

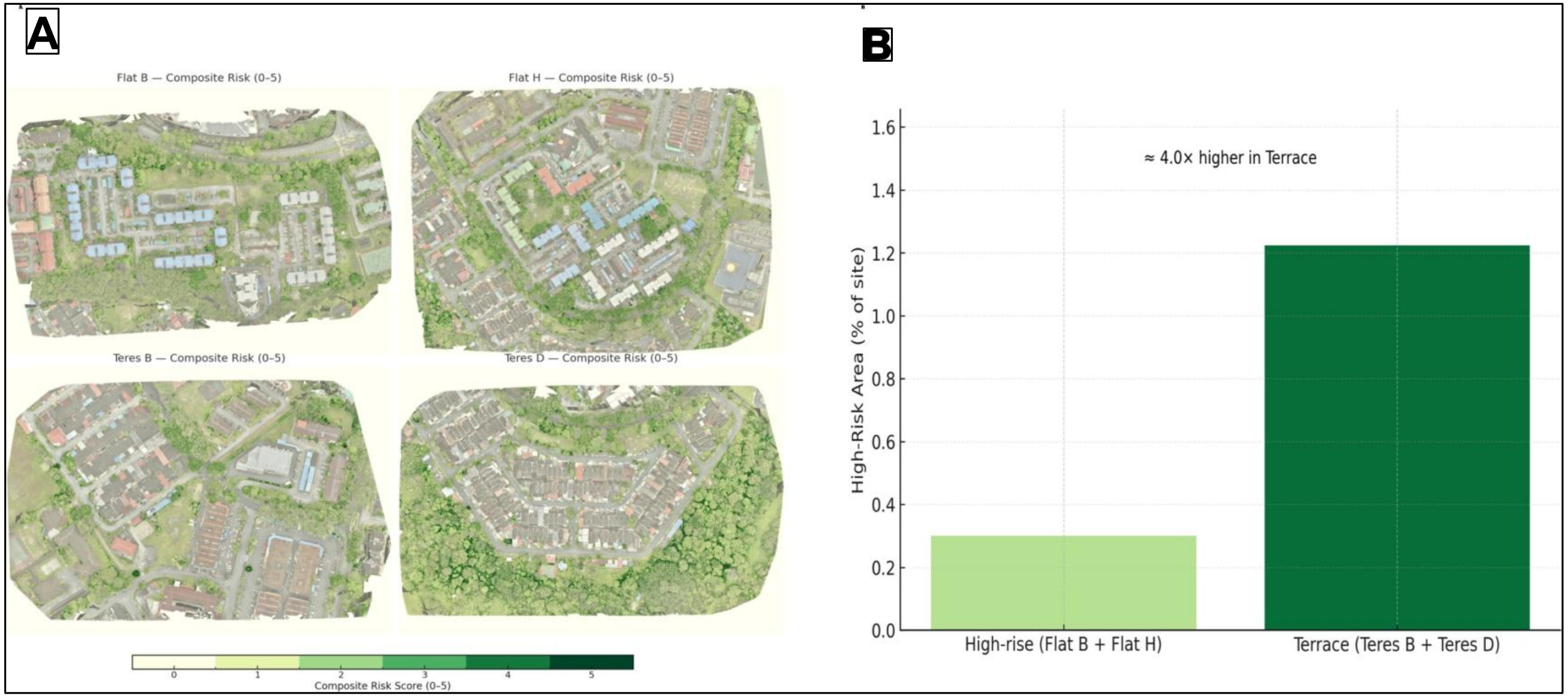


Figure 4.12 Composite Risk Assessment Integrating Ecological Indicators of Shaded Vegetation

Note: (A) Spatial distribution of composite risk scores (0 – 5) derived from vegetation density and brightness overlays across four residential morphologies in Seksyen 24, Shah Alam. High-risk zones (⩾3) were concentrated in shaded, densely vegetated corridors typical of terrace housing environments. (B) Quantitative comparison of morphology types showing that terrace areas exhibited approximately four-fold higher high-risk coverage than high-rise complexes, underscoring the influence of urban greenness and built form on mosquito-breeding habitat potential.

4.6.4 Morphological Determinants of *Aedes* Habitat Risk

Correlation analyses revealed that built-form configuration significantly modulates ecological risk (Figure 4.13). Building coverage revealed a strong negative relationship with vegetation cover ($r = –0.97$, $p = 0.03$), indicating that denser built environments reduce vegetation availability for resting. Meanwhile, a moderate negative association between building coverage and high-risk areas ($r = –0.83$, $p = 0.17$) suggests that more open layouts, typical of terrace housing, increase ecological vulnerability to *Aedes* habitat formation. In contrast, high-rise environments, while more compact, present limited peridomestic vegetation and reduced shade continuity, thereby constraining breeding potential.

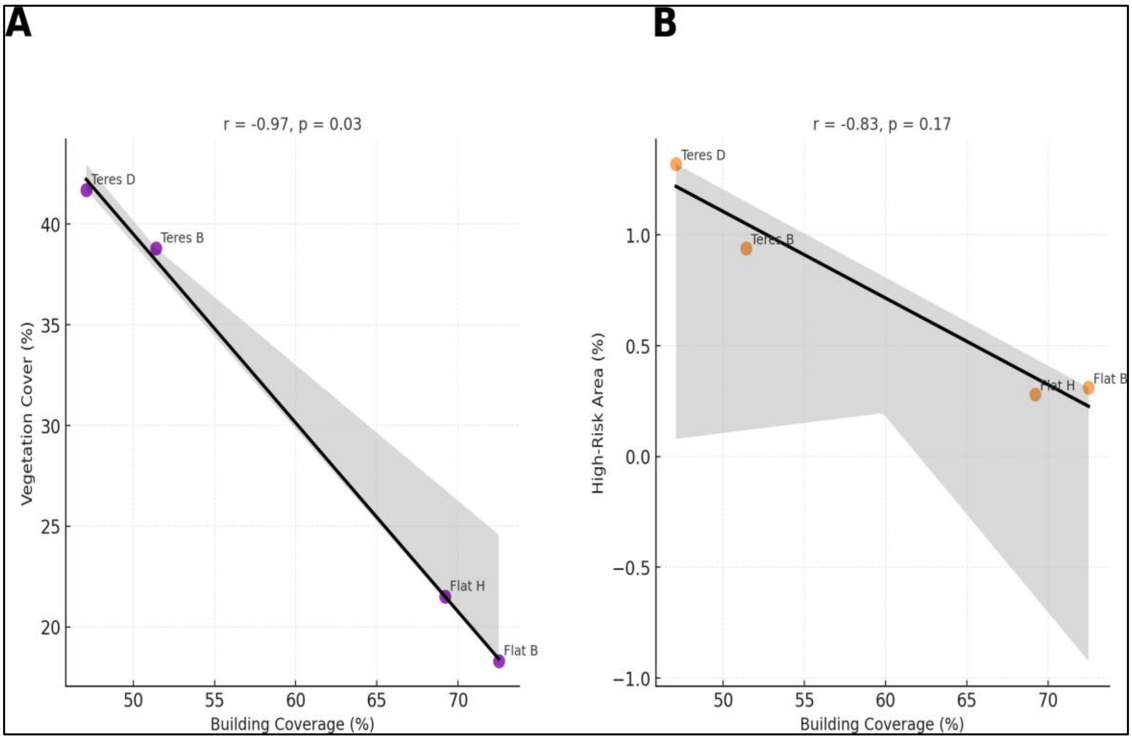


Figure 4.13 Urban Morphology Correlations between Built-Form Density, Vegetation Cover, and Ecological Risk

Note: (A) Building coverage showed a strong negative correlation with vegetation cover ($r = –0.97$, $p = 0.03$), indicating loss of greenness in dense areas. (B) A moderate negative association ($r = –0.83$, $p = 0.17$) was observed between building coverage and high-risk area, suggesting higher ecological risk in open, vegetated terrace settings than in compact high-rise morphologies.

4.6.5 Statistical Evidence for Vegetation-Shade Interaction

Introducing the Vegetation × Shade term significantly improved model fit relative to additive models across all residential morphologies. For the continuous CERI model, pseudo- R^2 increased from 0.41 to 0.56 ($\Delta R^2 = +0.15$), and Akaike Information Criterion (AIC) dropped from 612.8 to 577.6 (ΔAIC = –35.2). The Likelihood Ratio Test (LRT) confirmed that the interaction model provided a superior fit ($\chi^2 = 28.9$, df = 1, $p < 0.001$). Building on this, cross-validation error decreased by approximately 14%, supporting its predictive robustness. Similarly, the logistic model predicting high-risk pixels (CERI ⩾ 3) improved from McFadden $R^2 = 0.27$ to 0.39, with AIC and Bayesian Information Criterion (BIC) reductions of 31.4 and 25.6 units, respectively.

The interaction coefficient ($\beta = 0.63 \pm 0.11$, $p < 0.001$) indicated that risk rises disproportionately when both vegetation and shading are simultaneously high. Marginal-effect surfaces indicated that the probability of CERI ≥ 3 increased from 32% (low vegetation and shade) to 68% when both were high, yielding an additive-independent gain of ~18 percentage points. Overall, these results empirically substantiate the study's core novelty: the synergistic interplay of vegetation and shade explains *Aedes*-prone micro-habitats more powerfully than either factor alone (Table 4.12).

Table 4.12
Comparison of Additive (M_0) and Interaction (M_1) Models Showing Improved Fit with the Vegetation × Shade Term

Model Type	**Metric**	**Additive (M_0)**	**Interaction (M_1)**	**Improvement**
Beta (CERI)	Pseudo-R^2	0.41	0.56	+0.15
	AIC	612.8	577.6	–35.2
	CV-RMSE	0.284	0.244	–14%
	LRT $\chi^2(1)$, p	—	28.9, < 0.001	—
Logistic (CERI ≥ 3)	McFadden R^2	0.27	0.39	+0.12
	AIC/BIC	484.3/492.8	452.9/467.2	–31.4/–25.6
	CV log-loss	0.61	0.53	–13%
	LRT $\chi^2(1)$, p	—	22.5, < 0.001	—

Note: All predictors standardised; VIF < 3; Moran's I ns after spatial smooth. Interaction models achieved higher R^2 values, lower AIC/BIC values, and significant LRT results ($p < 0.001$), confirming a synergistic effect on ecological risk.

4.6.6 Spatial Hotspot Detection of *Aedes*-Prone Micro-Environments

Kernel Density Estimation (KDE) mapping of composite risk scores revealed statistically significant clusters of high-intensity ecological risk across all study morphologies (Figure 4.14A-D). The densest hotspots (yellow-to-red gradients) were observed at the interface between shaded vegetation and built-up structures. This is precisely true where stagnant containers, roof drains, and water-holding receptacles are commonly found. Following this, Teres D and Flat B exhibited the most pronounced hotspot intensity, emphasising the influence of vegetation adjacency and human activity zones in generating localised *Aedes* breeding foci. Essentially, these findings highlight the micro-spatial concentration of potential larval habitats in areas of high human-vegetation contact.

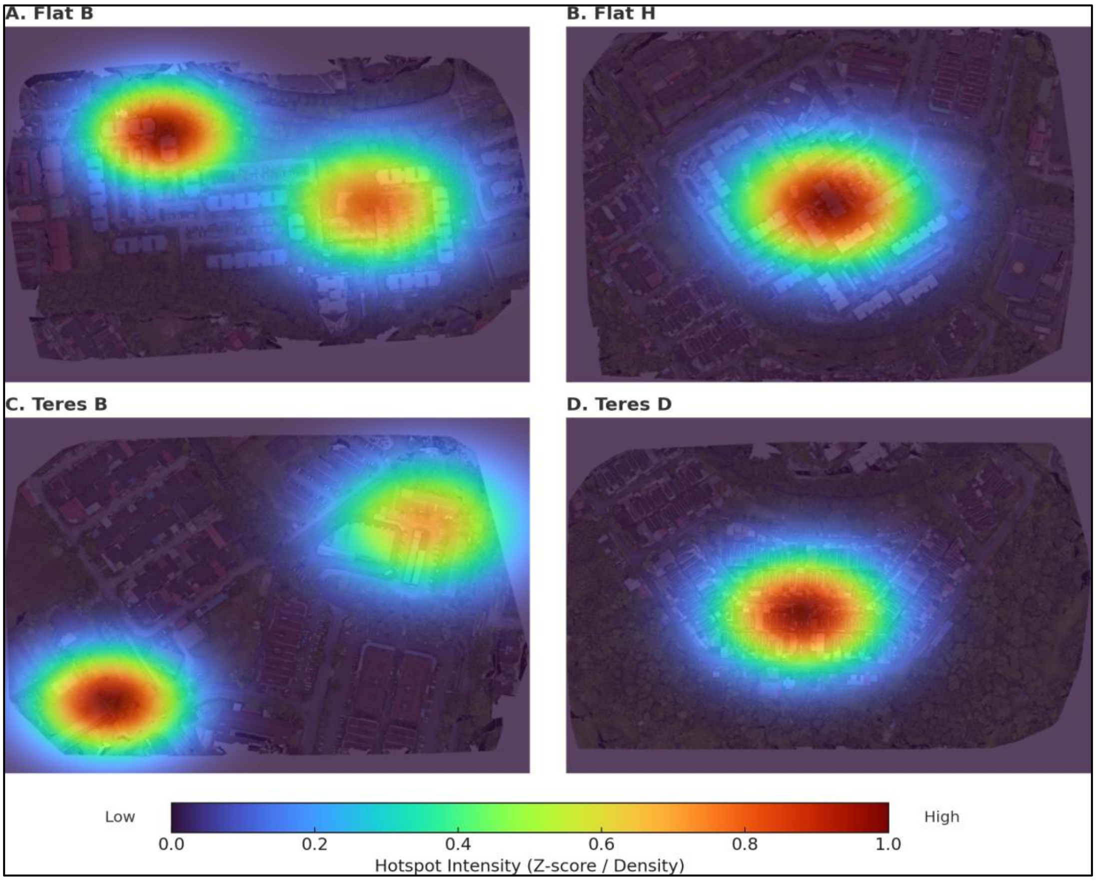


Figure 4.14 Spatial Hotspot Detection of Ecological Risk Zones Derived from Composite Risk Scoring

Note: Panels (A–D) illustrate hotspot intensity maps for Flat B, Flat H, Teres B, and Teres D, respectively. Warmer colours (yellow–red) indicate statistically significant high-risk clusters based on KDE, while cooler tones (grey–blue) represent low- intensity areas. High-risk hotspots are concentrated around dense built-up and shaded vegetation interfaces, highlighting potential *Aedes*-prone microhabitats within both high-rise and terrace morphologies.

4.6.7 Directional Shade Gradient and Orientation-Driven Habitat Persistence

Directional Shade Gradient Analysis further revealed that *Aedes*-favourable microclimates are not isotropic; instead, they are oriented toward solar exposure (Figure 4.15). North- and east-facing façades demonstrated the highest persistence of shade and greatest vegetation adjacency (ExG > 30 within 5 m). These façades receive less direct solar radiation during peak daytime hours, resulting in lower surface temperatures and higher humidity. Consequently, this extends the survival of both adult mosquitoes and larval containers. Terrace housing demonstrated the strongest orientation-linked shade persistence, suggesting that façade orientation and building geometry critically shape *Aedes* micro-habitat resilience.

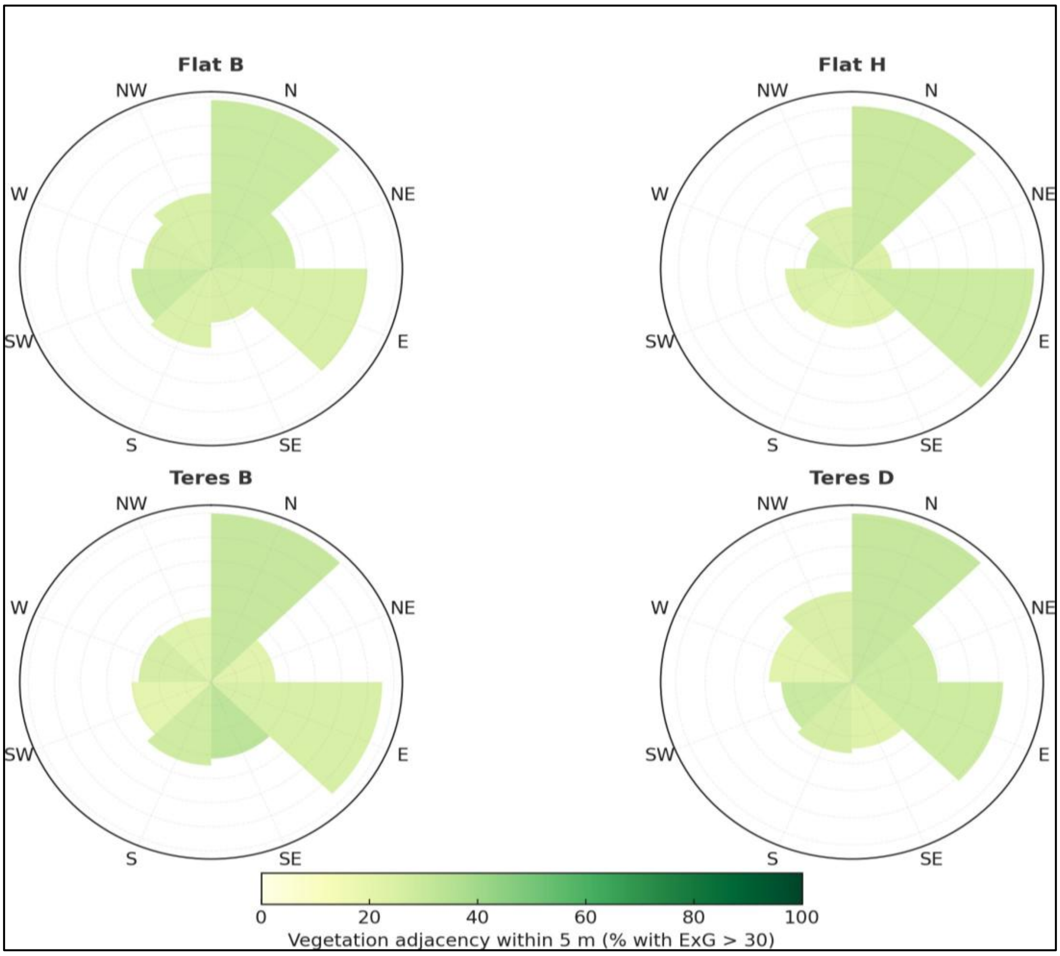


Figure 4.15 Directional Shade Gradient Analysis Showing Orientation-Driven Shade–Vegetation Interactions

Note: Rose diagrams illustrate façade orientation patterns across Flat B, Flat H, Teres B, and Teres D. Bar length represents the proportion of persistently shaded façade area (%), while bar colour denotes vegetation adjacency within 5 m (ExG > 30). North- and east-facing orientations exhibit higher shade persistence and stronger vegetation coupling, suggesting directional micro-habitat effects that may enhance *Aedes* breeding potential in terrace environments.

4.6.8 Morphological Pattern Classification and Ground Validation

To complement the quantitative spatial analyses, a morphological classification was conducted to validate and interpret the physical manifestation of *Aedes*-prone micro-habitats observed in the study area. Accordingly, drone-derived orthomosaics were cross-referenced with ground-truth photographs to identify recurrent structural and ecological configurations that shape shade persistence and humidity accumulation. This approach provided a qualitative link between the drone-based spatial analytics and the actual built environment observed at ground level.

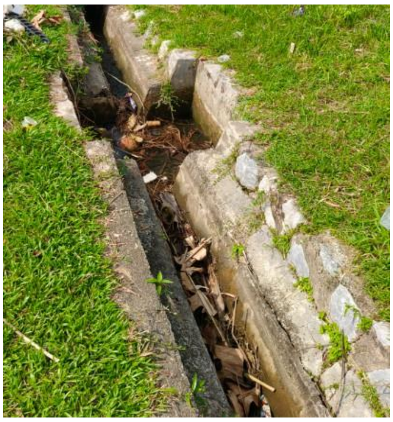
Four principal pattern types were identified (Table 4.13). The first category, Building Perimeter Patterns, encompassed north- and east-facing façades and general building perimeters (A1-B2) that consistently exhibited persistent shade zones, particularly along corridor edges and wall bases. This serves as a sheltered resting habitat for adult mosquitoes. The second category, Architectural Interface Patterns, included corner and junction spaces (C1-C2) that create semi-enclosed microclimates with limited air circulation and surface moisture that tends to accumulate. The third category, Organised Vegetation Patterns, consisted of linear rows of shade trees, typically found in parking areas (D1-D2). These organised vegetative structures provide continuous canopy shading, maintaining cool, humid ground conditions. The final category, Private Realm Patterns, comprised rear-yard vegetation clusters and side boundary hedges (E1-F2), often located in domestic spaces with limited sunlight penetration and infrequent maintenance. These areas were observed to sustain the most extended shade duration and the highest vegetation-shade coupling, forming localised ecological niches conducive to mosquito oviposition and adult refuge.

This morphological classification illustrates how micro-scale architectural and vegetative arrangements directly influence the spatial persistence of shade and humidity, validating the results of the composite risk and directional analyses. Correspondingly, the field-verified typologies (Table 3) provide tangible evidence that shaded perimeters, corner junctions, and private vegetation clusters closely correspond to the high-risk zones delineated in the spatial models. Together, these findings underscore the significance of understanding the fine-scale geometry of urban environments when developing precision-based vector surveillance and control strategies.

