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Perspective

Human-AI Decision Support for Vector-Borne Disease Control under Environmental and Population Change

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Abstract: Vector-borne diseases (VBDs), especially mosquito-borne infections, are shifting in range, seasonality, and intensity as climate variability, land-use change, urbanisation, mobility, population redistribution, and unequal control capacity reshape interactions among vectors, hosts, pathogens, and natural and social environments. Artificial intelligence (AI) is increasingly used for VBD surveillance, risk mapping, forecasting, and intervention planning, yet many applications are still judged mainly by predictive performance. The public health value of AI also depends on whether it improves decisions about when to act, where to intervene, which populations or ecological niches to prioritize, and how to allocate scarce resources under uncertainty. We synthesize the strengths, and limitations of AI applications across vector surveillance, risk assessment, early warning, and intervention decision support, with attention to dynamic at-risk population intelligence and local implementation. We argue that AI should be operationalized as part of a human-AI decision-support chain embedded in local disease prevention and control systems. Future efforts should strengthen multimodal data integration, dynamic population estimation, hybrid mechanistic-AI modelling, uncertainty quantification, implementation evaluation, and transparent governance. For VBD control, the priority is to embed interpretable, locally calibrated AI into accountable workflows that connect surveillance signals with timely, equitable, and feasible public health action.

Keywords: vector-borne diseases; artificial intelligence; decision support; dynamic at-risk population; disease surveillance; environmental change

1. Introduction

Vector-borne diseases (VBDs) cause more than 700,000 deaths annually [1] and impose the greatest burden on global public health among infectious diseases. Mosquitoes are the most common transmission vectors, and the diseases they cause, including malaria, dengue, chikungunya, as well as other high burden and developing infections, account for the majority of the overall VBD disease burden [2]. Their geography is changing because environmental and population processes increasingly interact. Climate variability, land-use change, unplanned urbanisation, peri-urban growth, human mobility, displacement, and unequal control capacity alter VBD vector suitability, human exposure, surveillance performance, and intervention feasibility [3,4]. Climate associated shifts in malaria risk have been documented and projected in many endemic countries [5], while other mosquito-borne infections such as dengue, chikungunya, and Zika continue to expand into areas with limited entomological surveillance or response capacity [6].

Population change matters for VBD control because exposure is determined by where susceptible people are present and move. Static residential denominators can misrepresent risk when commuting, seasonal migration, tourism, displacement, or peri-urban expansion change the daily or seasonal geography of exposure [7]. This is particularly important for mosquito-borne infections, where vector suitability, biting times, housing quality, water storage, drainage, and human presence combine to shape local transmission risk. In many current control systems, surveillance, risk analysis, early warning, and intervention planning remain fragmented and rely on delayed case reporting, periodic vector surveys, limited environmental monitoring, and expert interpretation. These inputs remain indispensable, but are often too slow, sparse, or siloed for rapidly changing transmission landscapes.

Artificial intelligence (AI) and related data-science methods, including machine learning, deep learning, and explainable AI, have attracted substantial attention in infectious disease modelling and public health [8,9]. Compared with directly transmitted infections such as influenza, COVID-19 and measles, many VBDs involve an additional transmission step in which vectors acquire pathogens from infected hosts and transmit them to other susceptible hosts [4]. This step links human infection to vector abundance and competence, breeding habitats, biting behaviour, climate suitability, land use, human or animal host mobility and exposure [3,7]. Modelling must therefore consider not only human infection, exposure and mobility, but also vector and habitat conditions and vector-human or vector-animal interaction parameters, making VBD modelling more spatially and ecologically complex. Intervention planning also extends beyond case management and protection of exposed populations to include vector surveillance, source reduction and management of transmission environments, creating operational decision points specific to vector ecology [1]. Accordingly, an AI-enabled decision-support framework for VBD control needs to consider these additional ecological dimensions and vector-human interactions, and support the resulting vector-specific operational decisions. AI can help process high-dimensional and nonlinear signals [10], but the operational questions of public health value are about what decision AI improves, for whom, at what point in the control chain, and under what uncertainty.

Here, we therefore suggest framing AI for VBD control as a human-AI decision-support problem under environmental and population change. This framing evaluates AI by asking whether AI can support threshold-based alerts, prioritization of sites and dynamic at-risk populations, adaptive deployment of interventions, and transparent communication of uncertainty. It also preserves the role of epidemiologists, geographers, demographers, modellers, public health practitioners, and communities in defining what a model should optimize and what evidence is sufficient for action.

2. AI across the VBD Decision Chain

AI applications in VBD control are best understood as four linked components of a decision-making chain. Each component requires a different balance of algorithmic processing, field evidence, and human judgement (Figure 1). To identify illustrative applications, we conducted four targeted searches in PubMed and the Web of Science Core Collection, covering publications from 2022 to 2026. Each search combined terms related to AI, machine learning or deep learning with mosquito- or vector-borne disease terms and one of four functions in the decision chain, with supplementary dengue and malaria searches where relevant. Records were manually screened for empirical studies applying AI to surveillance, risk assessment, forecasting or intervention support, which were prioritized as illustrative applications. Additional targeted searches using corresponding concept terms identified studies on AI in infectious disease, foundation models and human mobility for conceptual, methodological or epidemiological context. Because this was a targeted narrative search rather than a systematic review, the examples provided are illustrative rather than exhaustive and may be subject to incomplete coverage and selection bias.

