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Effect of AI-Powered Drones Versus Manual Surveillance in Larval Habitat Mapping for Malaria Control: A Cluster Review

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ABSTRACT

Effective larval source management (LSM) for malaria control relies on accurate and comprehensive mapping of mosquito breeding habitats. Traditionally, manual ground-based surveillance has been used, but it is labour-intensive, time-consuming, and prone to incomplete coverage in expansive or inaccessible terrains. Recent advancements in artificial intelligence (AI) and drone technology offer novel approaches to enhance larval habitat mapping for malaria vector control programmes. This review evaluated the comparative effectiveness of AI-powered drone surveillance versus manual surveillance in mapping *Anopheles* larval habitats for malaria control interventions. A cluster review approach was utilised to synthesise peer-reviewed studies, operational reports, and pilot evaluations published between 2010 and 2025 from databases including PubMed, Scopus, and Google Scholar that compared AI-powered drones with manual surveillance for larval habitat mapping. Evidence indicates that AI-powered drones provide superior spatial coverage, rapid mapping, and enhanced detection sensitivity, identifying up to 30% more potential breeding sites than manual surveys. They also reduce operational time from weeks to hours over large areas. However, drones cannot directly confirm larval presence, necessitating ground-truthing before interventions. High initial costs, regulatory restrictions, and technical expertise requirements pose implementation challenges, particularly in low-resource settings. Manual surveillance remains essential for larval confirmation and ecological assessment despite its operational limitations. AI-powered drone surveillance enhances the efficiency and precision of larval habitat mapping compared to manual surveillance. Integration within existing vector control programmes, capacity building, and development of ethical and regulatory frameworks are required to maximise its potential for malaria elimination.

Keywords: AI-powered drones, Malaria control, Larval habitat mapping, Manual surveillance, Vector management.

INTRODUCTION

Malaria continues to represent a major global health challenge, with approximately 249 million cases and over 600,000 deaths recorded worldwide in 2022, predominantly within sub-Saharan Africa [1, 2]. Vector control remains central to malaria elimination strategies, with larval source management (LSM) recognised as a critical intervention to reduce mosquito populations at their aquatic stages before adult emergence. Effective LSM relies on accurate, timely, and comprehensive mapping of mosquito breeding habitats, particularly for *Anopheles* species, which display highly heterogeneous spatial distribution influenced by rainfall, landscape features, and human activity [3].

Traditionally, larval habitat mapping has been conducted through manual ground-based surveillance involving field teams identifying, characterising, and georeferencing breeding sites [4]. Although effective at the micro-scale, this approach is labour-intensive, time-consuming, and prone to coverage gaps due to inaccessible terrain, observer variability, and limited spatial resolution over large endemic areas. Such limitations constrain the scalability and operational efficiency of LSM interventions, especially in resource-limited settings where health systems are overstretched.

Recent technological advances have introduced artificial intelligence (AI)-powered drone systems as a novel approach for larval habitat mapping [5, 6]. These systems integrate high-resolution aerial imagery captured by unmanned aerial vehicles (UAVs) with AI algorithms for automated identification and classification of potential breeding sites. AI-powered drones offer the potential for rapid, high-throughput, and precise mapping over wide areas, enhancing the accuracy and cost-effectiveness of vector control programmes. Despite increasing implementation in pilot settings, a systematic comparison of their effectiveness relative to manual surveillance is essential to inform evidence-based policy and scale-up. This cluster review synthesises existing evidence on the effectiveness, operational feasibility, and limitations of AI-powered drones compared to manual surveillance in larval habitat mapping for malaria control. It further discusses implications for programmatic integration, resource allocation, and future research priorities required to optimise this emerging technology within integrated vector management frameworks.

METHODOLOGY

A cluster review approach was employed, synthesising peer-reviewed articles, operational reports, and pilot evaluations published between 2015 and 2025 from databases including PubMed, Scopus, and Google Scholar. Studies were included if they compared AI-powered drone-based mapping to manual surveillance for malaria vector habitat identification in endemic settings.

Overview of Larval Habitat Mapping Approaches

i. **Manual Surveillance:** Manual surveillance remains the conventional gold standard for larval habitat mapping [7]. It involves systematic field surveys by trained entomological teams who physically inspect potential breeding sites, identify mosquito larvae morphologically, record geospatial coordinates using handheld GPS devices, and classify habitats based on ecological characteristics such as water permanence, vegetation type, and proximity to human dwellings. This approach benefits from direct larval confirmation and contextual ecological assessment. However, its limitations include high labor intensity, temporal constraints, observer variability, and limited coverage due to the physical inaccessibility of certain terrain types. Consequently, manual surveillance may miss cryptic habitats, resulting in incomplete larviciding coverage and persistent vector populations despite LSM interventions.

ii. **AI-Powered Drone Surveillance:** AI-powered drone surveillance integrates UAV platforms equipped with high-resolution multispectral or RGB cameras with AI algorithms capable of processing imagery to identify water bodies and classify breeding habitats [8, 9]. The workflow involves drone deployment, image processing using AI algorithms, and output generation of detailed habitat maps for targeted larviciding. Advantages include rapid coverage, high spatial resolution, reduced human resource requirements, and automated analysis, minimizing observer bias and improving consistency. However, operational challenges such as regulatory restrictions on drone flights, battery limitations, data processing infrastructure, and initial investment costs require careful consideration.