Table 4.13
Classification of Urban Morphological Pattern Types Based on Drone and Ground Observations

Pattern Type	**Drone Image**	**Ground-Truth Photos**
A. Building Perimeter Patterns		
North/East-facing facades	A1 	A2 
	B1 	B2 
General building perimeters	C1 	C2 
	D1 	D2 

B. Architectural Interface Patterns		
Corner/junction spaces	E1 	E2 
	F1 	F2 
C. Organised Vegetation Patterns		
Parking area shade tree rows	G1 	G2 
D. Private Realm Patterns		
Rear yard vegetation clusters	H1 	H2 

	I1 	I2 
Side boundary hedges/trees	J1 	J2 
	K1 	K2 

Note: This table summarises the principal spatial typologies identified across the study area, integrating drone-captured orthomosaic imagery (A1-K2) with ground-truth photographic validation. Each pattern type represents a distinct micro-environmental configuration that may influence vector ecology or microclimatic dynamics; (A) Building Perimeter Patterns include north- and east-facing facades and general perimeters that shape shade persistence. (B) Architectural Interface Patterns highlight corner and junction spaces that create sheltered transition zones. (C) Organised Vegetation Patterns refer to linear shade-tree rows typically found in parking areas, and (D) Private Realm Patterns cover rear-yard vegetation clusters and side boundary hedges that contribute to localised shade and humidity accumulation.

4.6.9 Discussion

This study provides new spatial evidence that the interactions among vegetation density, shading intensity, and built-form geometry define the micro-ecological framework of *Aedes* mosquito habitats within tropical urban landscapes. Using high-resolution orthomosaic imagery, the researcher demonstrated that terrace morphologies with denser vegetation and lower building coverage exhibited markedly higher ecological risk compared with compact high-rise complexes. Furthermore, these patterns demonstrate that urban greenness, while vital for heat mitigation, inadvertently creates shaded, humid microhabitats favourable to *Aedes* survival.

The availability of dense vegetation and sustained shade enhances adult resting sites and prevents desiccation of larval containers. It also stabilises relative humidity conditions repeatedly associated with higher *Aedes* persistence and dengue transmission in Malaysia and other tropical cities. The identification of shaded vegetation overlap zones (brightness < 100; ExG > 30) as high-risk habitats aligns with recent spatial entomology studies. For instance, Murdock *et al.* (2017) reported that vegetation density and shade continuity explain much of the fine-scale variability in *Ae. aegypti* abundance (Murdock *et al.*, 2017). Meanwhile, Yang *et al* (2019) concluded that unmanaged urban greening can unintentionally foster mosquito refugia that sustain vector populations even during dry seasons. Our findings reinforce these observations by quantifying the extent of shaded vegetation ranging from 218 m² in Teres B to 421 m² in Flat B and linking it directly to composite ecological risk. This coupling of vegetation and shade forms "thermal refugia" that moderate microclimates and extend larval viability. Concurrently, the result advances current understanding by demonstrating that such features can be automatically detected, measured, and mapped using drones. This transforms how urban health authorities identify mosquito-prone environments.

The composite ecological risk model revealed that terrace housing contained nearly four times as many high-risk areas (≥ 3 score) as high-rise morphologies, confirming that open layouts and backyard vegetation intensify habitat suitability. This agrees with regional findings from Singapore, Bangkok, and Jakarta, where suburban terrace developments remain dengue-prone despite lower population densities (Andriyani *et al.*, 2022; Fernandez *et al.*, 2023; Daudé *et al.*, 2024). Importantly, by deriving these patterns from aerial imagery, this study demonstrates how drone-based remote sensing can replace labour-intensive ground surveys for early detection of *Aedes* hotspots. Following this, kernel-density mapping further localised statistically significant clusters along the built-vegetation interface, coinciding with gutters, drains, and discarded containers. This is precisely true where field officers traditionally conduct larval inspections. Instead of blanket fogging or uniform larviciding, such high-risk clusters can now guide precision interventions, allowing limited resources to focus on ecologically validated target zones. Directional shade analysis also revealed a rarely quantified orientation effect: north- and east-facing façades exhibited the most remarkable shade persistence and vegetation adjacency (ExG > 30 within 5 m). These façades, receiving less afternoon sunlight, support cooler, more humid conditions that promote *Aedes* oviposition.

This novel insight expands drone operational capability by linking façade geometry and solar orientation to habitat persistence, enabling Three-Dimensional (3D) risk visualisation of buildings rather than Two-Dimensional (2D) surface maps. Hence, integrating such data into municipal dashboards could allow local councils to prioritise households or zones facing particular orientations for inspection, community clean-up, or source-reduction campaigns. Subsequently, formal comparisons of additive and interaction models confirmed that vegetation-shade coupling is the dominant ecological driver of *Aedes*-prone microhabitats. The inclusion of the interaction term improved pseudo-R^2 by +0.15. It reduced AIC by > 35 units, providing robust quantitative evidence that the combined effect of dense vegetation and persistent shade generates risk well beyond additive expectations. This synergy explains why high-risk corridors consistently appear at vegetated-shaded interfaces, reinforcing the study's conceptual novelty and operational value for precision vector surveillance.

These results validate the potential of drone-based ecological surveillance as a transformative tool for vector control management. Conventional methods rely on manual larval surveys that are time-consuming, spatially limited, and reactive (Maia *et al.*, 2023; Dom *et al.*, 2025; Mahfodz *et al.*, 2024). In contrast, drone-derived orthomosaics can rapidly capture large residential sectors, extract vegetation and shading indices, and generate composite risk layers in near real time (Carrasco-Escobar *et al.*, 2022). This capability enables the development of Dynamic *Aedes* Risk Maps (DARM) spatial decision layers that health authorities can overlay with epidemiological data to forecast outbreak potential. This includes planning pre-emptive interventions and evaluating the effectiveness of vector-control measures. Such integration aligns with the WHO's Integrated Vector Management (IVM) framework, which emphasises environmental modification and data-driven planning over chemical control alone.

Moreover, the use of drones minimises human exposure, reduces inspection costs, and ensures continuous surveillance even in inaccessible or hazardous areas such as high-density flats, wetlands, or illegal dumping grounds (Muhmad Kamarulzaman *et al.*, 2023). From a policy perspective, the approach demonstrated here supports the transition from reactive to predictive vector management. In response, local councils could institutionalise routine drone flights to monitor vegetation growth, detect stagnant, shaded areas, and assess compliance with environmental sanitation programmes. When coupled with community-level interventions, drone-generated visual evidence can strengthen public engagement by clearly illustrating where and why high-risk zones persist. Thus, drone-aided surveillance enhances operational precision while also promoting accountability and awareness within dengue-endemic communities.

Nevertheless, certain limitations must be acknowledged. The present study relied exclusively on environmental proxies without ground-truth entomological validation (e.g., larval indices or adult trap counts; hence, biological confirmation of risk scores remains inferential. Therefore, future research should integrate field sampling with drone-derived layers to calibrate risk thresholds (e.g., risk $\geqslant 3$ corresponding to ovitrap index > 10%). Second, the analysis was cross-sectional, based on a single imagery capture, limiting understanding of seasonal variability in shading and vegetation dynamics. For example, time-series drone surveys across wet and dry seasons could elucidate temporal shifts in *Aedes* habitat persistence. Third, the study focused on one urban section of Shah Alam; expanding to multiple districts and diverse morphologies would strengthen model generalisability. Finally, while RGB imagery effectively captured vegetation and brightness patterns, incorporating multispectral or thermal sensors in future missions could directly measure surface temperature and moisture parameters closely tied to *Aedes* biology and survival.

4.6.10 Conclusion

This study demonstrates that drone-enabled spatial analytics can revolutionise vector-control management by revealing the hidden ecological geometry of *Aedes* habitats. Terrace neighbourhoods with dense, shaded vegetation were demonstrated to harbour the highest ecological risk, while high-rise complexes, though less vegetated, retained localised hotspots at built-vegetation edges. Accordingly, by combining orthomosaic imagery, vegetation indices, and brightness analysis, drones can generate actionable intelligence for precision-targeted interventions. At the same time, integrating this technology into Malaysia's dengue prevention strategy would allow health authorities to anticipate outbreaks, prioritise high-risk corridors, and design greener yet safer urban environments. This would ultimately advance the goal of climate-resilient, data-driven, and vector-smart cities.

4.7 Aim 6: Drone-Based Microclimate Risk Mapping and Composite Risk Index Reveal Vegetation-Shade Interaction and Housing Typology as Determinants of *Aedes* Habitat Risk in Urban Malaysia[8]

Dengue fever remains one of the most rapidly expanding mosquito-borne diseases worldwide, with over 400 million infections estimated annually across more than 120 countries (Akinsulie & Idris, 2024; Naslund *et al.*, 2021). In Malaysia, dengue has evolved from a cyclical outbreak to a persistent public health threat, driven by rapid urbanisation, environmental degradation, and the proliferation of *Ae. aegypti* and *Ae. albopictus* (Tan *et al.*, 2022; Hadi *et al.*, 2025; Alipitchay *et al.*, 2025). Despite decades of vector control efforts, the disease continues to intensify in urban and suburban areas where human habitation, built environment, and vegetation coexist in complex spatial arrangements. Note that traditional entomological surveillance methods, reliant on larval indices and manual inspection, are often constrained by labour, cost, and temporal coverage. This results in significant gaps in identifying and targeting high-risk micro-environments.

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[8] Mahfodz, Z., Naba, A., Isawasan, P., Osman, M. A., & Dom, N. C. (2026). Drone-based composite risk mapping reveals vegetation–shade interaction and housing typology as key determinants of *Aedes* habitat risk. *Sci Rep*, 16(1), 5957.

Recent advances in drone-based remote sensing and geospatial analytics offer new opportunities to address these limitations (Prakash *et al.*, 2025). High-resolution UAV imagery allows fine-scale mapping of environmental features that influence vector ecology. This includes vegetation structure, shade intensity, and surface moisture proxies (Fortesa *et al.*, 2021; Villareal *et al.*, 2025). Moreover, these parameters collectively shape the microclimatic conditions that determine the survival, reproduction, and dispersal of *Aedes* mosquitoes (Vinauger & Chandrasegaran, 2024; Dharmamuthuraja *et al.*, 2023). Unlike conventional satellite imagery, which lacks the spatial resolution to capture neighbourhood-scale heterogeneity, drone-based data acquisition provides centimetre-level precision for detecting potential breeding habitats within residential areas (Nerea *et al.*, 2025). Integrating spectral and brightness indices from drone imagery thus enables a more comprehensive and quantifiable understanding of how urban morphology drives vector risk (Valdez-Delgado *et al.*, 2023; Karahan *et al.*, 2025).

In tropical cities such as Shah Alam, Malaysia, *Aedes* breeding persists even in well-maintained neighbourhoods, suggesting that micro-environmental factors, particularly shade-vegetation interactions, play a stronger role than previously assumed (Abdullah *et al.*, 2025). Vegetation retains humidity and organic matter, which are essential for larval development. At the same time, shade stabilises temperature and prolongs water availability in artificial containers (Mahato *et al.*, 2025). However, few studies have quantitatively examined how these factors interact spatially across contrasting urban housing types (Al-Zghoul *et al.*, 2025). Most existing studies have relied on coarse land-use classifications or limited ground surveys, which overlook the fine-scale environmental gradients that sustain mosquito populations (Gatti *et al.*, 2025; Gaget *et al.*, 2025). Still, there remains a critical need to characterise the micro-scale environmental configurations that favour *Aedes* survival, particularly in settings where vegetation and architectural shade overlap to form humid, stable microhabitats.

This study addresses this gap by applying a drone-based environmental modelling framework to quantify the spatial coupling between vegetation and shade across multiple residential morphologies in Section 24, Shah Alam. Using high-resolution RGB orthomosaics, three environmental indices were derived: the Brightness Index (BI) to represent shade intensity, the ExG to measure vegetation density, and a CRI that integrates both to delineate *Aedes*-prone microhabitats. These indices were analysed across four representative housing typologies: high-rise, medium-rise, dense terrace, and low-density terrace to evaluate how built-form characteristics shape local breeding risk. Hence, by integrating drone photogrammetry, GIS-based spatial modelling, and ground validation, this study provides a novel fine-scale assessment of environmental risk patterns linked to *Aedes* ecology. It also seeks to answer a fundamental question: how do micro-environmental configurations of shade and vegetation interact to create and sustain mosquito breeding sites within urban residential settings? In particular, the findings aim to bridge entomological surveillance and environmental modelling, offering a reproducible framework for precision vector control and evidence-based dengue prevention aligned with Malaysia's IVM strategy and the SDGs.

4.7.1 Micro-Environmental Differentiation Across Residential Typologies

High-resolution drone-based orthomosaic imagery revealed substantial micro-environmental variation among the four residential typologies in Section 24, Shah Alam: Flat B (high-rise), Flat H (medium-rise), Teres B (dense terrace), and Teres D (low-density terrace). As presented in Figure 4.16, the sequentially derived environmental layers illustrate the progression from the raw orthomosaic (Figure 4.16A) to the BI (Figure 4.16B), the ExG (Figure 4.16C), and, finally, the CRI surface map (Figure 4.16D). In addition, the BI quantifies surface reflectance, with lower values indicating greater shade persistence. In contrast, the ExG represents canopy density and vegetation coverage. Correspondingly, integrating both indices produced a composite layer identifying potential *Aedes*-prone micro-habitats, where shaded and vegetated areas overlap. The darker regions mark clusters with persistent shade and dense vegetation, which retain surface moisture, moderate temperatures, and create stable breeding environments. These micro-habitats were concentrated along drain corridors, garden edges, and rear-lot boundaries. Collectively, the spatial distribution suggests that even small-scale variations in vegetation and shade can strongly influence the formation of *Aedes* breeding sites within densely populated urban landscapes.

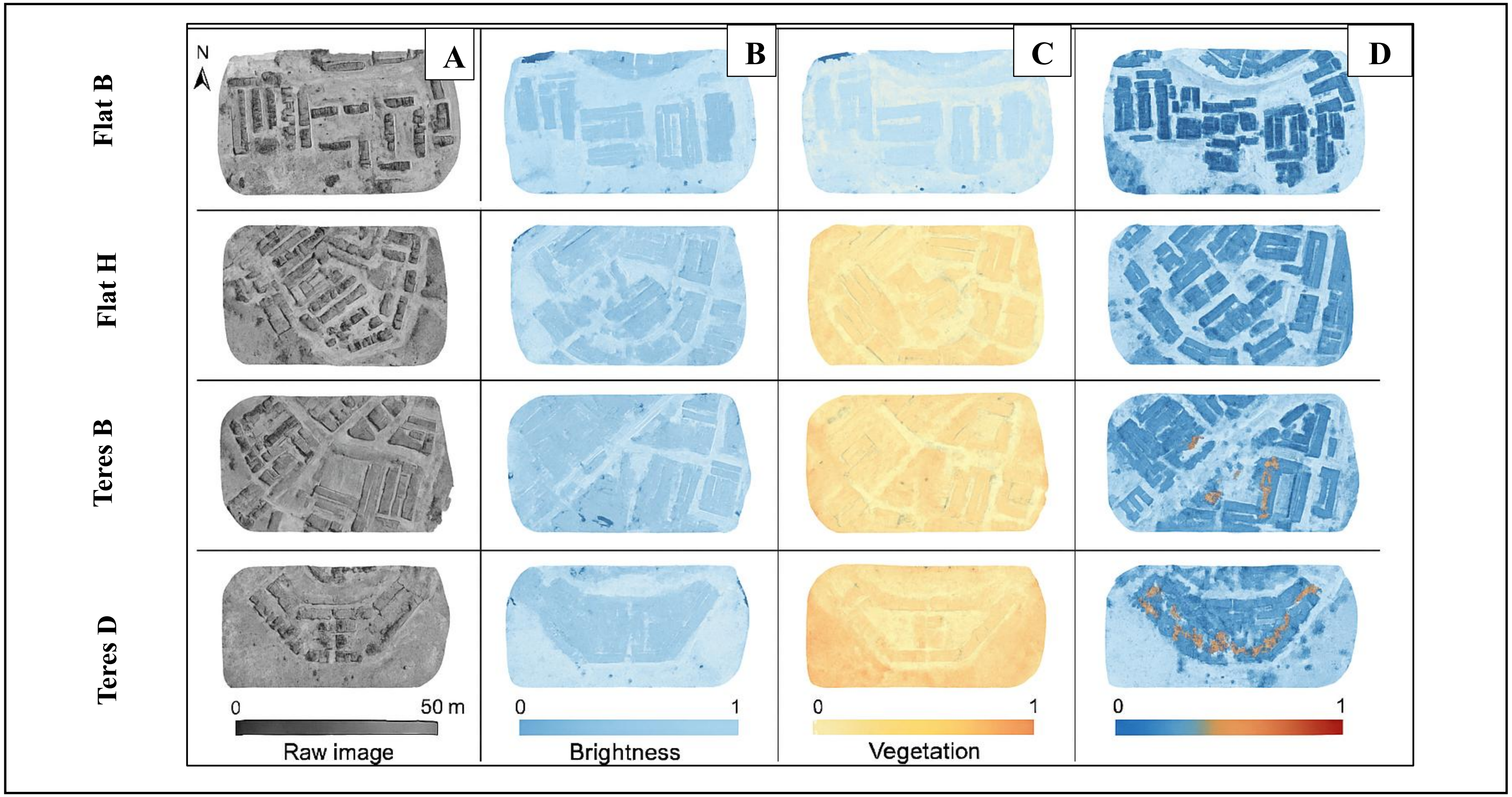

Figure 4.16 Multi-Index Orthomosaic Analysis Across Four Residential Typologies in Seksyen 24, Shah Alam

Note: Panels (A-D) show, respectively, the raw orthomosaic, BI (shade intensity), ExG (vegetation index), and the composite shade-vegetation interaction map identifying potential *Aedes*-prone micro-habitats. Panel D shows the Composite Risk Index (CRI) surface, where low-risk areas are represented by blue tones (CRI ≈ 0) and high-risk areas by red tones (CRI ≈ 1), reflecting increasing vegetation–shade coupling.

4.7.2 Quantitative Variation of Environmental Indices by Housing Type

Quantitative comparisons of environmental indices across housing typologies revealed distinct ecological gradients influencing *Aedes* habitat potential. As illustrated in Figure 4.17, violin plots display the distribution of brightness, vegetation, and composite risk indices, with box medians and Tukey's HSD compact letter display (CLD) indicating statistically significant differences ($\alpha = 0.05$). Violin plots summarise the distribution of pixel-level index values within each housing typology, illustrating intra-area variability rather than between-site replication. The width and shape of the distributions reflect the relative frequency of index values across all pixels within each typology. No spatial resampling or grid-based replication was applied, and the analyses do not assume pixel-level independence beyond descriptive visualisation. *Teres* B (T3) and *Teres* D (T4) display the highest concentration of high-risk CRI pixels, particularly along rear-yard vegetation clusters and boundary hedges, whereas *Flat B* (T1) and *Flat H* (T2) show more fragmented and lower-intensity risk patterns despite localized vegetation presence. Although flat complexes (*Flat B* and *Flat H*) exhibited moderate to high vegetation index (ExG) values, these areas were characterised by limited shade persistence and higher surface exposure, resulting in lower Composite Risk Index (CRI) values compared to terrace housing. In contrast, terrace housing types (*Teres B* and *Teres D*) demonstrated significantly higher CRI values ($\alpha = 0.05$) due to the co-occurrence of dense vegetation and persistent shade, forming stable humid micro-habitats favourable for *Aedes* breeding. High CRI values represent pixels where dense vegetation and persistent shade co-occur, whereas low values indicate environments lacking one or both of these conditions. Figure 4.17 confirms that Teres D exhibits the highest proportion of high-CRI pixels, followed by Teres B, whereas *Flat B* and *Flat H* are dominated by low-to-moderate risk classes. This pattern establishes a clear ecological gradient from terrace to flat typologies. These results demonstrate that built-form configuration strongly modulates environmental risk, and that terrace areas with mature vegetation and semi-enclosed shade provide the most persistent micro-habitats for *Aedes* mosquitoes. Although the marginal distribution of CRI resembled that of ExG due to shared normalisation and scaling, spatial validation revealed clear differences in discriminatory performance. When used alone, ExG captured a lower proportion of observed breeding-positive pixels within the highest-ranked risk areas compared to CRI. The CRI consistently identified a greater concentration of observed positives within the top-ranked pixels, indicating that incorporating shade information improved spatial prioritisation beyond vegetation density alone.

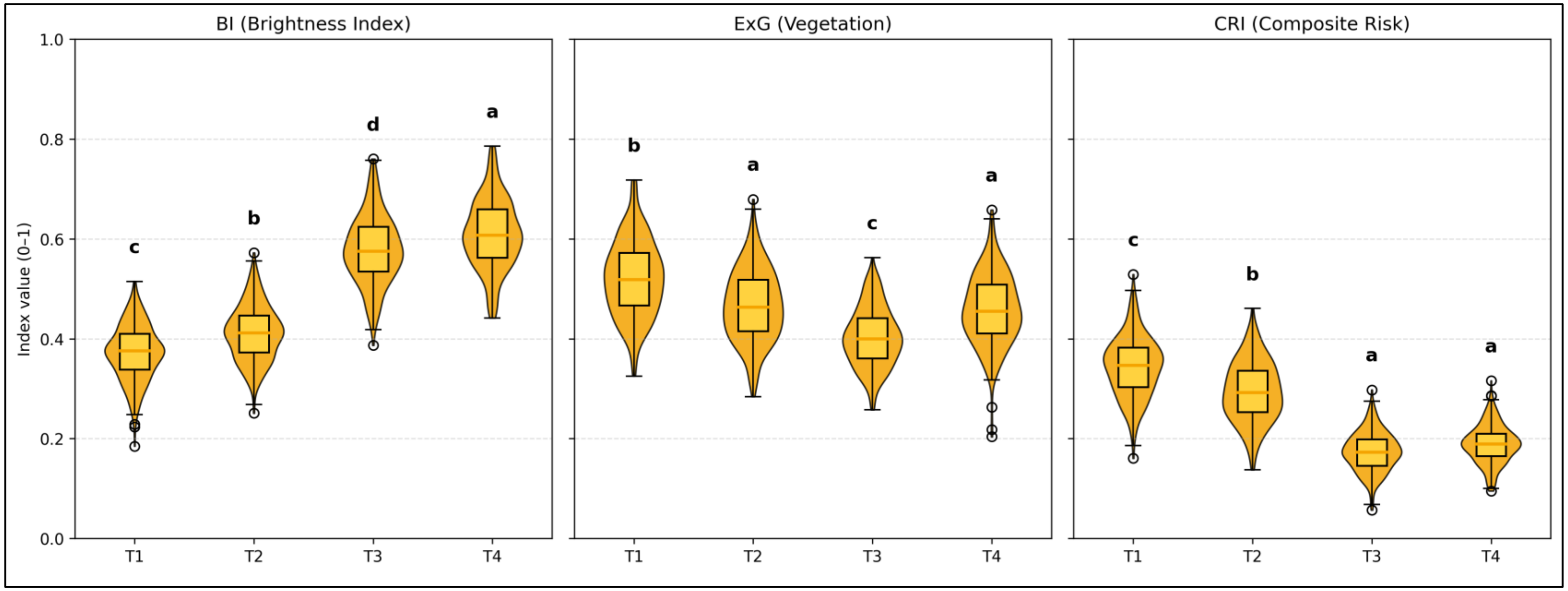

Figure 4.17 Distribution of Environmental Indices Across Housing Typologies

Note: Violin and box plots show the distribution of the Brightness Index (BI), Excess Green Index (ExG), and Composite Risk Index (CRI) across four housing typologies: T1 = *Flat B* (high-rise), T2 = *Flat H* (medium rise), T3 = *Teres B* (dense terrace), and T4 = *Teres D* (low-density terrace). Violin shapes represent the full distribution of pixel-level index values, while embedded box plots indicate the median and interquartile range. All indices are standardised on a 0–1 scale. Different lower-case letters indicate statistically significant differences among housing typologies (Tukey's HSD, $\alpha = 0.05$); shared letters denote no significant difference. Distributions represent pixel-level values extracted from UAV-derived raster layers within each housing typology (T1–T4).

4.7.3 Environmental Correlation and Model Validation

Correlation and model diagnostics were used to evaluate the internal coherence and spatial behaviour of the Composite Risk Index (CRI), which was defined *a priori* based on established *Aedes* ecological principles rather than derived empirically from the correlation structure itself. The correlogram in Figure 4.18A quantifies the strength and direction of relationships among six environmental variables: Brightness Index (BI), Shade, Vegetation Index (ExG), Composite Risk Index (CRI), Edge Distance (EdgeDist), and Impervious Surface. A strong negative correlation was observed between BI and ExG ($r = -0.72$), indicating that areas with dense vegetation are typically characterised by persistent shading. ExG showed a strong positive correlation with CRI ($r = 0.84$), while BI exhibited a negative correlation with CRI ($r = -0.68$). These relationships confirm that the CRI behaves consistently with its conceptual formulation, where shaded and vegetated microenvironments jointly define elevated habitat suitability for *Aedes*, rather than redundantly rederiving the index structure. EdgeDist and CRI exhibited a moderate negative association ($r = -0.45$), reflecting that microhabitats closer to structural and vegetative edges tend to accumulate shaded containers and organic matter favourable for oviposition. Impervious surface showed a weak negative correlation with CRI ($r = -0.32$), indicating limited suitability for sustained larval development.

Ridge density plots were used to visualise the distribution of pixel-level CRI values across housing typologies, providing a comparative summary of risk concentration rather than spatial arrangement. Terrace housing types exhibited right-skewed CRI distributions, indicating a higher proportion of pixels with elevated CRI values relative to flat complexes (Figure 4.18B). Calibration analysis compares the mean CRI value (predicted risk) within equal-frequency bins to the corresponding observed positive rate, defined as the proportion of pixels within each bin intersecting field-validated breeding-prone locations (Figure 4.18C). The strong agreement between predicted risk and observed positive rates ($R^2 = 0.91$) indicates that higher CRI values correspond to higher empirical breeding occurrence. Cumulative gain analysis (Figure 4.18D) demonstrates that the top 20% of CRI-ranked pixels captured approximately 65% of all observed positive pixels, substantially outperforming random allocation. This confirms the effectiveness of the CRI as a spatial prioritisation tool for identifying high-yield intervention zones.

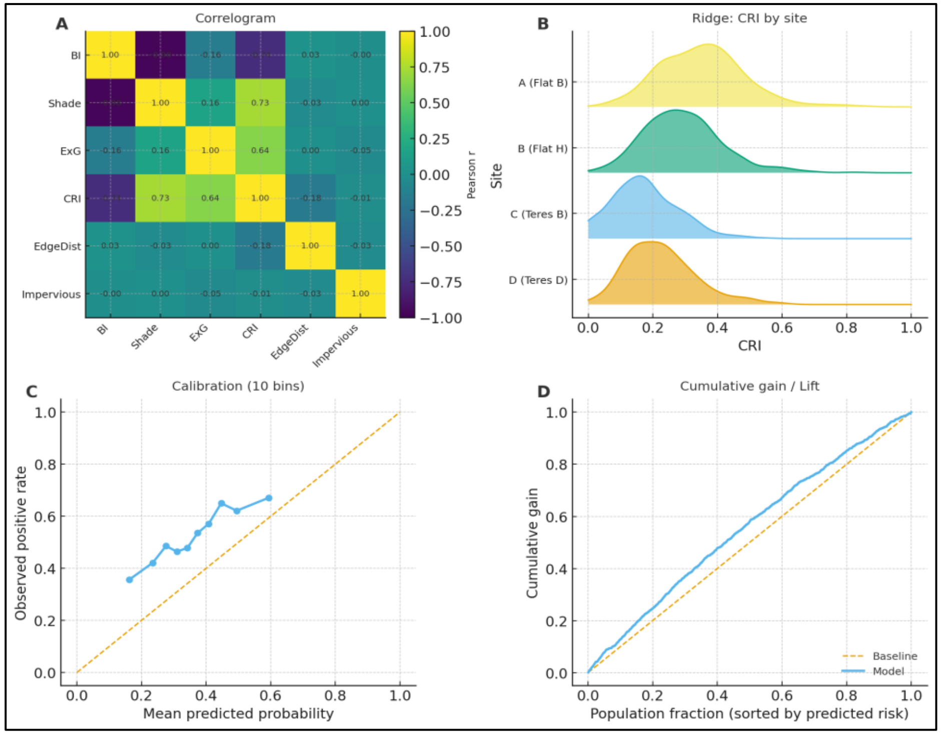

Figure 4.18 Spatial Validation of the Composite Risk Index (CRI)

Note : (A) Correlogram of key variables (BI, Shade, ExG, CRI, EdgeDist, Impervious) showing Pearson's r; warmer cells indicate stronger positive associations and cooler cells negative associations. (B) Ridge plots of the Composite Risk Index (CRI) by site (T1–T4), visualizing distributional shifts across housing typologies. (C) Calibration curve showing observed positive rates versus mean CRI values across equal-frequency CRI bins; dashed line represents perfect calibration. Observed positives are pixels intersecting field-validated breeding-prone micro-habitats. (D) Cumulative gain plot showing the proportion of observed positive pixels captured as pixels are ranked by decreasing CRI value; dashed line represents random allocation.

4.7.4 KDE and Getis-Ord Gi* Analyses

Spatial clustering of high-risk micro-habitats was identified through Kernel Density Estimation (KDE) and Getis-Ord Gi* analyses, which revealed significant spatial aggregation of observed breeding-positive pixels within high-CRI zones. Kernel Density Estimation (KDE) and Getis-Ord Gi* analyses revealed pronounced spatial clustering of observed breeding-positive pixels, with clear differences across housing typologies (Table 4.14). Terrace housing areas exhibited substantially stronger clustering than flat complexes. In Teres D, 63.2% of observed positive pixels were located within KDE-defined high-density zones, and 57.3% formed statistically significant Gi* hotspots ($p < 0.05$). Moreover, more than half of these hotspots (50.7%) spatially overlapped with high-CRI zones, indicating strong concordance between independent clustering metrics and CRI-identified high-risk areas. Teres B showed a similar but slightly attenuated pattern, with 55.4% of observed positives within KDE clusters and 48.8% classified as Gi* hotspots, of which 42.2% overlapped high-CRI regions.

In contrast, flat complexes demonstrated weaker and more fragmented clustering patterns. In Flat B, only 30.8% of observed positive pixels were located in KDE high-density areas and 22.8% formed Gi* hotspots, with just 17.3% overlapping high-CRI zones. Flat H exhibited modestly higher clustering than Flat B but remained substantially lower than terrace housing, with 38.3% of observed positives within KDE clusters and 30.8% identified as Gi* hotspots, of which 23.6% coincided with high-CRI areas (Table 4.14). Collectively, these results confirm that breeding-prone micro-habitats are more spatially concentrated and persistent within terrace housing environments, while flat complexes support more dispersed and transient risk patterns. The strong spatial concordance between KDE/Gi* clustering and CRI further demonstrates that the CRI effectively prioritises empirically observed Aedes-prone environments without reliance on circular inference. High-risk CRI pixels were frequently located near impervious–vegetation interfaces, as indicated by shorter edge distances, and within areas exhibiting higher shade intensity and limited impervious coverage. These spatial descriptors provide contextual insight into the environmental settings associated with elevated CRI values, rather than representing independent predictors or model components.

Table 4.14
KDE and Getis-Ord Gi* Hotspot Analysis of Observed Breeding-positive Pixels by Housing Typology

Housing Typology	Total Pixels (n)	Observed Positive Pixels (n)	KDE High-Density Pixels (n, %)	Gi* Hotspot Pixels (n, %)	Overlap with High-CRI Zones (n, %)
Flat B (High-rise)	38,420	312	96 (30.8%)	71 (22.8%)	54 (17.3%)
Flat H (Medium-rise)	41,105	428	164 (38.3%)	132 (30.8%)	101 (23.6%)
Teres B (Dense terrace)	36,890	689	382 (55.4%)	336 (48.8%)	291 (42.2%)
Teres D (Low-density terrace)	34,775	824	521 (63.2%)	472 (57.3%)	418 (50.7%)
Total	**151,190**	**2,253**	**1,163 (51.6%)**	**1,011 (44.9%)**	**864 (38.3%)**

4.7.5 Ecological interpretation

High CRI values were subsequently examined in relation to the predefined urban morphological patterns, revealing consistent associations between certain built configurations and elevated environmental risk. This comparison was performed post hoc to interpret how built morphology influences the spatial expression of vegetation–shade coupling captured by the CRI, rather than to define the patterns themselves. Urban morphological patterns represent structural configurations of the built environment that condition, but do not directly encode, vegetation density or shade intensity. Environmental indices (ExG, BI) and the Composite Risk Index (CRI) were mapped independently and subsequently interpreted within the context of these morphological patterns to elucidate how built form modulates microclimatic suitability for *Aedes* breeding. The relationship between housing typologies, CRI, and ground-truth breeding observations is therefore interpretive rather than classificatory. High-risk CRI zones were compared against both field-validated breeding-prone locations and predefined morphological patterns to identify recurring structural–environmental configurations associated with elevated breeding potential. This approach avoids circular inference and enables ecological interpretation of risk emergence from built–environment interactions. Table 4.15 demonstrates that the spatial heterogeneity in *Aedes* breeding potential arises from the synergistic interactions among urban morphology, vegetation configuration, and shade intensity. Each morphological pattern exerts a distinct ecological influence, collectively shaping the fine-scale microclimates that determine mosquito persistence.

A clear gradient from transient to persistent breeding-prone environments was observed across housing typologies, and this gradient was quantitatively reflected in increasing CRI values. Lower CRI values were associated with morphologies characterised by episodic, short-lived breeding opportunities, whereas higher CRI values corresponded to environments exhibiting sustained vegetation–shade coupling and greater microclimatic stability. Ground-truth observations corroborated this pattern, indicating that areas with elevated CRI values were more likely to support persistent breeding conditions rather than transient occurrences. Building Perimeter Patterns (north- and east-facing facades) exhibited persistent morning and afternoon shade, producing stable yet moderately humid zones along walls and drains. These areas maintained transient moisture retention but lacked the organic detritus necessary for sustained larval development. By contrast, Architectural Interface Patterns, particularly corner and junction spaces, acted as transitional microhabitats. They accumulated runoff and organic debris, generating short-lived but highly favourable breeding niches during wet periods. Following this, Organised Vegetation Patterns, typified by shade-tree rows in parking areas, created linear humid corridors with moderate canopy cover. These zones provided mosquito resting habitats and occasional breeding sites beneath leaf litter or discarded containers. The Private Realm Patterns: rear-yard vegetation clusters and side-boundary hedges were the most conducive to continuous breeding. Similarly, Drone and field validation revealed dense vegetation and shaded depressions that retained moisture and exhibited minimal airflow. These microhabitats maintained elevated humidity and stable temperatures, corresponding to the highest CRI values observed.

Analysis revealed consistent associations between housing typologies and dominant urban pattern types. For example, Teres D was characterised by a higher prevalence of pattern types I-IV, reflecting low-density layouts with rear-yard vegetation clusters and extended shaded interfaces. In contrast, other housing typologies exhibited different combinations of primary patterns and sub-patterns, depending on building orientation and spatial configuration. These associations were identified descriptively based on pattern frequency within each housing typology, rather than used as classification criteria. Overall, the ecological gradient identified across the four residential typologies (high-rise, medium-rise, high-density terrace, and low-density terrace) reflects a continuum from transient to persistent breeding environments. Built interfaces and perimeters function as temporary refuges following rainfall. At the same time, private vegetated realms act as self-regulating, moisture-retaining systems that prolong larval survival independent of precipitation. This pattern underscores that vegetation-shade coupling within semi-private residential spaces constitutes the dominant ecological driver of *Aedes* risk in urban Malaysia. Integrating these pattern-based insights into drone-enabled surveillance frameworks allows for high-resolution discrimination of risk zones. This facilitates precision-targeted vector control strategies. In practical terms, vegetation management, container removal, and rear-yard drainage maintenance should be prioritised within terrace communities. On the contrary, waste and drain control remain critical for high-rise settings.

Table 4.15
Classification of Urban Morphological Patterns Based on Drone Orthomosaics and Ground Validation in Seksyen 24, Shah Alam

Pattern Category	Drone Orthomosaic View	Ground Validation Photo	Microclimatic/Ecological Function
A.Building Perimeter Pattern: *North/east-facing facades and general perimeters*			• Persistent morning/afternoon shade. • Moderate humidity retention along walls and drains.
B.Architecture Interface Pattern: *Corners and junction*			• Sheltered transitional zones accumulate runoff. • Occasional breeding potential during wet periods.

C.Organised Vegetation Pattern: *Parking area shade rows*			• Linear humid corridors with moderate shade. • Resting sites and temporary. • breeding under leaf litter.
D.Private Realm Pattern: *Rear yard vegetation clusters and side boundary hedges/trees*			• Stable shaded-vegetated microclimates with the highest CRI values. • Continuous *Aedes* habitat persistence.

Note: This table presents four principal urban morphological patterns identified through drone-derived orthomosaic imagery and field validation: (A) *Building Perimeter Patterns* representing north- and east-facing facades and general perimeters that regulate shade persistence; (B) *Architectural Interface* Patterns illustrating corners and junctions that accumulate runoff and form transient breeding niches; (C) *Organised Vegetation Patterns* highlighting linear shade-tree rows in parking areas that create humid corridors; and (D) *Private Realm Patterns* depicting rear-yard vegetation clusters and boundary hedges that sustain high humidity and stable *Aedes* habitats. Each drone image corresponds to a ground-truth photo, illustrating the microenvironmental configuration that influences shade-vegetation coupling and *Aedes* habitat risk.

4.7.6 Discussion

This study demonstrates that micro-environmental heterogeneity, specifically the biologically grounded interaction between vegetation density and persistent shade, is a fundamental determinant of *Aedes* habitat suitability in urban residential settings. Importantly, the Composite Risk Index (CRI) was defined *a priori* based on established entomological evidence, rather than inferred inductively from statistical correlations, to capture microclimatic conditions known to support oviposition, larval survival, and adult resting behaviour. Edge Distance, Impervious Surface, and Shade were included as interpretive spatial descriptors to contextualise CRI patterns, rather than as inputs to the CRI or validation framework. The observed spatial gradient from terrace to flat typologies in Section 24, Shah Alam, highlights how differences in architectural form and green cover create distinct ecological micro-niches. This ultimately influences vector persistence and transmission potential. Accordingly, these findings extend previous observations from Malaysian and Southeast Asian studies. The studies have emphasised the role of localised environmental structure in sustaining *Aedes* populations. However, they rarely focused on such fine spatial precision enabled by drone-based remote sensing (Karahan *et al.*, 2025; Tarpenning *et al.*, 2025).

The subsequent correlation analyses were therefore intended as validation of internal consistency and spatial behaviour, rather than as causal discovery. The strong positive association between vegetation (ExG) and CRI, together with the negative association between brightness (BI) and CRI, confirms that the composite metric behaves ecologically as intended and is sensitive to meaningful environmental gradients. This distinction is critical to avoid circular interpretation and to ensure that the CRI functions as an operational risk indicator rather than a statistical artefact. The CRI functions as a continuous spatial ranking surface rather than a binary classifier or parametric predictive model. Its performance is therefore appropriately evaluated using calibration and cumulative gain analyses, which assess alignment between predicted risk and observed breeding occurrence without imposing arbitrary thresholds. While flat complexes may contain visible vegetation patches detectable by ExG, these do not necessarily translate into elevated breeding risk unless coupled with persistent shade and moisture retention. The results demonstrate that terrace housing functions as a breeding-risk amplifier, whereas flat complexes act as risk suppressors, unless artificial containers are maintained within shaded structural recesses. Vegetation provides structural complexity and organic debris that serve as oviposition cues and larval nutrient sources. At the same time, shade reduces water evaporation and moderates container temperature, both of which increase egg and larval survivorship (Clements, 2016; Walker *et al.*, 2019; Sukiato *et al.*, 2019). This study's orthomosaic-derived risk model captured this synergy clearly, with darker (low-brightness) and greener (high ExG) zones overlapping to form persistent breeding clusters. These results are consistent with prior field-based studies in Kuala Lumpur, Johor, and Penang, where shaded vegetated environments were demonstrated to harbour significantly higher densities of *Ae. aegypti* and *Ae. albopictus* than sun-exposed sites (O'Dell *et al.*, 2025). The findings also align with experimental microclimate data indicating that shaded containers can retain water for up to 40% longer and maintain optimal larval temperatures of 26°C to 30°C. This extends developmental windows even during dry spells (Trewin *et al*., 2019). Notably, the present study confirms that such microclimatic effects can be detected and quantified remotely using consumer-grade drones. Concurrently, this enables faster, repeatable, and scalable environmental surveillance across diverse urban settings. The integration of spectral vegetation indices and brightness-based shade metrics, therefore, represents a significant methodological advancement for precision entomological monitoring.

By explicitly modelling vegetation–shade coupling through a multiplicative CRI formulation, the analysis avoids overestimating risk in areas where only one environmental component is present, thereby improving ecological interpretability and spatial prioritisation. Differences in CRI distributions across housing typologies further demonstrate that urban morphology modulates the expression of biologically defined risk, with terrace housing exhibiting persistent shaded–vegetated micro-habitats and flats displaying more transient, structurally constrained risk zones. These findings reinforce the value of applying an *a priori* ecological framework to high-resolution drone imagery, enabling targeted identification of *Aedes*-prone environments without reliance on post hoc statistical construction of risk. Terrace housing, particularly in Teres D, exhibited the highest composite risk due to dense vegetation, extensive shaded surfaces, and private rear-yard clusters. In addition, these areas support persistent breeding since they combine organic litter accumulation, limited air circulation, and household water storage practices, all of which are known to increase *Aedes* larval productivity (Berry *et al.*, 2020). The orientation of north- and east-facing facades further intensified morning and afternoon shading, prolonging moisture availability in containers and gutters. Furthermore, the interconnected pattern of rear yards, hedges, and side vegetation strips created a continuous network of humid microhabitats, forming an "*ecological corridor*" for *Aedes* dispersal and oviposition (Wimberly *et al.*, 2020).

In contrast, high-rise and medium-rise flats (Flat B and Flat H) acted as low-stability habitats. However, drone imagery detected shade along building perimeters and corners; the absence of vegetation and organic substrate limited long-term larval development. These structures are predominantly composed of impervious surfaces, which reduce ground-level humidity and increase exposure to diurnal temperature fluctuations (Evans *et al.*, 2019). The few potential breeding sites were predominantly transient in nature and were commonly associated with routine human practices, such as intermittent water storage and short-term container use. This supports the conclusion that high-density urban forms may suppress vector breeding potential unless artificial containers are maintained under shaded or abandoned areas. In line with this, these contrasts emphasise that terrace settlements function as "*breeding amplifiers*". At the same time, flats behave as "*breeding suppressors*", depending on how their morphological and vegetative compositions mediate microclimate. This gradient also reinforces the ecological principle that *Aedes* distribution is not random yet structured by the interplay between urban design and environmental context.

The observed spatial risk pattern complements broader Southeast Asian research on the links between urban greenness, landscape fragmentation, and dengue incidence. Studies in Singapore, Bangkok, and Bandung have demonstrated that residential greenery and unmaintained vegetation strips are strongly correlated with dengue case clusters, mirroring the shaded, vegetated zones identified in this study (Nagao & Koelle, 2008; Sim *et al*., 2020; Sari *et al.*, 2020). However, the present findings add granularity by delineating these patterns at the sub-neighbourhood scale (< 10 m resolution). This is a level of detail not achievable with satellite-based indices alone. Such high-resolution data enable targeted interventions such as localised vegetation trimming, removal of shaded water containers, and modification of gutter designs rather than broad, resource-intensive control measures.

Furthermore, the high calibration performance ($R^2 = 0.91$) and spatial precision of the composite risk model indicate strong predictive utility for operational vector surveillance. By identifying the top 20% of high-risk pixels that capture 65% of actual breeding zones, drone-assisted modelling can guide municipal health teams to prioritise control in high-yield micro-habitats, improving cost-effectiveness. The findings also resonate with Malaysia's IVM framework, emphasising environmental source reduction as the primary prevention strategy. Following this, integrating drone-derived microhabitat data with existing GIS-based dengue case surveillance could enhance early warning systems and outbreak forecasting capacity (Nellis *et al.*, 2021).