Comparative Effectiveness: AI-Powered Drones Versus Manual Surveillance

i. **Accuracy and Coverage:** Studies comparing AI-powered drone mapping with manual surveillance consistently report superior spatial coverage and habitat detection rates with drones [10, 11]. For instance, pilot studies in western Kenya demonstrated that drone-based mapping identified over 30% more potential breeding habitats compared to concurrent manual surveys, including small, scattered, or inaccessible water bodies missed by field teams. High-resolution imagery coupled with AI classification algorithms enables the detection of water bodies as small as 0.01 m^2, enhancing microhabitat mapping crucial for targeted larviciding. Conversely, manual surveillance achieves near-perfect specificity by confirming larval presence directly. AI-powered drones infer breeding suitability based on habitat features rather than larval presence, necessitating validation sampling before intervention deployment. However, the substantial improvement in detection sensitivity by drones compensates for this limitation, especially in pre-intervention mapping phases.

ii. **Operational Efficiency:** AI-powered drones dramatically reduce mapping time. Reports from Tanzania indicate that drone systems mapped 20 km^2 within a single day, a task requiring up to two weeks with manual field teams [12]. This rapid turnaround enhances operational planning and allows for timely interventions, particularly in dynamic seasonal environments. Manual surveillance remains preferable for confirmatory sampling before larviciding, but drone data streamlines field team deployment by prioritising high-risk sites, reducing unnecessary coverage of non-habitat areas.

iii. **Cost-Effectiveness:** Cost analyses reveal that while AI-powered drones have high initial capital and maintenance costs, they become cost-effective over time when deployed at scale due to reduced labour costs and improved intervention efficiency [13]. In contrast, manual surveillance incurs recurrent human resource costs, limiting scalability.

Implementation Feasibility and Programmatic Integration

i. **Technical Requirements:** The successful deployment of AI-powered drones necessitates trained pilots, data analysts skilled in AI model development and imagery interpretation, and a computational infrastructure for large dataset processing and storage [14, 15]. These requirements may pose barriers in resource-limited settings lacking established drone operations or AI expertise. Strategic capacity building and partnerships with technology providers are essential to address these gaps.

ii. **Regulatory and Ethical Considerations:** Drone operations are subject to civil aviation regulations, which may restrict flights over populated areas or protected ecosystems. Additionally, ethical considerations regarding privacy and community acceptance must be addressed through stakeholder engagement and transparent communication.

iii. **Environmental and Weather Constraints:** Drone performance is influenced by weather conditions such as wind speed, rainfall, and solar radiation, which affect image clarity and flight safety [16, 17]. Manual surveillance, while labour-intensive, is less susceptible to such constraints in certain terrain types.

Limitations of AI-Powered Drone Surveillance

Despite its advantages, AI-powered drone surveillance has limitations:

i. Inability to directly confirm larval presence, necessitating ground-truthing before interventions.

ii. Potential algorithm biases if training datasets are geographically limited, reducing generalisability to new ecological settings.

iii. Battery life constraints limiting flight durations, particularly in large-scale operations [18].

iv. High initial investment costs, which may be prohibitive for small-scale programmes without external funding support [19].

Future Directions in AI-Powered Larval Habitat Mapping

i. **Advancements in AI Algorithms:** Ongoing research aims to enhance AI models' predictive accuracy by integrating multispectral imagery, terrain data, and hydrological models to predict not only current breeding habitats but also future sites based on rainfall and landscape features [20, 21].

ii. **Integration with Other Surveillance Tools:** Combining drone-based mapping with satellite imagery, environmental sensors, and community-based reporting can create an integrated surveillance ecosystem to maximise coverage and accuracy [22].

iii. **Policy and Governance Frameworks:** Development of national guidelines for drone deployment in public health, standardisation of AI model validation protocols, and establishment of data governance frameworks are critical to ensure safe, ethical, and effective implementation.

CONCLUSION

AI-powered drones represent a transformative advancement in larval habitat mapping for malaria control, offering substantial improvements in spatial coverage, operational efficiency, and detection sensitivity compared to manual surveillance. While manual ground-based surveys remain critical for direct larval confirmation and ecological characterisation, drone-based mapping significantly enhances pre-intervention planning by rapidly identifying and classifying potential breeding sites, including those inaccessible to field teams. The cost-effectiveness of drones increases over time and scale, though initial capital, technical expertise, and regulatory constraints pose implementation challenges, particularly in low-resource settings. Future efforts should prioritise capacity building, development of locally adaptable AI models, integration with conventional surveillance systems, and formulation of regulatory frameworks to govern drone use ethically and safely. Large-scale operational research is needed to quantify the impact of AI-powered drone mapping on larviciding effectiveness, malaria incidence reduction, and cost-benefit outcomes relative to manual approaches. Ultimately, harnessing AI-powered drones within integrated vector management programmes has the potential to accelerate malaria elimination efforts by enhancing the precision, efficiency, and scalability of larval source management interventions.

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