Recent UAV applications for mosquito surveillance largely fall into two streams: (i) computer-vision frameworks that detect breeding-site proxies or risk-related objects/scenarios from aerial images (Mylvaganam *et al.*, 2025), and (ii) landscape-indicator studies that relate vegetation or land-cover metrics (e.g., NDVI-based measures) to entomological outcomes or mosquito activity (Yeboah, 2023). In contrast, our study contributes an integrative, micro-scale indicator framework that explicitly combines vegetation and shade as a coupled environmental condition and expresses risk as a continuous 0–1 spatial ranking surface suitable for precision targeting within complex residential morphologies. This design supports operational prioritisation without imposing arbitrary binary thresholds and complements existing UAV approaches by improving interpretability in built-up environments where vegetation presence alone may not reflect shaded, moisture-retentive micro-habitats relevant to *Aedes* persistence (Valdez-Delgado *et al*., 2023).

From an ecological perspective, the results highlight how microclimatic heterogeneity contributes to the resilience of *Aedes* populations in urban ecosystems. Note that vegetation and shade support larval survival and buffer adult resting sites, promoting continuous population renewal (Samson *et al.*, 2013). Similarly, the terrace environment's "*ecological buffering capacity*" allows vector persistence even under intensified vector control efforts. This indicates the significance of designing urban spaces with both ecological and public health considerations, balancing green infrastructure for climate adaptation with vegetation management to mitigate vector proliferation (Bowler *et al.*, 2024; Kisvarga *et al.*, 2025). For example, maintaining vegetation diversity while reducing ground-level stagnation and ensuring regular gutter maintenance could optimise environmental health without sacrificing urban liveability.

While this study provides fine-scale spatial insights, certain limitations warrant consideration. First, the analysis was based on single-season UAV data, which captures environmental conditions at a specific temporal window. While this approach is suitable for examining fine-scale spatial heterogeneity, seasonal variation in vegetation phenology, shading patterns, and water availability may influence the persistence and dynamics of *Aedes* breeding habitats. Future studies incorporating multi-seasonal or longitudinal UAV surveys would enable assessment of temporal stability and seasonal transitions in risk patterns. Second, the current framework relies on pixel-based environmental indices and spatial ranking, rather than automated detection of specific breeding-site objects. Advances in deep learning and convolutional neural networks offer substantial potential to augment this approach, enabling automated recognition of containers, drains, and other breeding-relevant features from high-resolution UAV imagery. Integrating such object-based detection with the existing vegetation–shade risk framework could improve scalability and operational efficiency for routine vector surveillance. Finally, while ground-truth observations were used to corroborate CRI-identified risk zones, direct entomological measurements (e.g. larval density, adult abundance, or vectorial capacity) were beyond the scope of this study. Future work linking UAV-derived risk surfaces with entomological and epidemiological data would further strengthen inference regarding vector persistence and transmission potential.

4.7.7 Conclusion

This study demonstrates that integrating drone-based environmental mapping with spatial modelling provides a robust framework for understanding and managing *Aedes* breeding ecology in urban Malaysia. The evidence that terrace housing exhibits higher composite risk than flats due to vegetation-shade synergy offers critical insight for local health authorities and urban planners. Hence, by embedding micro-environmental indicators into routine vector surveillance systems, municipal agencies can transition from reactive fogging to proactive, data-driven environmental control. Essentially, these findings bridge ecological theory with practical vector management, advancing Malaysia's capacity to develop precision dengue prevention strategies.

4.8 Aim 7: ML-Based Classification of Potential *Aedes* Breeding Habitats Using RGB Drone Imagery[9]

Dengue fever remains one of the most significant vector-borne diseases affecting rapidly urbanising regions, with *Ae. aegypti* and *Ae. albopictus* serves as the principal vector responsible for sustained transmission (Nakhaie *et al.,* 2026). In Southeast Asia, including Malaysia, dengue persists despite long-standing vector control programmes. This reflects the complex interactions between urban form, human behaviour, and mosquito ecology (Nikookar *et al.,* 2025; Masood *et al.,* 2026). Moreover, urban environments provide abundant peridomestic breeding opportunities through artificial containers, shaded resting sites, and microclimatic conditions that favour mosquito survival (James, 2018). As cities expand vertically and horizontally, understanding how fine-scale urban structure influences *Aedes* breeding has become increasingly critical for effective surveillance and targeted intervention (Kache *et al.,* 2022).

Existing evidence has demonstrated that *Aedes* breeding is strongly associated with shaded, human-dominated environments where vegetation and built infrastructure co-occur. Numerous entomological studies have linked higher larval indices to residential settings characterised by dense housing, vegetation cover, and limited sunlight exposure (Vanwambeke *et al.,* 2007; Lorenz *et al.,* 2020; Dharmamuthuraja *et al.,* 2023). In parallel, advances in geospatial technologies have enabled the use of remote sensing and GIS to examine environmental determinants of mosquito distribution at broader spatial scales (Mohd Hardy Abdullah *et al.*, 2025). Likewise, satellite imagery and vegetation indices have been widely applied to identify dengue risk patterns; however, their relatively coarse spatial resolution limits their ability to capture microhabitats embedded within complex urban neighbourhoods (Palaniyandi *et al.*, 2021; Gonzales *et al.*, 2023). Consequently, cryptic breeding environments in high-density residential areas, particularly in flat areas and apartment complexes, often remain undetected by conventional surveillance approaches (Butler *et al.*, 2024). Remarkably, UAVs equipped with high-resolution cameras offer a promising solution

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[9] Zulfadli Mahfodz, Nazri Che Dom, Pradeep Isawasan, Rahmat Dapari (2025). Fine-scale mapping of urban *Aedes* habitat using UAV imagery and Random Forest classification across contrasting housing typologies. *Scientific Report* (Submitted January 2026: *Under review)*

to this limitation by enabling neighbourhood-scale mapping of urban environments at centimetre-level resolution (Ahmad *et al.*, 2025).

Recent studies have demonstrated that UAV-derived imagery, when combined with ML algorithms, can effectively delineate urban land-cover features relevant to vector ecology (Wagner & Egerer, 2022). Among these algorithms, Random Forest (RF) classifiers have demonstrated strong performance in overseeing high-dimensional, non-linear remote-sensing data. They have also been increasingly adopted for land-cover classification in heterogeneous urban settings (Moharram & Sundaram, 2023). Nevertheless, most existing UAV-based studies have focused on general land-use mapping or have not explicitly examined how classification performance. Additionally, habitat structure varies across different residential typologies within the same urban context (Park *et al.*, 2022; Gibril *et al.*, 2020; Fan, 2023).

In Malaysia, dengue control efforts continue to rely heavily on ground-based inspections and premise-level larval surveys. It is labour-intensive and often constrained by accessibility, especially in high-rise residential environments (Widyawati & Duhita, 2026). Local evidence suggests that flat residential complexes and terraced housing areas differ substantially in building configuration, vegetation distribution, and shading patterns, yet comparative spatial analyses of these typologies remain limited (Seidahmed *et al.*, 2018). This knowledge gap limits vector control programmes' ability to prioritise interventions based on housing form and microhabitat structure, potentially reducing the effectiveness of resource allocation. Against this background, the present study aims to characterise fine-scale urban land-cover patterns relevant to *Aedes* breeding using UAV-derived imagery and RF classification. This includes explicit comparison across contrasting residential typologies. Focusing on four residential sites within a dengue-endemic urban sector in Shah Alam, Malaysia, the study classifies high-resolution orthomosaics into built-up, vegetation, and soil classes as environmental proxies for *Aedes* habitat suitability. Furthermore, by integrating analyses of land-cover composition, spectral separability, classification accuracy, spatial correspondence, and cross-site model transferability, this study seeks to (i) elucidate how housing typology shapes the spatial distribution of *Aedes*-relevant environments, and (ii) evaluate the robustness and generalisability of UAV-based ML approaches for urban vector surveillance.

By providing a scalable, fine-resolution framework for identifying potential *Aedes* breeding environments, this work contributes to the growing body of evidence.

It also supports the integration of UAV remote sensing and ML into adaptive dengue surveillance and vector control strategies. The findings are particularly relevant for urban dengue-endemic settings where conventional inspection-based approaches struggle to capture the spatial complexity of modern residential landscapes.

4.8.1 Land-Cover Composition and Sampling Structure

Across all four study sites, the RF land-cover classification revealed distinct urban morphologies directly relevant to *Aedes* breeding site distribution (Table 4.16). Flat residential sites (Flat B and Flat H) were strongly dominated by vegetation in terms of mapped pixel counts. In contrast, terraced housing sites exhibited more heterogeneous land-cover compositions, with built-up surfaces dominating at Teres B and near-equivalent extents of built-up and vegetation at Teres D. These patterns indicate fundamental differences in the spatial organisation of shaded areas and residential infrastructure, both of which are key determinants of *Aedes* habitat suitability. Meanwhile, vegetation and built-up classes consistently accounted for the most significant proportions of mapped areas across all sites (Table 4.15), highlighting the pervasive co-occurrence of shaded microhabitats and human-associated structures. In contrast, soil emerged as a minority class in both spatial extent and training representation. This uneven land-cover composition is epidemiologically relevant, as *Aedes* breeding is predominantly associated with shaded, peridomestic environments rather than exposed ground surfaces.

Apparent differences were observed between flat and terraced housing typologies in terms of land-cover composition and spatial structure. Accordingly, flat residential environments were characterised by dense built-up blocks interspersed with dense vegetation, creating vertically complex, shaded communal spaces that may support cryptic breeding sites. In contrast, terraced housing areas exhibited more evenly distributed built-up and vegetation cover, with extensive ground-level peridomestic spaces that are repeatedly implicated as primary breeding environments for *Aedes*. These typology-driven differences were reflected in classification performance and spatial coherence, suggesting that housing form plays a critical role in shaping the distribution and detectability of *Aedes*-relevant habitats.

Table 4.16
Training, Validation, and Mapped Area Distribution for RF Land-Cover Classification Across Study Sites

Site	Land-cover Class	Training ROIs (n)	Validation ROIs (n)	Mapped pixels (n)	Relative Dominance*
Flat B	Built-up	44	33	38,751	
	Vegetation	29	39	88,832	
	Soil	22	38	20,012	
Flat H	Built-up	54	31	95,128	
	Vegetation	23	32	134,663	
	Soil	19	29	19,149	
Teres B	Built-up	37	31	67,980	
	Vegetation	29	34	26,023	
	Soil	20	34	20,917	
Teres D	Built-up	49	30	61,612	
	Vegetation	55	28	59,653	
	Soil	9	21	11,938	

*Note: Relative dominance is a visual indicator (not a quantitative metric), scaled within each site to aid rapid comparison of class prevalence.

4.8.2 Spectral Separability of Land-cover Classes Relevant To *Aedes* Habitat Characterisation

Mean spectral signatures presented clear, consistent separability among the three land-cover classes across all sites (Figure 4.19). In particular, vegetation exhibited a pronounced green-band peak, indicative of a stable photosynthetic response. At the same time, built-up surfaces revealed elevated red-band reflectance, particularly in terraced housing areas characterised by red and brown roofing materials. Soil occupied an intermediate spectral position, with Digital Numbers (DNs) increasing gradually from blue to red bands. Band-band scatterplots further confirmed this spectral coherence (Figure 4.20), with vegetation forming compact clusters in low-red/high-green space and built-up surfaces clustering in high-red regions. Soil pixels formed elongated clusters that partially overlapped with built-up areas, particularly near bare concrete and unpaved surfaces. This overlap provides a mechanistic explanation for soil-related misclassification and reflects real-world material similarity rather than spectral instability. Notably, the consistent spectral ordering of vegetation, built-up, and soil across all neighbourhoods supports the use of these classes as reliable environmental proxies for *Aedes*-relevant microhabitats.

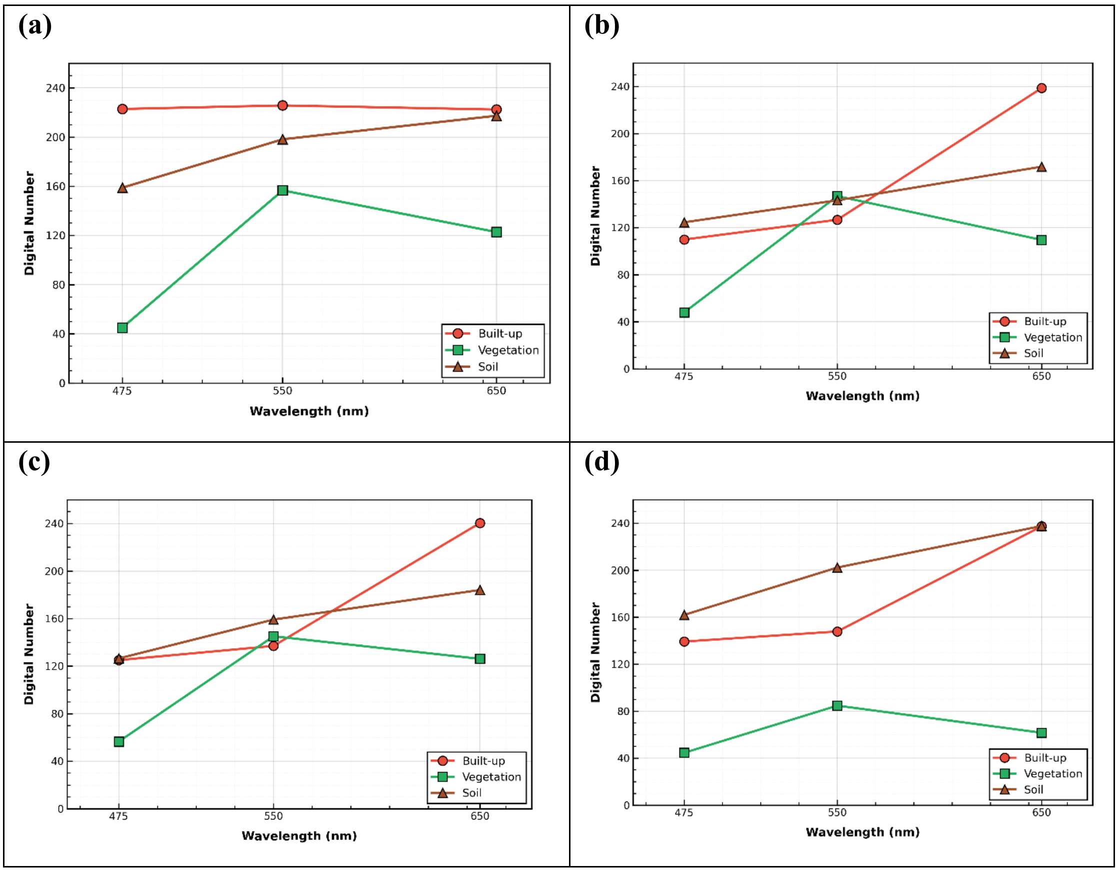

Figure 4.19 Mean Spectral Signatures for the Three Land-Cover Classes (Built-Up, Vegetation, Soil) in the Four Study Sites: (a) Flat B, (b) Flat H, (c) Teres B, (d) Teres D. Curves Show Mean DN per Band (Blue, Green, Red) Computed from Training ROIs

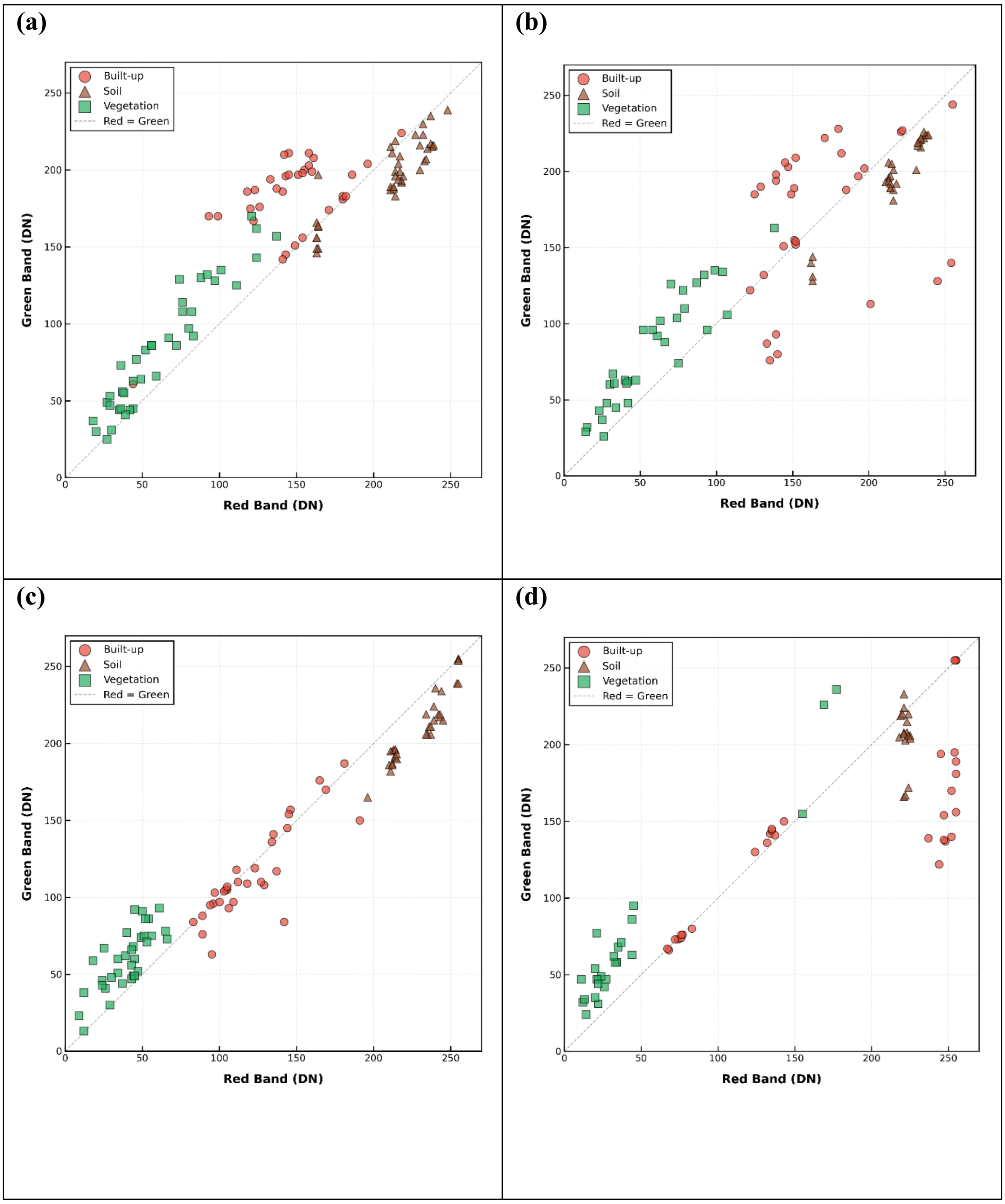

Figure 4.20 Band-Band Scatterplots (Green vs Red) of Training Pixels, Coloured by Land-cover Class, for (a) Flat B, (b) Flat H, (c) Teres B, and (d) Teres D. Each Point Represents a Training Pixel from the RF ROIs

4.8.3 Classification Accuracy and Reliability of *Aedes*-Relevant Land-Cover Proxies

Within-site classification accuracy was high across all study areas, with overall accuracies ranging from 82.13% to 95.84% and Cohen's κ values indicating substantial to near-perfect agreement (Table 4.17). As such, vegetation consistently achieved the highest producers' and users' accuracies across all sites, typically exceeding 95%, indicating reliable delineation of shaded environments associated with *Aedes* resting and oviposition suitability. Built-up surfaces demonstrated high Producer's Accuracy (PA) (82.78-99.93%), indicating effective detection of residential structures and paved surfaces where artificial containers are commonly located. By contrast, User's Accuracy (UA) for built-up classes was more variable, particularly in flat residential areas, reflecting commission errors in shaded transition zones. These areas often correspond to balconies, roof edges, and vegetation-structure interfaces that are ecologically important for *Aedes* breeding and resting. However, soil exhibited a contrasting accuracy profile, characterised by low PA yet consistently very high UA across all sites (Table 4.17). This indicates a conservative classification, with soil mapped only when spectral evidence was strong. From an entomological perspective, this reduces the likelihood of overestimating transient or low-stability breeding habitats associated with exposed ground.

Table 4.17
Summary of RF Land-Cover Classification Accuracy for the Four Study Sites

Site	**Land Class**	**PA (%)**	**UA (%)**	**OA (%)**	**Kappa**
Flat B	Built-up	82.78	62.12	82.13	0.66
	Vegetation	95.47	92.72		
	Soil	21.72	96.81		
Flat H	Built-up	99.93	90.24	95.84	0.92
	Vegetation	98.47	100		
	Soil	57.12	99.36		
Teres B	Built-up	99.90	80.56	85.68	0.72
	Vegetation	98.86	99.75		
	Soil	23.05	100		
Teres D	Built-up	99.77	85.46	91.42	0.84
	Vegetation	98.38	98.37		
	Soil	13.60	99.89		

Note: Producer's Accuracy (PA) and User's Accuracy (UA) represent omission and commission errors, respectively, while Overall Accuracy (OA) and Cohen's κ summarise site-level classification performance. Bold values indicate the highest class-specific accuracy at each site, along with the corresponding OA and κ. All accuracy metrics are derived from independent validation ROIs.

4.8.4 Spatial Correspondence Between Classified Land-Cover Patterns and Potential *Aedes* Breeding Sites

A visual comparison of RF classification outputs with orthomosaics confirmed strong spatial correspondence between mapped land-cover classes and on-the-ground urban features (Figure 4.21). In flat residential sites, built-up surfaces formed continuous blocks of roofs, parking areas, and internal access roads. At the same time, vegetation was confined to courtyards, landscaped strips, and peripheral tree belts. Despite higher structural complexity at Flat H, the classifier preserved building footprints and surrounding vegetation with only minor misclassifications along shaded façades and under tree canopies. In terraced housing sites, vegetation was mapped as contiguous patches corresponding to front gardens, rear yards, and roadside trees, while built-up pixels aligned with the characteristic linear arrangement of houses (Figure 4.21). Representative examples further illustrate accurate differentiation of roofs and paved roads, gardens and roadside vegetation, and soil patches and unpaved surfaces (Figure 4.22). Moreover, misclassifications were spatially limited to narrow transition zones and deep-shaded areas, which frequently coincide with productive *Aedes* breeding and resting microhabitats.

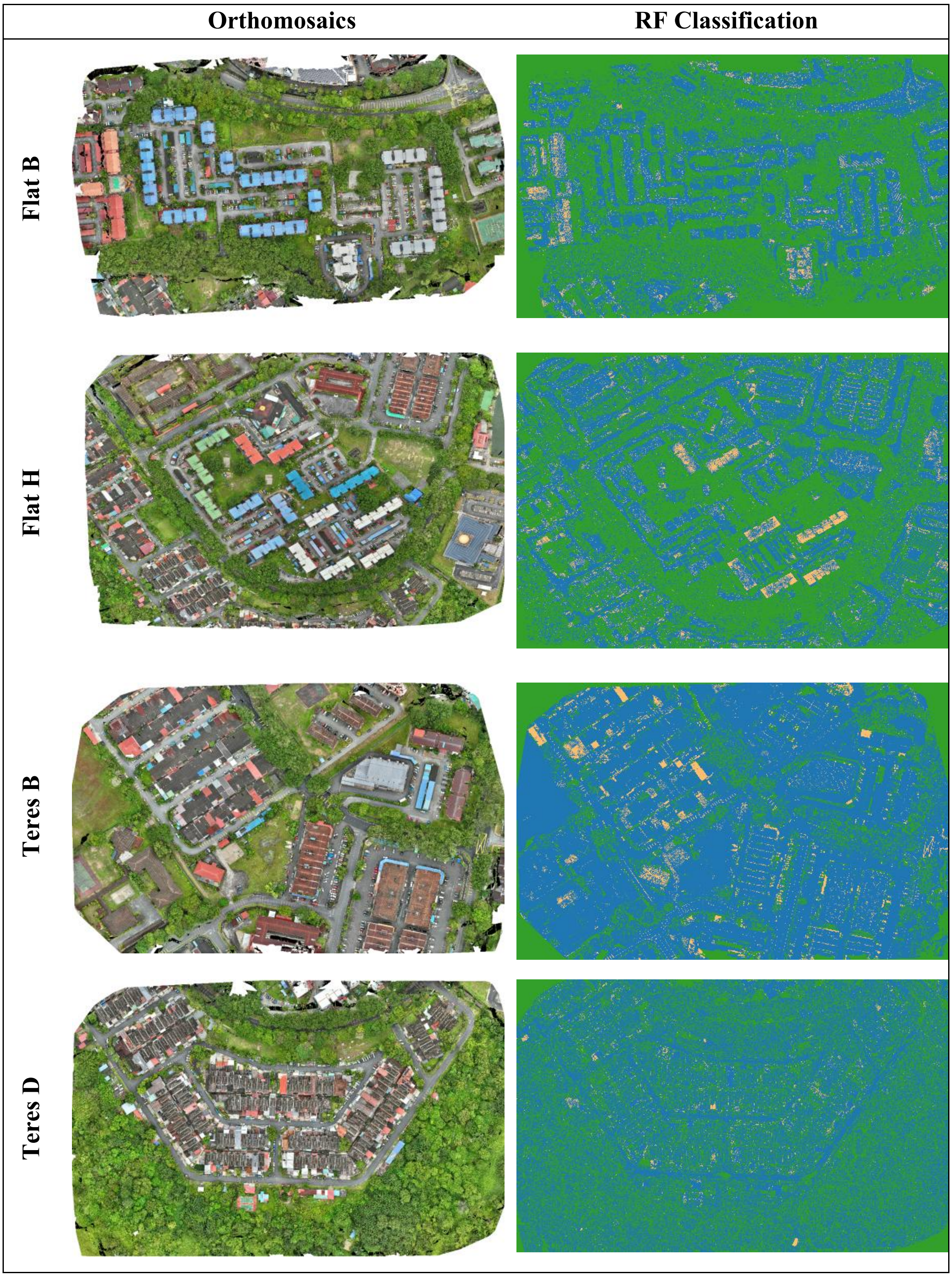

Figure 4.21 Overview of UAV-Derived Orthomosaics and Corresponding RF Land-Cover Classification Outputs for the Four Study Sites

Note: For each site, the upper panels show high-resolution orthomosaic imagery, while the lower panels display the classified land-cover maps distinguishing built-up (blue), vegetation (green), and soil (brown) classes. The maps illustrate apparent differences in urban morphology between flat residential (Flat B, Flat H) and terraced housing (Teres B, Teres D) environments, highlighting the spatial distribution of shaded vegetation and built structures that are relevant to potential *Aedes* breeding habitats.

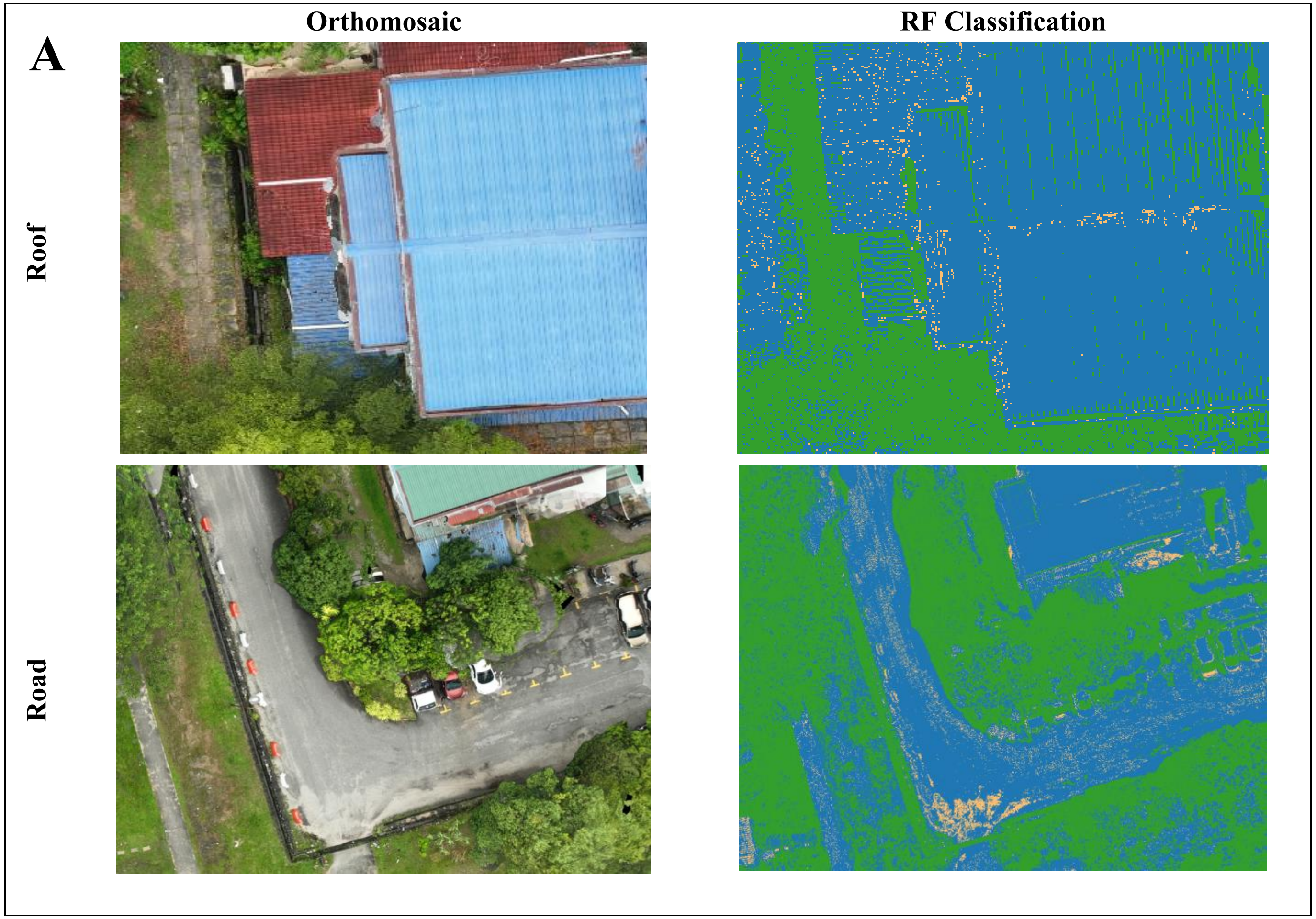

Figure 4.22 Representative Land-Cover Classes Used for Supervised Classification, Showing Paired Orthomosaic Imagery (left) and RF Outputs (right). Panels Illustrate (A) Roofs and Paved Roads, (B) Gardens and Roadside Trees, and (C) Soil Patches and Unpaved Roads. The Examples Demonstrate the Correspondence Between UAV-derived Orthomosaics and ML Classifications in Distinguishing Built Surfaces, Vegetation, and Exposed Ground in Heterogeneous Urban Environments

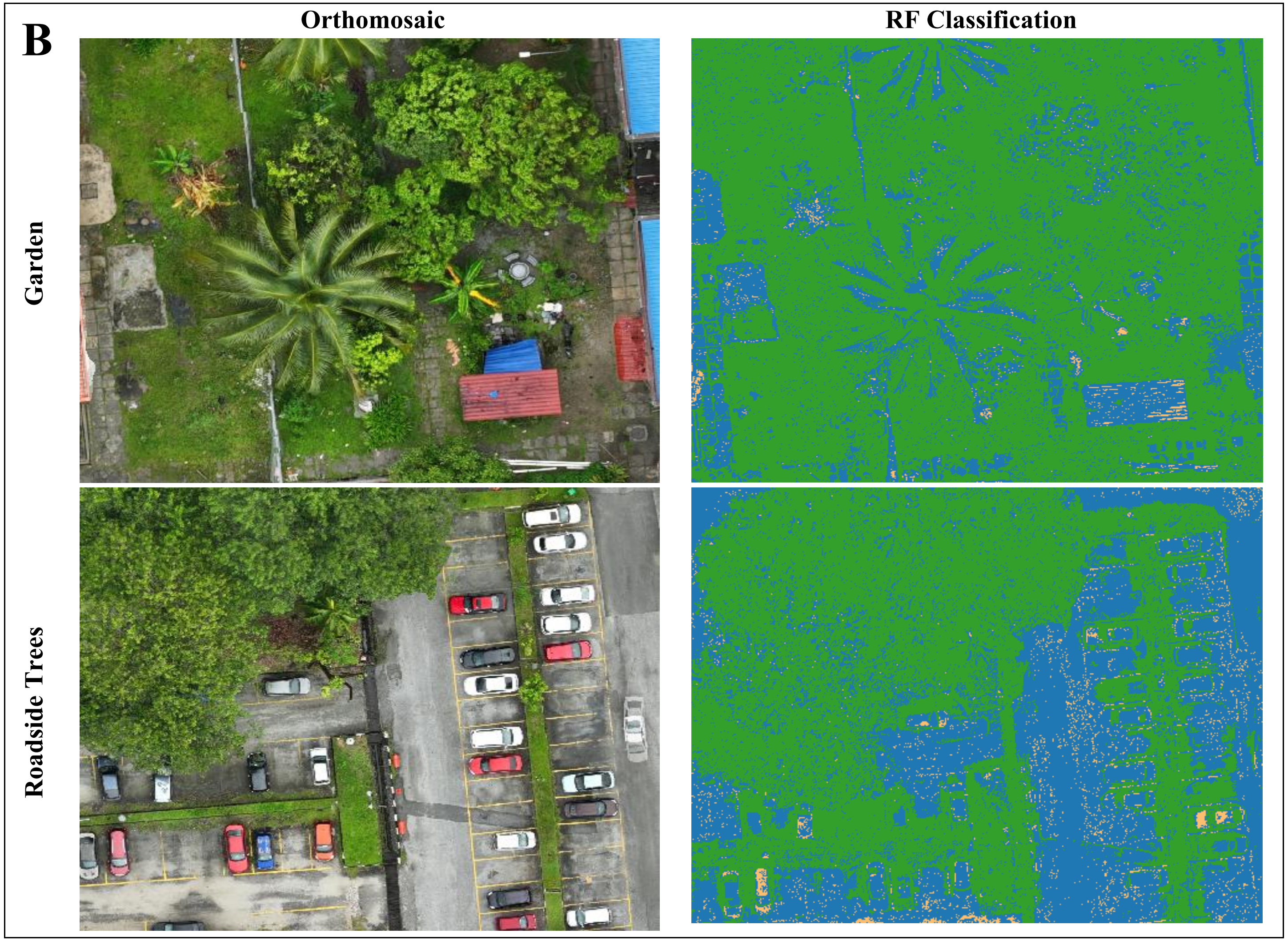

Figure 4.22 Continued…

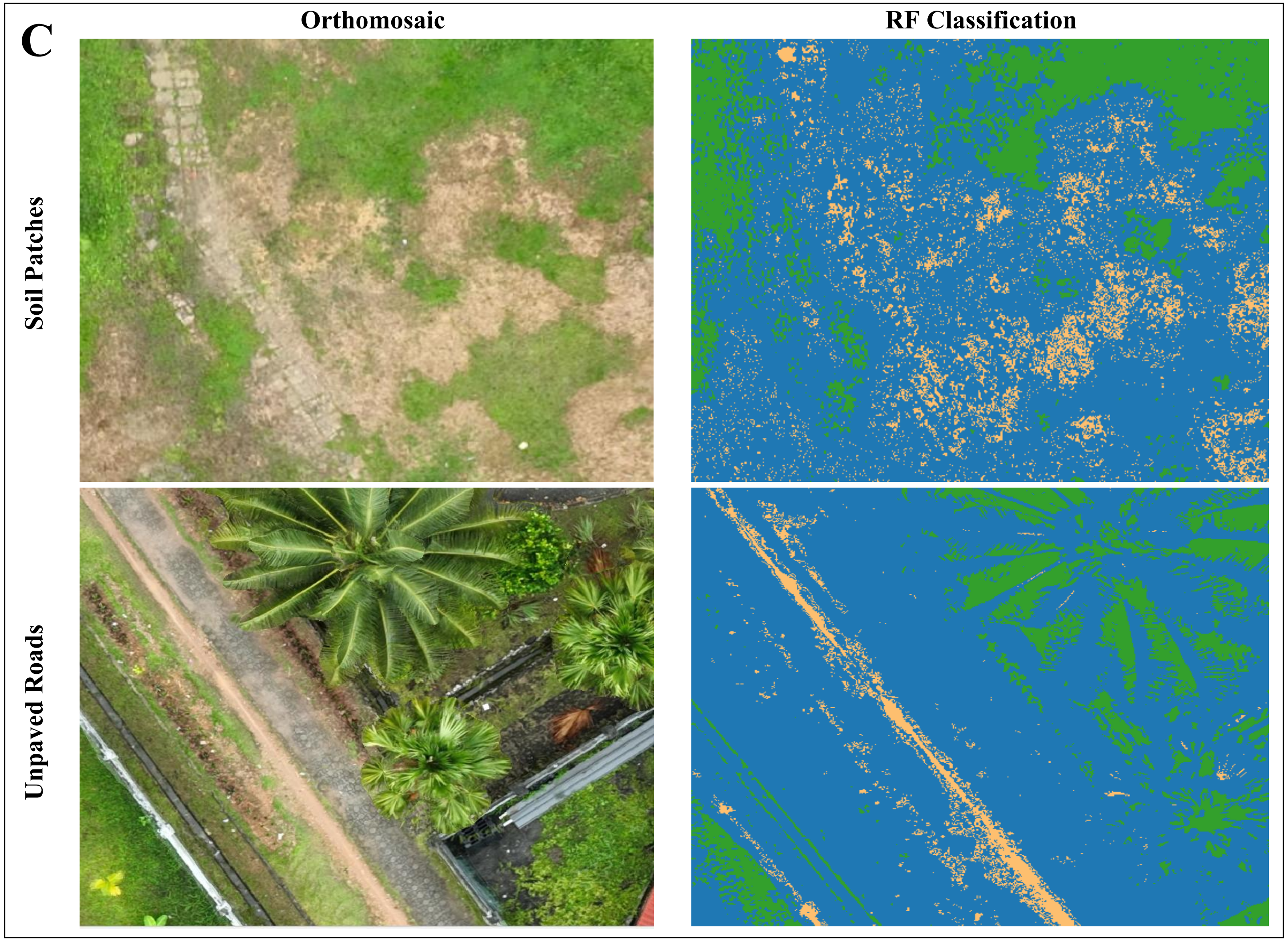

Figure 4.22 Continued…

4.8.5 Cross-Site Transferability of Land-Cover Classifiers and Implications for *Aedes* Habitat Consistency

Cross-site transferability analysis revealed strong dependence on housing typology (Table 4.18). Specifically, RF models transferred between flat residential sites performed poorly and exhibited weak agreement, despite high sensitivity to built-up surfaces. In contrast, transferability between terraced housing sites was substantially stronger, with the Teres B-to-Teres D configuration achieving the highest Overall Accuracy (OA) and κ value. Across all transfer scenarios, vegetation maintained high user accuracy, indicating consistent identification of shaded environments. However, soil demonstrated severe omission; nonetheless, minimal commission. These patterns suggest that *Aedes*-relevant land-cover features are more structurally consistent across terraced housing environments than across flat residential complexes, enhancing model generalisability.

Table 4.18
Cross-Site Transferability of RF Land-Cover Classifiers and Implications for *Aedes* Habitat Consistency

Training Site (RF model)	Test Site	Land-cover Class	Producer's Accuracy (%)	User's Accuracy (%)	Overall Accuracy (%)	Cohen's κ
Flat H	Flat B	Built-up	97.76	31.41	45.08	0.22
		Vegetation	39.57	100.00		
		Soil	7.09	78.06		
Flat B	Flat H	Built-up	96.75	35.53	41.18	0.12
		Vegetation	21.74	100.00		
		Soil	4.98	59.26		
Teres D	Teres B	Built-up	68.96	40.13	54.68	0.33
		Vegetation	94.51	71.74		
		Soil	3.60	100.00		
Teres B	Teres D	Built-up	93.40	58.79	68.76	0.49
		Vegetation	89.75	90.40		
		Soil	5.48	98.83		

Note: PA and UA represent omission and commission errors, respectively, while OA and Cohen's κ summarise cross-site classification performance. Bold values indicate the highest class-specific accuracy and site-level OA and κ within each transfer scenario. All metrics are derived from independent validation ROIs at the test sites.

4.8.6 Discussion

This study demonstrates that UAV-derived RF land-cover classification can reliably characterise urban environmental proxies that are directly relevant to *Aedes* breeding ecology. Thus, by integrating land-cover composition, spectral separability, classification accuracy, and cross-site transferability, the findings provide mechanistic insights into how housing typology and microhabitat structure shape potential breeding environments for *Aede*s.

The dominance of vegetation and built-up classes across all study sites is consistent with extensive entomological evidence highlighting that *Ae. aegypti* and *Ae. albopictus* preferentially exploit shaded, peridomestic environments closely associated with human activity (Ruairuen *et al.*, 2022). Still, the limited spatial extent of soil observed in all sites aligns with prior findings that exposed ground surfaces contribute minimally to persistent *Aedes* breeding, except under transient conditions following rainfall (Newman *et al.*, 2024). In addition, clear contrasts between flat and terraced housing typologies further reinforce the role of urban form in shaping *Aedes* habitat suitability (Cofone *et al.*, 2025). Notably, flat residential sites were characterised by vertically complex built-up blocks surrounded by concentrated vegetation. This produces shaded communal spaces such as corridors, balconies, and landscaped courtyards. These environments are well documented as cryptic breeding hotspots where water-holding containers are challenging to detect through conventional ground inspections (Boyer *et al.*, 2014). In contrast, terraced housing areas exhibited more evenly distributed built-up and vegetation cover. This includes extensive ground-level peridomestic spaces such as front yards, rear lanes, and roadside vegetation. Such settings are consistently identified in previous studies as primary *Aedes* breeding zones due to frequent container availability and regular human-vector contact (Smith *et al.*, 2005; Walmsley, 1995).

The consistent spectral separation of vegetation, built-up, and soil classes across all sites supports the ecological validity of these land-cover proxies for *Aedes* habitat characterisation. Vegetation indicated a pronounced green-band response. This reflects dense canopy and understory cover that contributes to reduced solar radiation, lower surface temperatures, and higher humidity. Meanwhile, microclimatic conditions known to enhance *Aedes* survival and resting behaviour (Dom *et al.*, 2025). In addition, built-up surfaces exhibited elevated red-band reflectance, particularly in terraced housing areas dominated by red and brown roofing materials. These have been associated with increased indoor-outdoor container density and roof-associated breeding sites in previous urban entomological surveys (Dom *et al.*, 2025). In line with this, partial spectral overlap between soil and built-up classes, especially near bare concrete and unpaved surfaces, reflects material-level similarity rather than classification instability. As such, such transition zones frequently coincide with shaded edges, drains, and informal container storage areas that have been reported as productive breeding microhabitats in earlier studies (Bashir & Liaquat, 2025). Thus, the observed spectral behaviour mirrors real-world ecological gradients relevant to *Aedes* proliferation.

High within-site classification accuracy (OA up to 95.84% and κ up to 0.92) indicates that UAV-based RF models can robustly delineate *Aedes*-relevant land-cover features at the neighbourhood scale. Remarkably, vegetation consistently achieved the highest producers' and users' accuracies (> 95%), reinforcing its reliability as a proxy for shaded environments associated with oviposition and adult resting. This finding aligns with previous remote sensing studies that identified vegetation indices and canopy cover as strong predictors of *Aedes* abundance and dengue risk (Sureshkumar & Shekhar, 2025). Built-up surfaces demonstrated high producers' accuracy yet more variable users' accuracy, particularly in flat residential environments. In particular, these commission errors were concentrated in shaded interfaces between buildings and vegetation areas, repeatedly identified in entomological investigations as high-risk zones due to container accumulation, poor drainage, and limited sunlight exposure. Rather than representing a methodological weakness, this behaviour highlights ecologically meaningful ambiguity in which built and vegetated features interact to create optimal *Aedes* microhabitats. The conservative classification of soil, characterised by low producers'; however, very high users' accuracy, is epidemiologically advantageous. Hence, by limiting soil mapping to spectrally unambiguous areas, the model reduces overestimation of low-stability breeding habitats. This is consistent with field evidence that exposed soil contributes little to sustained *Aedes* production compared with shaded artificial containers.

Visual correspondence between RF outputs and orthomosaics confirms that classified land-cover patterns accurately reflect on-ground urban features associated with *Aedes* breeding. In both flat and terraced housing sites, vegetation was correctly mapped in courtyards, gardens, and roadside trees, while built-up pixels aligned with roofs, parking areas, and access roads. Meanwhile, misclassifications were spatially confined to deep-shadow zones and structural-vegetation interfaces, which are frequently reported in previous studies as productive breeding and resting microhabitats. This correspondence strengthens confidence that UAV-derived land-cover maps can serve as operational tools for identifying priority surveillance and intervention zones (Karahan *et al.*, 2025; Sutcuoglu & Kalayci, 2025). Additionally, cross-site transferability analysis revealed strong dependence on housing typology. Poor transferability between flat residential sites suggests that vertical complexity, building height, and internal shading patterns create highly site-specific *Aedes* habitat configurations. This finding is consistent with earlier work reporting that high-rise residential environments exhibit heterogeneous breeding patterns driven by floor level, orientation, and microclimate variability (Stanforth & Johnson, 2025; Mansouri & Zarghami, 2025).

In contrast, substantially stronger transferability between terraced housing sites indicates greater structural consistency in *Aedes*-relevant environments, supporting previous observations that low-rise residential areas exhibit more predictable breeding patterns (Huang *et al.*, 2025). Conversely, the consistently high UA for vegetation across all transfer scenarios further underscores the stability of shaded environments as a universal predictor of *Aedes* habitat suitability, regardless of site. Collectively, these findings align with and extend previous entomological studies by demonstrating that UAV-based land-cover classification can reliably capture environmental proxies central to *Aedes* breeding ecology (Yones & Ma'moun, 2025). Therefore, by explicitly linking classification performance to housing typology and microhabitat structure, this study provides a scalable framework for integrating high-resolution remote sensing into adaptive *Aedes* surveillance and targeted vector control. Such an approach is particularly relevant for urban dengue-endemic settings where conventional larval surveys are resource-intensive and often miss cryptic breeding sites embedded within complex residential environments.

Several limitations should be acknowledged when interpreting this study's findings. First, the land-cover classification was based on three broad spectral classes: built-up, vegetation, and soil, which were intentionally selected as environmental proxies rather than direct indicators of *Aedes* breeding. While these classes are well supported by entomological literature as determinants of shaded, peridomestic microhabitats, the approach does not explicitly capture fine-scale container characteristics (e.g., water presence, container type, or productivity). Consequently, the classified outputs represent potential breeding environments rather than confirmed larval habitats. Second, the analysis relied on visible-band UAV imagery (blue, green, and red bands) without near-infrared or thermal data. Although the results demonstrated strong spectral separability and high classification accuracy (Tables 2 and 3), the inclusion of additional spectral or thermal information could further improve discrimination of shaded, moisture-retaining surfaces that are particularly relevant to *Aedes* ecology. This limitation may partly explain misclassifications observed in deep shadow zones and vegetation-structure interfaces, which are also known to be ecologically complex environments. Third, the study focused on a limited number of residential sites representing two dominant housing typologies (flat and terraced). While this design enabled detailed within- and cross-typology comparisons, it restricts the generalisability of the findings to other urban forms such as detached housing, informal settlements, or mixed-use commercial-residential areas. Notably, the reduced cross-site transferability observed between flat residential sites further suggests that vertical complexity and site-specific architectural features may limit the applicability of a single classifier across heterogeneous high-rise environments.

Furthermore, temporal variability was not explicitly assessed since UAV data were collected during a single survey period. *Aedes* breeding dynamics are known to fluctuate with rainfall, maintenance practices, and seasonal vegetation changes. As such, the static land-cover maps presented here may not fully capture short-term changes in habitat suitability, particularly for transient soil-associated or container-dependent breeding sites. Finally, entomological ground-truthing data (e.g., larval indices or adult mosquito abundance) were not directly integrated into the classification framework. While the environmental proxies used are strongly supported by previous field studies, future work linking UAV-derived land-cover patterns with concurrent entomological surveillance would strengthen causal inference. This includes improving the operational relevance of the model for vector control planning.

4.8.7 Conclusion

This study demonstrates that UAV-derived RF land-cover classification provides a reliable and ecologically meaningful framework for characterising urban environments relevant to *Aedes* breeding. Across contrasting residential typologies, vegetation and built-up surfaces were consistently identified as dominant land-cover classes. This reflects the co-occurrence of shaded microhabitats and peridomestic structures that underpin *Aedes* habitat suitability. In particular, high within-site classification accuracy and stable spectral separability support the robustness of these land-cover proxies. At the same time, observed misclassifications were primarily confined to shaded transition zones that are themselves epidemiologically important. The findings further highlight the influence of housing typology on the spatial consistency and transferability of *Aedes*-relevant habitats, with terraced housing environments exhibiting greater structural uniformity than flat residential complexes. Together, the results underscore the potential of high-resolution UAV imagery combined with ML classification as a scalable tool to support targeted *Aedes* surveillance and adaptive vector control in urban dengue-endemic settings. This is especially true where conventional ground-based inspections are constrained by accessibility and resource limitations.

CHAPTER 5
CONCLUSION

5.1 Introduction

This chapter synthesises the study's main findings and reflects on their implications for dengue prevention from an environmental health perspective. Guided by three objectives and seven aims, the thesis examined (i) sociodemographic determinants of public perception, willingness to adopt drone-assisted interventions, and expert views on drone use in dengue control; (ii) the role of vegetation, shade, and housing typology in shaping *Aedes* habitat risk using drone-based geospatial and microclimate modelling; and (iii) the performance and operational feasibility of ML classification of drone imagery for land-cover mapping in Malaysian urban areas. This chapter draws together these elements into an integrated interpretation. It emphasises that the social, environmental, and technological dimensions must be jointly addressed for drone- and Machine Learning (ML)-based dengue surveillance to be both practical and sustainable. It then concludes by outlining recommendations for future practice, policy, and research.

5.2 Summary of the Results

This study highlights the critical role of sociodemographic factors in shaping public perceptions, engagement, and willingness to adopt drone-based dengue surveillance. While the introduction of drone technology presents a transformative opportunity for vector control, the findings demonstrate that its uptake is stratified by age, residence, housing type, digital connectivity, and contextual factors. As such, younger populations demonstrated a clear preference for technology-driven interventions, including mobile applications and digital surveillance tools. At the same time, older individuals tended to favour more traditional, community-based training. Following this, urban residents were more accepting of drone surveillance than rural communities. Furthermore, concerns regarding privacy, data security, and the legitimacy of surveillance were substantial across both areas, particularly in rural areas. Overall, these patterns highlight that technological innovation is not self-implementing. However, the acceptance depends on perceived fairness, transparency, and relevance to local needs, and is mediated by preexisting levels of trust in organisations and the wider sociopolitical environment.

The study further demonstrates that dengue-related knowledge and practices are unevenly distributed across Malaysia, shaped by both state-specific and urban-rural contexts. Several states exhibited high awareness but weak adoption of preventive behaviours, revealing a persistent knowledge-practice gap. In other states, low knowledge scores coincided with limited preventive action. This heterogeneity indicates that only a customised approach is likely to be effective. In essence, states with high knowledge yet poor practice require intensive behavioural and structural interventions to address barriers to action. In contrast, states with uniformly poor Knowledge, Attitude, and Practice (KAP) need basic awareness, together with environmental and social support. Therefore, these findings provide critical evidence for designing state-tailored, context-specific strategies that extend beyond information provision towards sustainable, community-centred dengue prevention programmes.

The expert perspectives analysed in this study reinforce the view that the success of drone-based mosquito surveillance depends on technical performance, legal, operational, and sociocultural considerations. Accordingly, regulatory constraints, airspace rules, data governance, and privacy protections were viewed as fundamental preconditions for legitimate drone deployment. Equally, public trust and acceptance were found to hinge on transparent communication, meaningful community involvement, and adherence to ethical standards in data collection and use. At the sme time, clear articulation of the purpose and limits of surveillance, responsible data handling, and alignment with existing institutional frameworks emerged as essential to maintaining trust and encouraging participation. Taken together, the social and governance dimensions revealed by this study indicate that drone implementation must be embedded in robust regulatory frameworks and participatory practices if it is to be acceptable and durable.

From an environmental and spatial perspective, this study demonstrates that drone-derived vegetation and shading analytics can precisely delineate *Aedes*-prone microhabitats. This enables precision surveillance and proactive vector management in dense urban tropical settings. Moreover, the combined influence of vegetation, shade, and housing form governs *Aedes* habitat persistence, with low-density terrace neighbourhoods exhibiting higher ecological risk than high-rise environments. Drone-based microclimate modelling and composite risk indices further indicate that shaded, vegetated conditions associated with specific housing morphologies sustain favourable environments for mosquito development. This includes elevated risk concentrates along built vegetation interfaces and persistently shaded facades. Building on this, notified dengue cases were higher in flats. This pattern can occur despite lower vegetation and shade indices since dense occupancy increases human vector contact, host movement shifts exposure beyond the household, and container or infrastructure breeding. This is in addition to variable access for control and differences in surveillance sensitivity in shared spaces, which can elevate transmission and notifications. Overall, the findings suggest that terrace neighbourhoods can sustain persistent ecological risk for *Aedes*, and that derived indices provide fine-scale targets for inspection and source reduction that complement case-based surveillance.

Finally, the study demonstrates that Random Forest (RF) classification of RGB drone imagery can deliver land-cover maps of sufficient accuracy for operational dengue surveillance in Malaysian urban areas. In particular, high accuracies for built-up and vegetation classes are key determinants of *Aedes* habitat suitability, enabling spatial prioritisation of inspection and control resources. At the same time, the limited transferability of models across sites, reflected in reduced accuracies for specific classes, such as soil, in cross-site applications, highlights the importance of spectral and structural heterogeneity between locations. This includes variation in roofing materials, vegetation composition, and illumination. Furthermore, the findings suggest that a hybrid approach, in which modest local training data are collected to recalibrate models while reusing the overall model structure, is operationally feasible. On a similar note, integrated with traditional house-to-house inspections, ML-enhanced surveillance has the potential to transform resource-intensive programmes into more efficient, targeted strategies. As drone technology becomes increasingly accessible, such integrated systems are likely to become standard practice in dengue endemic regions where conventional surveillance infrastructure struggles to cope with high caseloads and rapid urban change.

Overall, this study contributes conceptually by linking community readiness, environmental risk profiling, and algorithmic classification into a single integrated framework for drone-assisted dengue prevention. Methodologically, it demonstrates how household surveys, expert consultation, drone-based geospatial and microclimate modelling, and ML classification can be combined into a coherent workflow for environmental health surveillance. Practically, it provides empirically grounded guidance on how to employ emerging technologies in ways that are socially acceptable, environmentally precise, and operationally realistic.

5.3 The Implication of the Study

This study has important implications for environmental health surveillance and dengue prevention, as it demonstrates that the efficacy of drone and ML approaches depends on more than technical capability. Firstly, the study presents that the effectiveness of drone-assisted dengue surveillance depends on social legitimacy and differentiated community readiness. Building on this, acceptance and willingness to adopt drone-enabled surveillance are patterned by sociodemographic and contextual factors (including age, urban and rural areas, housing type, and digital literacy). Conversely, privacy concerns, data security expectations, and institutional trust strongly shape them. This has a direct implication for implementation. Note that drone surveillance cannot be introduced as a purely technical upgrade. It requires visible governance safeguards, transparent communication about purpose and limits, and engagement approaches tailored to local contexts. Without these conditions, uptake is likely to be uneven, and resistance may be concentrated in settings where surveillance acceptability is contested. Moreover, the public health value of the technology may be undermined despite its technical capability.

Next, the environmental analyses demonstrate that *Aedes* habitat suitability in Malaysian urban settings is structured by micro-scale interactions among vegetation, persistent shade, and housing morphology. This can be measured at an actionable resolution using drone-derived analytics and microclimate modelling. Correspondingly, this shifts dengue prevention from broad area coverage to precision surveillance. For example, field inspections and source reduction can be prioritised around built-vegetation interfaces and persistently shaded surfaces that sustain favourable microclimates for mosquito development. At the same time, the observed divergence between ecological suitability patterns and reported dengue cases confirms that habitat suitability is not equivalent to transmission burden. Consistent with this, ecological risk indices are most defensible when used as hazard and prioritisation tools integrated with case surveillance, operational knowledge of access constraints, and an understanding of exposure pathways in high-density housing.

Lastly, the ML results indicate that land-cover classification using RGB drone imagery can support dengue surveillance by producing maps that are operationally useful for identifying classes central to habitat suitability. This is especially true in built-up surfaces and vegetation. Nevertheless, reduced performance across sites indicates that classifier reliability depends on local heterogeneity in materials, vegetation composition, and illumination and shadow conditions. The practical implication is that ML classification should be treated as a maintained capability rather than a one-off product. Moreover, deployment must include local recalibration with modest site-specific training data and routine validation. The study, therefore, contributes to technical feasibility and an implementation-oriented model for sustaining performance and credibility as environments vary across districts and change over time.

In general, the success of this proposed framework relies on the direct interaction between its three core pillars: social acceptance, environmental modelling, and machine learning. Social acceptance acts as the operational foundation; without community trust, privacy safeguards, and regulatory compliance, drone deployment cannot legally or ethically occur, nor will communities engage with the resulting surveillance data. Once deployment is socially sanctioned, ML provides the scalability, automating the rapid classification of high-resolution drone imagery into relevant land-cover proxies (vegetation, built-up, soil). Finally, environmental modelling translates these classified features into ecologically meaningful targets, identifying the precise shade-vegetation interactions that sustain *Aedes* microhabitats. Together, they form a cohesive workflow where technology (ML) accelerates the extraction of ecological risk (environmental modelling), which is ultimately governed and acted upon by the local population and stakeholders (social acceptance).

5.4 The Strengths and Limitations of the Study

A significant strength of the study is that it treats adoption, acceptability, and legitimacy as empirical determinants of efficacy rather than assumptions. By analysing sociodemographic patterning in perceptions and willingness to adopt drone-assisted approaches, and triangulating these findings with expert and stakeholder perspectives, the study produces evidence that speaks directly to real-world constraints in regulation, ethics, and institutional feasibility. This strengthens the credibility of the conclusions about what would be required for socially acceptable deployment. Despite this, the limitations are consistent with survey-based, cross-sectional evidence. As such, responses may be affected by self-report and social desirability bias, and stated willingness may not fully predict behaviour once drones are deployed in practice.

As for the second objective, drone-derived vegetation and shade analyses, combined with housing typology and microclimate-informed modelling, capture fine-scale conditions relevant to *Aedes* habitat persistence that are often missed by coarser data sources. This provides a stronger basis for precision targeting and advances environmental health surveillance by operationalising microhabitat theory in a measurable workflow. In addition, the key limitation relates to temporal dynamics and the interpretation of dengue notifications. Notably, drone surveys may not capture seasonal variation in rainfall and temperature that shapes breeding conditions, and notification patterns can be influenced by mobility, reporting delays, and infections acquired outside the immediate residential environment. For these reasons, the indices are best interpreted as indicators of habitat suitability and prioritisation tools rather than direct predictors of upcoming incidence.

Finally, the ML component is enhanced by its practical and operational emphasis. Applying an interpretable algorithm to readily available RGB imagery demonstrates the approach's feasibility within practical resource limitations. Additionally, evaluating cross-site performance addresses the common misconception that achieving high accuracy at a single site ensures generalisability to other locations. This provides a credible basis for a scalable calibration strategy. In essence, limitations arise from constraints on sensor information and contextual variability. In particular, RGB imagery is vulnerable to confusion among spectrally similar classes and to shadow and illumination effects. Furthermore, model performance can decline across locations with different materials and vegetation. Accordingly, the approach is best positioned as decision support that requires routine local validation and periodic updating. It should also be integrated with field verification rather than treated as an autonomous classification solution.

5.5 Recommendation

Drone-assisted dengue surveillance should be introduced using a community-centred strategy that prioritises local engagement and feedback. Hence, public health authorities should tailor engagement approaches to sociodemographic differences in preferences and technology readiness. This includes combining digital channels where appropriate with community-based briefings and demonstrations where trust and privacy concerns are heightened. Following this, communication should clearly state the purpose and limitations, describe data-handling practices in plain language, and provide channels for feedback and complaints. In parallel, transparent, publicly accessible procedures should be established for regulatory compliance, data privacy, and access controls. As a result, these steps strengthen trust, reduce resistance, and create the conditions for translating technical surveillance outputs into sustained participation and operational uptake.

Environmental health operations should incorporate drone-derived vegetation-shade analytics and housing morphology insights into routine planning to support precision targeting of surveillance and source reduction. In terrace neighbourhoods, field activities should prioritise microhabitats associated with persistent shade and built-vegetation interfaces. This translates mapped hotspots into targeted inspection routes and environmental management actions. Meanwhile, in high-density flats, where notifications may remain high despite lower ecological indices, interventions should prioritise shared-space breeding opportunities, infrastructure-related water accumulation, waste and container management in communal areas, and access strategies that enable consistent coverage. Across settings, ecological risk maps should be embedded within existing surveillance systems and used alongside case information to guide prioritisation.

When deploying drone-derived RGB land-cover classification for dengue surveillance, acknowledge that performance is context-dependent. Models can achieve strong within-site accuracy. However, they decline markedly when transferred across sites since housing estates differ in spectral and structural characteristics. Thus, embed land-cover classification as a maintained operational system by retaining a baseline architecture, assemble limited locally labelled training data at each new deployment area, and monitor performance routinely. It also prioritises classes most relevant to dengue habitat suitability and field operations.

5.6 Future Research

Several improvements can be made for future work to strengthen the integration of drones and ML into dengue prevention. First, future studies should incorporate more systematic community engagement components. This aims to evaluate how different communication strategies, levels of transparency, and modes of participation influence acceptance of drone-based surveillance over time. Furthermore, comparative studies across urban and rural settings and across age and socioeconomic groups would help identify which approaches are most effective in addressing privacy concerns. This includes building trust and sustaining participation in technology-enabled vector control. Additionally, embedding formal assessments of digital literacy and access into such work would also clarify how application-based, drone-assisted interventions can be designed to avoid excluding digitally marginalised populations.

Second, future research should also refine and extend the environmental risk modelling framework developed in this study. Longitudinal drone surveys across seasons would deepen understanding of how vegetation, shade, and housing typology, in interaction with microclimate, sustain *Aedes* habitats across various housing types and other endemic areas. This, in turn, supports more context-specific, microclimate-informed vector control strategies.

Third, further methodological advances are recommended for the ML component. For instance, applying and comparing different algorithms, including deep learning, may improve classification robustness and cross-site transferability. Future studies should also explore integrating multispectral and thermal sensors with RGB imagery to distinguish better land cover classes that are spectrally similar in standard imagery yet differ in thermal or moisture characteristics relevant to *Aedes* breeding. On a similar note, developing and testing simplified, user-friendly interfaces for these models and evaluating their performance when operated by environmental health personnel rather than researchers would be notable steps towards operational deployment.

Finally, future work should systematically assess the public health impact and cost-effectiveness of drone- and ML-based surveillance when integrated into real-world practice. This includes economic evaluations comparing these approaches with conventional entomological surveys, as well as longitudinal studies linking dynamic risk maps and land cover classifications to entomological indices and dengue incidence.

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APPENDICES

APPENDIX 1

Methodological Quality Appraisal of Included ML/UAV studies (*n* = 8)

Study ID	Data representativeness	Ground truth & labeling	Leakage prevention	Validation design	Reporting transparency	Overall judgment	Key justification
S1	High	High	Moderate	Moderate	High	**High**	Multiple sites and conditions; field-verified labels; train–test split reported but spatial independence not fully discussed.
S2	Moderate	High	Moderate	High	High	**High**	Good labeling and robust validation; limited geographic diversity.
S3	Moderate	Moderate	Low	Moderate	Moderate	**Moderate**	Annotation protocol insufficiently detailed; potential spatial leakage not addressed.
S4	High	Moderate	Moderate	Moderate	High	**High**	Diverse environments and clear model reporting; no independent external validation.
S5	Moderate	Moderate	Moderate	Moderate	Moderate	**Moderate**	Single-site study with adequate but limited validation and reporting.
S6	High	High	High	High	High	**High**	Strong field validation, explicit leakage prevention, and comprehensive reporting.
S7	Moderate	Low	Low	Moderate	Moderate	**Moderate**	Limited description of labeling and no explicit leakage controls.
S8	Moderate	High	Moderate	Moderate	High	**High**	Clear workflow and metrics; external validation absent.

Note. This methodological quality appraisal is specifically designed for drone-based remote sensing and machine-learning workflow studies and therefore evaluates technical and analytical rigor, rather than participant-based bias. Domains focus on data representativeness, ground-truth and labeling procedures, prevention of data leakage, validation design, and reporting transparency; key sources of bias and reproducibility risk in image-based ML research. Ratings were assigned using predefined criteria (High/Moderate/Low) for each domain, and overall judgments were derived from the pattern of domain ratings rather than from numerical score aggregation. This approach aligns with best-practice recommendations for assessing ML and remote-sensing studies and supports transparent interpretation of methodological strengths and limitations across the included literature.

APPENDIX 2

Questionnaire

Section 1: Socio-Demographics

1. Gender
   - ❑ Male
   - ❑ Female

2. Age
   - ❑ 18-30
   - ❑ 31-40
   - ❑ 41-50
   - ❑ 51-60
   - ❑ >60

3. Ethnicity
   - ❑ Malay
   - ❑ Chinese
   - ❑ Indian
   - ❑ Other ______________________________

4. What kind of area do you live in?
   - ❑ Urban
   - ❑ Rural

5. State?
   - ❑ __________

6. How long have you been living in this area?

   - ❑ Below 6 months
   - ❑ 6 months to < 1 year
   - ❑ 1-3 years
   - ❑ Above 3 years

7. What kind of home do you live in?
   - ❑ Bungalow
   - ❑ Semi-Detached
   - ❑ Townhouse
   - ❑ Flat/Apartment
   - ❑ Terrace house
   - ❑ Other (please specify) ____

8. How many individuals live in your household, including yourself?
   - ❑ 1
   - ❑ 2
   - ❑ 3
   - ❑ 4
   - ❑ 5 or more

Section 2 - Technology/Internet Access/Drones:

9. Do you have access to any of the following technological devices? (Please select all that apply)
   - ❑ Mobile/cell phone
   - ❑ Computer
   - ❑ Laptop
   - ❑ Tablet/Notebook/iPad
   - ❑ None of the above
10. How often do you have access to the internet?
    - ❑ Daily
    - ❑ A few times in a week
    - ❑ A few times in a month
    - ❑ Never

11. What device do you most commonly use to access the internet?
    - ❑ Mobile phone
    - ❑ Computer
    - ❑ Laptop
    - ❑ Tablet/Notebook/iPad
    - ❑ None of the above

12. What social media platforms do you or your family use? (Please select all that apply)
    - ❑ Instagram
    - ❑ Facebook
    - ❑ Twitter
    - ❑ Snapchat
    - ❑ WhatsApp
    - ❑ Tiktok
    - ❑ Other ___________(Please specify)

13. How often do you use social media?
    - ❑ Daily
    - ❑ A few times in a week
    - ❑ A few times in a month
    - ❑ A few times in a year
    - ❑ Never

14. How often do you see a drone flying near your home? (Since the answer is referring to the frequency)
    - ❑ Daily
    - ❑ A few times in a week
    - ❑ A few times in a month
    - ❑ A few times in a year
    - ❑ Never

15. Are there any negative things about drones?
    - ❑ Yes
    - ❑ No
    - ❑ Not sure

16. Do you have any concerns about drones flying near your home?
   - ❑ Yes
   - ❑ No
   - ❑ Not sure

Section 3 - Rapid Alert System Application:

17. In this future study, drones would fly over study participants' homes once each week to identify potential mosquito breeding sites. Would you have concerns if a drone flew over your home to capture images around your house(s)?
   - ❑ Yes
   - ❑ No
   - ❑ Not sure

18. Based on drone surveillance, we would develop an app and send people a rapid alert system each week. If you were a participant in a study like this, and this was made available to you, would you be willing to download our app/rapid alert system on your technological device(s)?
   - ❑ Yes
   - ❑ No
   - ❑ Not sure

Section 4 - Participation & Feedback:

19. If alerted about a breeding site using the App, how comfortable would you be with cleaning up that breeding site.
   - ❑ Very comfortable
   - ❑ Somewhat comfortable
   - ❑ Comfortable
   - ❑ Somewhat uncomfortable
   - ❑ Very uncomfortable

20. If alerted about a breeding site, how far would you be willing to travel to help clean up that breeding site?
   - ❑ 100-200 meters
   - ❑ 200-500 meters
   - ❑ 500m- 1km
   - ❑ 1-5km
   - ❑ > 6 km

21. Ovitraps or oviposition traps are devices used to collect the eggs laid down by the mosquitoes which develop into larva, pupa and adult mosquitoes. Would you be comfortable and willing to complete a training session about mosquito control (cleaning the breeding sites, counting the eggs from ovitraps, and receive educational materials/resources, etc.)?
   - ❑ Yes
   - ❑ No
   - ❑ Not sure

22. Do you think you would naturally share your experience about the rapid alert system, breeding sites detection and your prompt action via social media (Facebook, Instagram, Twitter, etc.)?
   - ❑ Yes
   - ❑ No
   - ❑ Not sure

Section 5: Household Mosquito Breeding Prevention

23. What diseases can mosquitoes cause? (choose all that apply)
    - ❑ Dengue Fever
    - ❑ Chikungunya
    - ❑ Zika
    - ❑ Malaria
    - ❑ West Nile Virus
    - ❑ Do not know

24. Do you personally feel at risk of mosquito diseases?
    - ❑ Yes
    - ❑ No
    - ❑ Not sure

25. In the last year, did you take any measures to eliminate mosquitos in your household?
    - ❑ Yes
    - ❑ No
    - ❑ Not sure

26. *What measures did you take for mosquito control?* (Please circle your answer)

Used insecticide sprays to reduce mosquitoes	Yes	No	Not Applicable
Cleaned water containers	Yes	No	Not Applicable
Covered water containers	Yes	No	Not Applicable
Treated water in water containers	Yes	No	Not Applicable
Used professional pest control to reduce mosquitoes	Yes	No	Not Applicable
Used screen windows to reduce mosquitoes	Yes	No	Not Applicable
Eliminated standing water around the house to reduce mosquitoes	Yes	No	Not Applicable
Used mosquito coils to reduce mosquitoes	Yes	No	Not Applicable
Cleaned garbage/trash	Yes	No	Not Applicable
Cut down vegetation around the house	Yes	No	Not Applicable
Used smoke to drive away mosquitoes	Yes	No	Not Applicable
Covered body with protective clothing	Yes	No	Not Applicable
Turned containers upside down to avoid water collection	Yes	No	Not Applicable
Disposed of old tires	Yes	No	Not Applicable

27. How often did you use measures to control mosquitos?
    - ❑ Weekly
    - ❑ Bi-weekly
    - ❑ Every month
    - ❑ Every few months

28. Are any of the following items present in your yard? (Please circle your answer)

Discarded tires	Yes	No	Not Applicable
Cans	Yes	No	Not Applicable
Plastic bottles	Yes	No	Not Applicable
Coconut shells	Yes	No	Not Applicable
Flower vases	Yes	No	Not Applicable
Holes in ground	Yes	No	Not Applicable
Water jars	Yes	No	Not Applicable
Water tanks	Yes	No	Not Applicable
Window/door screens	Yes	No	Not Applicable
Water duct	Yes	No	Not Applicable

29. What methods do you use to eliminate *Aedes* mosquito breeding sites? (Please select all that apply)
- ❑ Cleaning water containers regularly
- ❑ Covering water containers
- ❑ Cut down vegetation around the home
- ❑ Dispose old tires
- ❑ Treat water in water containers
- ❑ Remove area where water can be stagnant

30. How often do you clean water filled containers and ditches around the house?
- ❑ Always
- ❑ Often
- ❑ Sometimes
- ❑ Never

31. Do you use any kind of mosquito control **against larvae (baby mosquitoes)** in your household?
- ❑ Yes
- ❑ No
- ❑ Not sure

32. Do you use any kind of mosquito control **against adult mosquitoes** in your household?
- ❑ Yes
- ❑ No
- ❑ Not sure

33. What kind of adult control do you use? (Please select all that apply)
- ❑ **Mosquito nets**
- ❑ **Household insecticide sprays**
- ❑ **Fogging**
- ❑ **Mosquito swatter**
- ❑ **Repellent**
- ❑ **Other:** ______________________________

34. How often do you use the following methods for adult mosquito control?

	Daily	Weekly	Monthly	Every 3 months	More than 3 months
Mosquito nets					
Household insecticide sprays					
Fogging					
Mosquito swatter					
Repellent					

35. This coming rainy season, I will check my house and yard for mosquito breeding sites regularly and eliminate them if necessary.
- ❑ Strongly Agree
- ❑ Agree
- ❑ Neutral
- ❑ Disagree
- ❑ Strongly Disagree

36. I will check for mosquito breeding grounds and, if necessary, eliminating them.
- ❑ Strongly Agree
- ❑ Agree
- ❑ Neutral
- ❑ Disagree
- ❑ Strongly Disagree

37. I still try to prevent mosquitoes from living around my home even if my neighbors do not.
- ❑ Strongly Agree
- ❑ Agree
- ❑ Neutral
- ❑ Disagree
- ❑ Strongly Disagree

38. If there was a new, non-chemical/non-insecticide method of killing mosquitoes around my home, I would try it.
- ❑ Strongly Agree
- ❑ Agree
- ❑ Neutral
- ❑ Disagree
- ❑ Strongly Disagree

39. If you had standing water around your home, could you identify if mosquito larvae (baby mosquito) were living in it?
- ❑ Yes
- ❑ No

APPENDIX 3

Table of Item Code for Questionnaire

Metric	Item Code	Item
Technology and internet access	TI_1	Do you have access to any of the following technological devices?
	TI_2	How often do you have access to the internet?
Social media	SM_1	What device do you most commonly use to access the internet?
	SM_2	What social media platforms do you or your family use?
	SM_3	How often do you use social media?
Drone perception	DP_1	How often do you see a drone flying near your home?
	DP_2	Are there any negative things about drones?
	DP_3	Do you have any concerns about drones flying near your home?
	DP_4	In this future study, drones would fly over study participants' homes once each week, at a specific time, to identify potential mosquito breeding sites. Would you have concerns if a drone flew over your home to capture images around your house(s)?
Alert system development	AS_1	Based on drone surveillance, we would develop an app and send people a rapid alert system each week. If you were a participant in a study like this, which was made available to you, would you be willing to download our app/rapid alert system on your technological device(s)?
	AS_2	If alerted about a breeding site using the App, how comfortable would you be with cleaning up that breeding site?
	AS_3	If alerted about a breeding site, how far would you be willing to travel to help clean up that breeding site?
	AS_4	Ovitraps or oviposition traps are devices used to collect the eggs laid down by the mosquitoes which develop into larvae, pupa, and adult mosquitoes. Would you be comfortable and willing to complete a training session about mosquito control?
	AS_5	Do you think you would naturally share your experience about the rapid alert system, breeding sites detection, and your prompt action via social media?
Knowledge level about mosquito borne diseases	KL_1	What diseases can mosquitoes cause?
	KL_2	Do you personally feel at risk of mosquito diseases?
Behavior and practice related to mosquito control	BP_1	In the last year, did you take any measures to eliminate mosquitos in your household?
	BP_2	What measures did you take for mosquito control?
	BP_3	How often did you use measures to control mosquitos?
	BP_4	Are any of the following items present in your yard?
	BP_5	What methods do you use to eliminate *Aedes* mosquito breeding sites?
	BP_6	How often do you clean water-filled containers and ditches around the house?
	BP_7	Do you use any kind of mosquito control against larvae (baby mosquitoes) in your household?
	BP_8	Do you use any kind of mosquito control against adult mosquitoes in your household?
	BP_9	What kind of adult control do you use?
	BP_10	How often do you use the following methods for adult mosquito control?

	BP_11	This coming rainy season, I will check my house and yard for mosquito breeding sites regularly and eliminate them if necessary.
	BP_12	I will check for mosquito breeding grounds and, if necessary, eliminating them.
	BP_13	I still try to prevent mosquitoes from living around my home even if my neighbors do not.
	BP_14	If there were a new, non-chemical/non-insecticide method of killing mosquitoes around my home, I would try it.
	BP_15	If you had standing water around your home, could you identify if mosquito larvae (baby mosquitoes) lived in it?

APPENDIX 4

Table of Face Validity Index Scores for the Questionnaire

Metric	Item Code	Rater											
		1	2	3	4	5	6	7	8	9	10	Raters in agreement	I-FVI
Technology and internet access	TI_1	1	1	1	1	1	1	1	1	1	1	10	1
	TI_2	1	1	1	1	1	1	1	1	1	1	10	1
Social media	SM_1	1	1	1	1	1	1	1	1	1	1	10	1
	SM_2	1	1	1	1	1	1	1	1	1	1	10	1
	SM_3	1	1	1	1	1	1	1	1	1	1	10	1
Drone perception	DP_1	1	1	1	1	1	1	1	1	1	1	10	1
	DP_2	1	1	1	1	1	1	1	0	1	1	9	0.9
	DP_3	1	1	1	1	1	1	1	1	1	1	10	1
	DP_4	1	1	1	1	1	1	1	1	1	1	10	1
Alert system development	AS_1	1	1	1	1	1	1	1	1	1	1	10	1
	AS_2	1	1	1	1	1	0	1	1	1	1	9	0.9
	AS_3	1	1	1	0	1	1	1	1	1	1	9	0.9
	AS_4	1	1	1	1	1	1	1	1	1	1	10	1
	AS_5	1	1	1	1	1	1	1	1	1	1	10	1
Knowledge level about mosquito borne diseases	KL_1	1	1	1	1	1	1	1	1	1	1	10	1
	KL_2	1	1	1	1	1	1	1	1	1	1	10	1
Behavior and practice related to mosquito control	BP_1	1	1	1	1	1	1	0	1	1	1	9	0.9
	BP_2	1	1	1	1	1	1	1	1	1	1	10	1
	BP_3	1	1	1	1	1	1	1	1	1	1	10	1
	BP_4	1	1	1	1	1	1	1	1	1	1	10	1
	BP_5	1	1	1	1	1	1	1	1	1	1	10	1
	BP_6	1	1	1	1	1	1	1	1	1	1	10	1
	BP_7	1	1	1	1	1	1	1	1	1	1	10	1
	BP_8	1	1	1	1	1	1	1	1	1	1	10	1
	BP_9	1	1	1	1	1	1	1	1	1	1	10	1
	BP_10	1	1	1	1	1	1	1	1	1	1	10	1
	BP_11	1	1	1	1	1	0	1	1	1	1	9	0.9
	BP_12	1	1	1	1	1	1	1	1	1	1	10	1
	BP_13	1	1	1	1	1	1	1	1	1	1	10	1
	BP_14	1	1	1	1	1	1	1	1	1	1	10	1
	BP_15	1	1	1	1	1	1	1	1	1	1	10	1
												S-FVI/Ave	0.98

APPENDIX 5

Table of Content Validity Index Scores for the Questionnaire

Metric	Item Code	Expert (Rating 1-4)					Number of experts rating 3 and 4	I-CVI	Interpretation
		1	2	3	4	5			
Technology and internet access	TI_1	4	4	4	4	4	5	1	Relevant
	TI_2	4	4	4	4	4	5	1	Relevant
Social media	SM_1	4	4	4	4	4	5	1	Relevant
	SM_2	4	4	4	4	4	5	1	Relevant
	SM_3	4	4	4	4	4	5	1	Relevant
Drone perception	DP_1	4	3	3	2	4	4	0.8	Relevant
	DP_2	4	4	4	4	4	5	1	Relevant
	DP_3	4	4	4	4	4	5	1	Relevant
	DP_4	4	4	4	4	4	5	1	Relevant
Alert system development	AS_1	4	3	4	4	4	5	1	Relevant
	AS_2	4	3	3	2	4	4	0.8	Relevant
	AS_3	4	3	3	2	4	4	0.8	Relevant
	AS_4	3	4	4	3	3	5	1	Relevant
	AS_5	3	3	3	4	4	5	1	Relevant
Knowledge level about mosquito borne diseases	KL_1	4	4	4	4	4	5	1	Relevant
	KL_2	4	4	4	4	4	5	1	Relevant
Behavior and practice related to mosquito control	BP_1	4	3	4	3	4	5	1	Relevant
	BP_2	4	4	4	4	4	5	1	Relevant
	BP_3	4	4	4	4	4	5	1	Relevant
	BP_4	4	4	4	4	4	5	1	Relevant
	BP_5	4	4	4	4	4	5	1	Relevant
	BP_6	4	4	4	4	4	5	1	Relevant
	BP_7	4	4	4	4	4	5	1	Relevant
	BP_8	4	4	4	4	4	5	1	Relevant
	BP_9	4	4	4	4	4	5	1	Relevant
	BP_10	4	4	4	4	4	5	1	Relevant
	BP_11	4	3	3	2	4	4	0.8	Relevant
	BP_12	4	4	4	4	4	5	1	Relevant
	BP_13	4	4	4	3	4	5	1	Relevant
	BP_14	4	4	4	4	4	5	1	Relevant
	BP_15	4	4	4	4	4	5	1	Relevant
S-CVI/Ave (minimum 0.8)								**0.97**	**Accepted**

APPENDIX 6

Table of Content Validity Index Scores for the Questionnaire

Metric	Item Code	Expert (Rating 1-4)					ne (Essential)	CVR	Interpreatation
		1	2	3	4	5			
Technology and internet access	TI_1	4	4	4	4	4	5	1	Essential
	TI_2	4	4	4	4	4	5	1	Essential
Social media	SM_1	4	4	4	4	4	5	1	Essential
	SM_2	4	4	4	4	4	5	1	Essential
	SM_3	4	4	4	4	4	5	1	Essential
Drone perception	DP_1	4	3	3	3	4	5	1	Essential
	DP_2	4	4	4	4	4	5	1	Essential
	DP_3	4	4	4	4	4	5	1	Essential
	DP_4	4	4	4	4	4	5	1	Essential
Alert system development	AS_1	4	3	4	4	4	5	1	Essential
	AS_2	4	3	3	3	4	5	1	Essential
	AS_3	4	3	3	3	4	5	1	Essential
	AS_4	3	4	4	3	3	5	1	Essential
	AS_5	3	3	3	4	4	5	1	Essential
Knowledge level about mosquito borne diseases	KL_1	4	4	4	4	4	5	1	Essential
	KL_2	4	4	4	4	4	5	1	Essential
Behavior and practice related to mosquito control	BP_1	4	3	4	3	4	5	1	Essential
	BP_2	4	4	4	4	4	5	1	Essential
	BP_3	4	4	4	4	4	5	1	Essential
	BP_4	4	4	4	4	4	5	1	Essential
	BP_5	4	4	4	4	4	5	1	Essential
	BP_6	4	4	4	4	4	5	1	Essential
	BP_7	4	4	4	4	4	5	1	Essential
	BP_8	4	4	4	4	4	5	1	Essential
	BP_9	4	4	4	4	4	5	1	Essential
	BP_10	4	4	4	4	4	5	1	Essential
	BP_11	4	3	3	3	4	5	1	Essential
	BP_12	4	4	4	4	4	5	1	Essential
	BP_13	4	4	4	3	4	5	1	Essential
	BP_14	4	4	4	4	4	5	1	Essential
	BP_15	4	4	4	4	4	5	1	Essential
Minimum CVR required (for each item)								**0.99**	**Accepted**

APPENDIX 7

Research Ethics Approval

www.uitm.edu.my

UNIVERSITI TEKNOLOGI MARA | Pejabat Timbalan Naib Canselor (Penyelidikan dan Inovasi)

Reference : 600-TNCPI (5/1/6)
Our reference : REC/07/2023 (ST/MR/183)
Date : 21 July 2023

Mr Zulfadli bin Mahfodz
Centre for Environmental Health and Safety Studies
Faculty of Health Sciences
UiTM Puncak Alam Campus
42300 Puncak Alam
SELANGOR

Dear Mr Zulfadli,

APPROVAL LETTER - UiTM RESEARCH ETHICS COMMITTEE

Thank you for submitting your research proposal to the Research Ethics Committee (REC). After considering your application, the Committee approved your proposal titled "Development of an Automated Drone-based Model to Identify Potential Breeding Sites of Aedes Mosquitoes Using Machine Learning Algorithms" in Selangor.

Details of the approval are as follows:

Ref. number:	REC/07/2023 (ST/MR/183)
Approval Period:	21 July 2023 until 31 December 2024
Authorised personnel:	1. Zulfadli bin Mahfodz 2. Assoc. Prof. Dr Nazri bin Che Dom

The UiTM Research Ethics Committee operates in accordance to the ICH Good Clinical Practice Guidelines, Malaysian Good Clinical Practice Guidelines and the Declaration of Helsinki. The approval of this project is conditional upon your continuing compliance with these guidelines and declaration.

We draw to your attention the requirement that a report on this research, must be submitted every 12 months from the date of the approval or on the completion of the project, whichever occurs first. Failure to submit reports will result in withdrawal of consent for the project to proceed. Amendments, if any, to the study documents are to be submitted to the REC for approval.

If you require further information, please contact the REC Secretariat at 03-55448069/03-55442794 or email at recsecretariat@uitm.edu.my.

Yours sincerely,

EMERITUS PROFESSOR DATO' DR RAYMOND AZMAN ALI
Chairman
UiTM Research Ethics Committee

c.c.: Dean, Faculty of Health Sciences, UiTM

Universiti Teknologi MARA
Aras 3, Bangunan Wawasan
40450 Shah Alam, Selangor, MALAYSIA
Tel: (+603) 5544 2004/2755
Faks: (+603) 5544 2070

UiTM di hatiku

APPENDIX 8

Research Ethics Approval (Ministry of Health)

JAWATANKUASA ETIKA & PENYELIDIKAN PERUBATAN
(*Medical Research & Ethics Committee*)
KEMENTERIAN KESIHATAN MALAYSIA
d/a Kompleks Institut Kesihatan Negara
Blok A, No 1, Jalan Setia Murni U13/52,
Seksyen U13, Bandar Setia Alam,
40170 Shah Alam, Selangor.

Tel: 03-3362 8888/8205

Ref : 24-00374-8SP (2)
Date: 25-March-2024

DR. NAZRI BIN CHE DOM
UNIVERSITI TEKNOLOGI MARA (UITM)

Dear Sir/ Mdm,

ETHICS INITIAL APPROVAL: NMRR ID-24-00374-8SP (IIR)
Development of An Automated Drone-based Model to Identify Potential Breeding Sites of Aedes Mosquitoes Using Machine Learning Algorithms

This letter is made in reference to the above matter.

2. The Medical Research and Ethics Committee (MREC), Ministry of Health Malaysia (MOH) has provided ethical approval for this study. Please take note that all records and data are to be kept strictly **CONFIDENTIAL** and can only be used for the purpose of this study. All precautions are to be taken to maintain data confidentiality. Permission from the District Health Officer / Hospital Administrator / Hospital Director and all relevant heads of departments / units where the study will be carried out must be obtained prior to the study. You are required to follow and comply with their decision and all other relevant regulations.

3. The investigators and study sites involved in this study are:

PEJABAT KESIHATAN DAERAH KUALA LANGAT
Dr. Nazri Bin Che Dom (Principal Investigator)
Zulfadli Bin Mahfodz

PEJABAT KESIHATAN DAERAH KLANG
Dr. Nazri Bin Che Dom (Principal Investigator)
Zulfadli Bin Mahfodz

PEJABAT KESIHATAN DAERAH GOMBAK
Dr. Nazri Bin Che Dom (Principal Investigator)
Zulfadli Bin Mahfodz

PEJABAT KESIHATAN DAERAH KUALA SELANGOR
Dr. Nazri Bin Che Dom (Principal Investigator)
Zulfadli Bin Mahfodz

PEJABAT KESIHATAN DAERAH PETALING
Dr. Nazri Bin Che Dom (Principal Investigator)
Zulfadli Bin Mahfodz

PEJABAT KESIHATAN DAERAH SEPANG
Dr. Nazri Bin Che Dom (Principal Investigator)
Zulfadli Bin Mahfodz

PEJABAT KESIHATAN DAERAH HULU LANGAT
Dr. Nazri Bin Che Dom (Principal Investigator)
Zulfadli Bin Mahfodz

Ref : 24-00374-8SP (2)

PEJABAT KESIHATAN DAERAH SABAK BERNAM
Dr. Nazri Bin Che Dom (Principal Investigator)
Zulfadli Bin Mahfodz

PEJABAT KESIHATAN DAERAH HULU SELANGOR
Dr. Nazri Bin Che Dom (Principal Investigator)
Zulfadli Bin Mahfodz

4. The following study documents have been received and reviewed with reference to the above study:

Documents received and reviewed with reference to the above study: 1. Study Protocol_Version 1.3, dated 16-Mar-2024 2. Patient Information Sheet & Informed Consent Form (Eng)_Version 1.3, dated 16-Mar-2024 3. Patient Information Sheet & Informed Consent Form (BM)_Version 1.3, dated 16-Mar-2024 4. Interview Guide_Version 1.3, dated 16-Mar-2024 5. Investigator's documents : Declaration of Conflict of Interest (COI), IA-HOD-IA, and CV: a) Dr. Nazri Bin Che Dom (Principal Investigator) b) Zulfadli Bin Mahfodz

5. Please note that ethical approval is valid until **24-March-2025**. The following are to be reported upon receiving ethical approval. Required forms can be obtained from the National Medical Research Regisry (NMRR) website:

i. **Continuing Review Form** has to be submitted to MREC within 2 month (60 days) prior to the expiry of ethical approval.
ii. **Study Final Report** upon study completion to the MREC.
iii. Ethical approval is required in the case of **amendments / changes** to the **study documents/ study sites/ study team**. MREC reserves the right to withdraw ethical approval if changes to study documents are not completely declared.

6. This study involves the following methods:

i. Interview

7. Please take note that the reference number for this letter must be stated in all correspondence related to this study to facilitate the process.

Comments (if any): NIL

Project Sites:
PEJABAT KESIHATAN DAERAH KUALA LANGAT
PEJABAT KESIHATAN DAERAH KLANG
PEJABAT KESIHATAN DAERAH GOMBAK
PEJABAT KESIHATAN DAERAH KUALA SELANGOR
PEJABAT KESIHATAN DAERAH PETALING
PEJABAT KESIHATAN DAERAH SEPANG
PEJABAT KESIHATAN DAERAH HULU LANGAT
PEJABAT KESIHATAN DAERAH SABAK BERNAM
PEJABAT KESIHATAN DAERAH HULU SELANGOR

Ref : 24-00374-8SP (2)

Decision by Medical Research & Ethics Committee:
(√) Approved
(   ) Disapproved

Date of Approval : 25-March-2024

DR NURAIN MOHD NOOR
Chairperson
Medical Research & Ethics Committee
Ministry of Health Malaysia
MMC No: 31576

MKY/Approval2024/Mrecshare

APPENDIX 9

Drone Flight Permit from Jabatan Ukur & Pemetaan Malaysia (JUPEM)

JUPEM

PERMIT PENGGAMBARAN / PEMETAAN UDARA

KELULUSAN PERMIT

JENIS PERMIT	PERMIT PENGGAMBARAN UDARA
NO, RUJUKAN PERMIT	JUPEM.BGSP.2024.2444.UDARA
ZULFADLI BIN MAHFODZ	5, JALAN CEMPAKA KUNING 3, TAMAN CEMPAKA, 42700 BANTING, SELANGOR , 42700, BANTING, SELANGOR
KAWASAN PENGGAMBARAN	SEKSYEN 24, SHAH ALAM
TUJUAN PENGGAMBARAN	BAGI TUJUAN PENYELIDIKAN OLEH FAKULTI SAINS KESIHATAN, UITM CAWANGAN SELANGOR, KAMPUS PUNCAK ALAM
HAD KETINGGIAN (METER)	120

TARIKH PENERBANGAN / PENAWANAN DATA

BIL	TARIKH	BIL	TARIKH
1	21-09-2024	2	22-09-2024

SENARAI JURUTERBANG & JURUGAMBAR YANG DIDAFTARKAN DI DALAM PERMIT INI

NAMA	NO KP / PASSPORT	KERAKYATAN	NO. TELEFON
ZULFADLI BIN MAHFODZ (PEMOHON)		MALAYSIA	
NIK NORFATHIN NADZIRAH BT NIK MOHAMMED ZAIRUL (JURUTERBANG)		MALAYSIA	
NIK NORFATHIN NADZIRAH BT NIK MOHAMMED ZAIRUL (JURUGAMBAR)		MALAYSIA	

SENARAI PESAWAT YANG DIDAFTARKAN DI DALAM PERMIT INI

JENIS	DIPUNYAI OLEH	NO DAFTAR
UAV	TEGUH INOVASI (M) SDN BHD	1581F5FHB22A70020ACS

PERINGATAN

1. PERMIT YANG DIKELUARKAN UNTUK MEMBUAT PENAWANAN DAN PENCITRAAN DATA DI SEKITAR KAWASAN SEKSYEN 24, SHAH ALAM DILULUSKAN DENGAN BERSYARAT.
2. PEMOHON ADALAH BERTANGGUNGJAWAB UNTUK MEMAJUKAN PERMOHONAN NOTICE TO AIRMEN (NOTAM) KEPADA PIHAK BERKUASA PENERBANGAN AWAM MALAYSIA (CIVIL AVIATION AUTHORITY OF MALAYSIA) BAGI KELULUSAN PENGGUNAAN RUANG UDARA.
3. PEMOHON DIKEHENDAKI MENYERAHKAN SALINAN CITRAAN ASAL DENGAN SERTA MERTA (14 HARI) SETELAH DIPROSES UNTUK KELULUSAN SEBELUM IANYA DIGUNAKAN.

PERMIT

4.	PEMOHON DIKEHENDAKI MEMBUAT PENYERAHAN DATA PRODUK AKHIR HASIL PENGAMBILAN CITRAAN KEPADA PIHAK JUPEM DALAM TEMPOH 3 BULAN DAN 6 BULAN SEBAGAIMANA YANG TERMAKTUB DI BAHAGIAN II PARA 13 (III) DAN PARA 14 (V), PEKELILING AM BIL. 1 TAHUN 2007
5.	SEBARANG KEHILANGAN, HENDAKLAH DILAPORKAN DENGAN SERTA-MERTA DI BALAI POLIS YANG BERDEKATAN. SATU SALINAN LAPORAN POLIS HENDAKLAH DIHANTAR KEPADA PENGARAH PEMETAAN NEGARA MALAYSIA SELEWAT-LEWATNYA DUA (2) MINGGU DARIPADA TARIKH LAPORAN DIBUAT.
6.	SEKIRANYA PERLU, PEMERHATI RASMI DIREKTORAT AKAN MENGIRINGI OPERASI PENGAMBILAN CITRAAN SEPERTI YANG TERMAKTUB DI BAHAGIAN II PARA 14 (VI), PEKELILING AM BIL. 1 TAHUN 2007 DAN KOS DITANGGUNG SEPENUHNYA OLEH PEMOHON.

DATO' PAHLAWAN Sr DR MOHD
ZAMBRI BIN MOHAMAD RABAB
BRIG JEN
BP PENGARAH PEMETAAN NEGARA
MALAYSIA
IBU PEJABAT JABATAN UKUR DAN
PEMETAAN MALAYSIA
BAHAGIAN GEOSPATIAL PERTAHANAN
TINGKAT 2, BANGUNAN UKUR
JALAN YAHYA PETRA
50578 KUALA LUMPUR MALAYSIA
TEL: 03-2617941

NOTA: CETAKAN KOMPUTER. TIDAK PERLU DITANDATANGANI.

APPENDIX 10

Drone Flight Permit from Majlis Bandaraya Shah Alam (MBSA)

مجليس بندراي شاه عالم
MAJLIS BANDARAYA SHAH ALAM
WISMA MBSA, PERSIARAN PERBANDARAN,
PETI SURAT 7200, 40000 SHAH ALAM,
SELANGOR DARUL EHSAN.

Talian Bebas Tol : 1800-88-4477
Tel : 03-5510 5133
Faks : 03-5510 8010
Portal Rasmi : www.mbsa.gov.my
E-mel : mbsa@mbsa.gov.my

#KitaSelangor

Ruj Tuan :
Ruj Kami : MBSA.LSN.700-3/36/10
Tarikh : 29 Ogos 2024
24 Safar 1446H

Falkulti Sains Kesihatan
Universiti Teknologi Mara (UiTM),
Cawangan Selangor,
Kampus Puncak Alam,
42300 Bandar Puncak Alam,
SELANGOR DARUL EHSAN.

Tuan,

PERMOHONAN KEBENARAN MELAKUKAN PENGGAMBARAN DI SEKITAR BANDAR SHAH ALAM.

Dengan segala hormatnya perkara di atas adalah dirujuk.

2. Sukacitanya dimaklumkan bahawa, permohonan pihak tuan/puan untuk mengadakan penggambaran kajian bertajuk "Pembangunan Model Berasaskan Dron Menggunakan Algoritma Pembelajaran Mesin Untuk Pengawasan Nyamuk Aedes" di lokasi seperti berikut adalah **dipertimbangkan tertakluk kepada syarat-syarat Majlis** :

BIL	TARIKH	LOKASI
1.	**21 dan 22 September 2024 (9.00 pagi – 5.00 petang)**	**Sekitar kawasan Seksyen 24, Shah Alam**

3. Sehubungan dengan ini, Majlis berharap pihak tuan menjalankan aktiviti penggambaran di kawasan tersebut dengan mematuhi syarat-syarat berikut :-

i) Mendapatkan kebenaran / ulasan daripada Jabatan Korporat bagi semakkan perisian penggambaran.

ii) Mendapatkan kebenaran daripada Jabatan Kejuruteraan bagi meletakkan "skylift" semasa sesi penggambaran (sekiranya ada).

iii) Memastikan sepanjang aktiviti pengambaran dijalankan tidak menggangu ketenteraman awam dari segi had masa dan halang laluan awam sehingga boleh mengakibatkan kesesakan lalulintas di kawasan tersebut,

iv) Mendapatkan kelulusan daripada Pihak Berkuasa Penerbangan Awam Malaysia (CAAM) sekiranya ada aktiviti yang melibatkan penggunaan drone,

v) Sebarang penutupan jalan dan kawalan lalulintas hendaklah dimaklumkan kepada pihak PDRM,

vi) Perlu dapatkan kelulusan agensi seperti PUSPAL sekiranya melibatkan artis luar negara dan agensi-agensi lain yang berkaitan.

…/-

vii) Waktu penggambaran dibenarkan sehingga jam 12.00 malam sahaja,

viii) Menjalankan aktiviti penggambaran dengan aman dan menjaga kebersihan setempat dan tidak melakukan sebarang kerosakan kepada harta benda Majlis.

ix) Tidak mendirikan / memasang sebarang bentuk struktur binaan di kawasan penggambaran tanpa kelulusan daripada pihak Majlis Bandaraya Shah Alam,

x) Menjaga etika pemakaian / kelakuan pelakon sepanjang aktiviti pengambaran dijalankan,

xi) Majlis juga berhak untuk menarik semula kebenaran mengadakan penggambaran ini sekiranya pihak tuan gagal mematuhi perkara-perkara (i, hingga vi) yang telah ditetapkan seperti di atas,

xii) Semua aktiviti pengambaran yang terlibat di lokasi adalah tertakluk kepada arahan, peraturan dan undang-undang MBSA yang berkuasa dari semasa ke semasa.

4. Pihak Majlis juga tidak akan bertanggungjawab jika berlaku sebarang kejadian yang tidak diingini semasa aktiviti penggambaran dijalankan. Sebarang pertanyaan lanjut, sila hubungi Encik Amir Hamzah Bin Amir Nordin, Penolong Pegawai Tadbir di talian 03-5510 5133 sambungan 1549/ 1384.

Sekian, terima kasih.

"#*KITA*SELANGOR MAJU BERSAMA"
"MALAYSIA MADANI"
"BERKHIDMAT UNTUK NEGARA"

'Khidmat Terbaik'

Saya yang menjalankan amanah,

(MOHD RIZAL BIN JOHARI)
Timbalan Pengarah Pelesenan
b/p Pengarah Pelesenan
DJ-surat pengambaran

sk. 1. Jabatan Korporat

2. Jabatan Kejuruteraan

3. Jabatan Penguatkuasaan

-2-

APPENDIX 11

Drone Flight Permit from Civil Aviation Authority of Malaysia (CAAM)

CIVIL AVIATION AUTHORITY OF MALAYSIA (CAAM)

AUTHORISATION TO FLY (ATF)

UNMANNED AIRCRAFT SYSTEM (UAS)

Tel: 03: 8871 4000 Email: drone.atf@caam.gov.my Fax: 03 8871 4334

Permit No.	CAAM/BOP/ATF/P2024/09/2481	Permit Issued Date	11/09/2024
Application No.	CAAM/BOP/ATF/A2024/08/2539	Application Date	29/08/2024

UAS OPERATOR DATA

1	UAS Operator Name	ZULFADLI BIN MAHFODZ
2	Accountable Person	ZULFADLI BIN MAHFODZ
3	Telephone No.	017-3823404
4	Email	zulfa2015@uitm.edu.my

UAS OPERATION DETAILS

1	Purpose	Conducting aerial mapping work involving the area of section 24, Shah Alam, Selangor for research purposes by the Faculty of Health Sciences, Puncak Alam Campus, Universiti Teknologi MARA (UiTM) Selangor Branch.
2	Start Date	12/09/2024
3	End Date	22/09/2024
4	Start Time/End Time	0900 – 1700 LOCAL TIME
5	Height In Feet (AGL)	**Ketinggian tidak melebihi 330FT AGL**

LIST OF UA(S) PERMITTED

Series	Manufacturer	Model	Amount / Unit	UA Serial No.
1	DJI	MAVIC 3 ENTERPRISE	1	1581F5FHB22A70020AC5

LIST OF REMOTE PILOT AND GROUND CREW

No.	Name	NRIC	Telephone No.	Email	Role
1	ZULFADLI BIN MAHFODZ	880413-10-5619	017-3823404	N/A	ACCOUNTABLE MANAGER
2	NIK NORFATHIN NADZIRAH BINTI NIK MOHAMMED ZAIRUL	980911-04-5450	012-2821171	N/A	DRONE PILOT

LOCATIONS PERMITTED

No.		Coordinate
1	**A3651/24 NOTAMN**	(A3651/24 NOTAMN Q) WMFC/QWULW/IV/BO/W/000/004/0302N10131E001 A) WMFC B) 2409210100 C) 2409220900 D) 0100-0900 E) UA ACT WILL TAKE PLACE AT FLW COORD: 030230.41N 1013039.17E - 030238.76N 1013053.47E - 030234.62N 1013110.02E - 030205.65N 1013128.39E - 030149.27N 1013104.76E (SEKSYEN 24, SHAH ALAM) F) SFC G) 330FT AGL)

NOTE(s):

LIMITATIONS AND CONDITIONS FOR THE UAS OPERATION		
No.	Item	Details
1	Airspace Limitation(s)	Bertujuan menjamin keselamatan dan kecekapan pergerakan trafik udara, pihak berkuasa ini memohon pematuhan pihak tuan kepada butiran sebagaimana berikut: i. **Aktiviti perlu berada dalam lingkungan koordinat-koordinat dan masa yang seperti di NOTAM sahaja;** ii. **Ketinggian yang diluluskan adalah 330ft AGL dan ke bawah sahaja;** iii. **Pihak operator perlu menghubungi pihak Pusat Kawalan Trafik Udara Kuala Lumpur (FIS) di talian +603-85291243, 20 minit sebelum memulakan aktiviti dan sejurus selepas aktiviti tamat. Jika tiada pemakluman, aktiviti dianggap tidak aktif;** iv. **Keselamatan awam di kawasan operasi adalah tanggungjawab pihak operator.** Dilampirkan bersama **NOTAM A3651/24** bagi menampung keperluan penggunaan ruang udara sebagaimana yang diluluskan tersebut. Kelulusan ini juga bergantung kepada kelulusan dari agensi-agensi dan bahagian-bahagian lain yang terlibat.
2	Operation Limitation(s)	**Pihak PDRM atau pihak berkuasa dan keselamatan boleh memberhentikan penerbangan UAS jika diperlukan mengikut keadaan semasa.**
3	Others: **JUPEM**	**JUPEM.BGSP.2024.2444.UDARA**

In accordance with Regulation 189, this authorisation certifies that

ZULFADLI BIN MAHFODZ

is authorised to conduct UAS operations based on the application form submitted and supplemented by the conditions and limitations set above, as long as it complies with Civil Aviation Regulations 2016 Part XVI and its supporting legislations pertaining UAS. The UAS Operator shall also abide and meet the approval of other agencies that holds legislations on UAS (as applicable).

Effective date: 11/09/2024	Signature : OPS Name : **DATO' CAPTAIN NORAZMAN MAHMUD** Title : Chief Executive Officer Civil Aviation Authority of Malaysia

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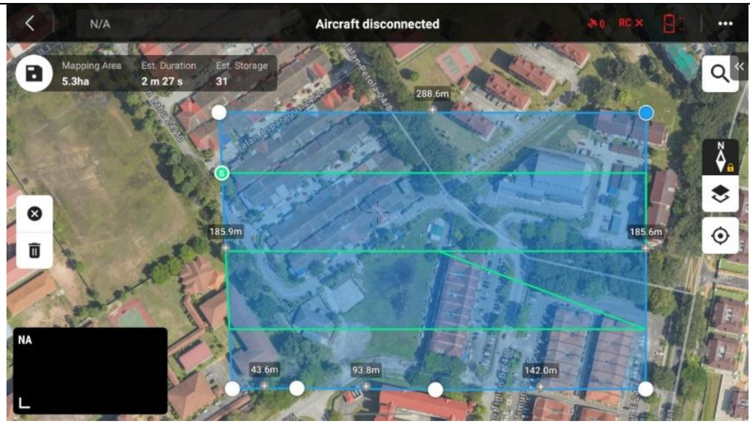
	https://docs.google.com/spreadsheets/d/1gZqhl8BEO7RH5KVgecofSb2kWBr5S0Ts/edit?usp=drive_link&ouid=102920673792288691235&rtpof=true&sd=true https://drive.google.com/drive/folders/1lqEP5E93_polkxge_fYhpg9gHp-abUAf?usp=drive_link

APPENDIX 12

Table of Drone Flight Mission Map

Location : Seksyen 24, Shah Alam, Selangor	
1. Flat B	**2. Flat H**
	
3. Teres B	**4. Teres D**
	

AUTHOR'S PROFILE

Zulfadli Bin Mahfodz obtained Bachelor of Ecology and Biodiversity (Hons.) in 2010 from Universiti Malaya, Kuala Lumpur, MSc in Entomology (2013) from Universiti Kebangsaan Malaysia, Bangi. His PhD research develops and evaluates an integrated dengue prevention framework in Malaysia, combining mixed-methods community engagement with high-resolution drone mapping, geospatial risk modelling, and machine learning based habitat classification to identify potential mosquito breeding sites. He has published articles in peer-reviewed journals on related topics, presented at international conferences, and received a gold award in an innovation competition for a drone-based approach to support mosquito surveillance.

LIST OF PUBLICATION:

Mahfodz, Z., Dom, N. C., Abdullah, S., & Precha, N. (2024). Viability of unmanned aerial vehicles in identifying potential breeding sites for mosquito. *The Medical Journal of Malaysia*, *79*(Suppl 1), 148-157.

Mahfodz, Z., Dom, N. C., Salim, H., & Precha, N. (2024). A conceptual framework for assessing the field efficiency of drones in identifying potential breeding sites of the *Aedes* mosquito. *Alam Cipta: International Journal on Sustainable Tropical Design Research & Practice*, *17*(1).

Mahfodz, Z., Dapari, R., Salleh, S.A., Camalxaman, S.N., Aljaafre, A.F. & Dom, N.C. (2026). Sociodemographic determinants of willingness to adopt surveillance technology and mosquito control training for dengue in Malaysia. *Sci Rep, 16*, 3069.

Mahfodz, Z., Naba, A., Isawasan, P., Osman, M. A., & Dom, N. C. (2026). Drone-based composite risk mapping reveals vegetation–shade interaction and housing typology as key determinants of Aedes habitat risk. *Sci Rep*, 16(1), 5957.

Mahfodz, Z., Naba, A., Isawasan, P., Ngesom, A. M. M., & Dom, N. C. (2026). Drone-based machine learning approaches for mosquito vector surveillance. *Discover Applied Sciences*, 8, 657.

Mahfodz, Z., Naba, A., Isawasan, P., Salleh, S.A., Osman, M.A. & Dom, N. C. (2026). Drone-Based Microclimate Analytics Reveal Vegetation–Shade Interaction as a Key Environmental Drivers of Aedes-Prone Microhabitat Suitability. *Sci Rep*. (*Accepted May 2026*).

Mahfodz, Z., Dapari, R., Salleh, S.A., Camalxaman, S.N., Yusop, M.M. & Dom, N. C. (2026). Uneven Mosquito Control Knowledge, Attitudes, and Practices in Malaysia Shape Sustainable Dengue Prevention Across Urban And Rural Settings. *Sci Rep*. (*Accepted May 2026*).