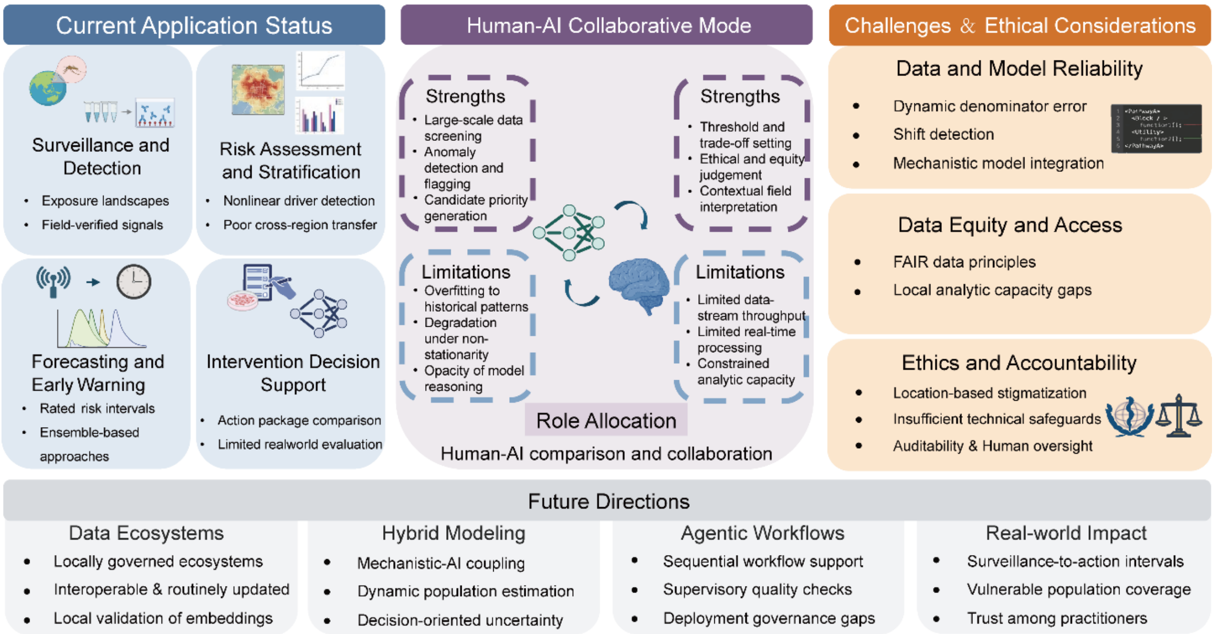

Figure 1. Human-AI decision support for VBD control under environmental and population change. The framework links current AI applications, human-AI decision roles, implementation challenges, ethical considerations, future priorities for data infrastructure, predictive intelligence, and public health action with findable, accessible, interoperable, and reusable (FAIR) principles highlighted.

3. Surveillance and Detection: From Automated Risk Recognition to Exposure Intelligence

AI has been applied to stages of vector surveillance. Deep learning methods such as convolutional neural networks (CNNs) have been used to classify mosquito images from smart traps [11], and detect potential breeding sites from unmanned aerial vehicle (UAV) imagery [12]. When linked with sensors and geospatial data, these approaches can reduce workload and improve surveillance coverage. Their immediate operational value is helping decide where field teams should verify signals, where source reduction should be considered, and where surveillance gaps remain.

Recent Geospatial eXplainable AI (GeoXAI) frameworks integrating geographically weighted neural networks, kriging, and Shapley Additive Explanation (SHAP) interpretation further support site-specific vector surveillance and control [13]. Such multimodal surveillance would help programmes identify where vector suitability, human presence, vulnerability, and operational feasibility coincide. Among the three mosquito-surveillance applications cited here, evaluation was focus on technical validation within each study. The smart-trap used held-out images and controlled tent or simulated indoor settings; the UAV study compared detections with manually labelled imagery from one study site; and the GeoXAI study relied on internal training, testing and validation splits with simulation-based robustness checks. These evaluations did not include independent external validation, longitudinal or cross-season assessment, or programme-level effects on surveillance or vector-control outcomes. Importantly, none of the three studies reported prospective, repeated evaluation embedded in a routine vector-surveillance programme. Operational deployment still requires field verification and clear response protocols.

4. Risk Assessment and Stratification: Identifying Intervention Priorities

Machine learning, ensemble learning, and interpretable methods have been used to identify high-risk areas and reveal nonlinear drivers of VBD occurrence. Examples include Extreme Gradient Boosting (XGBoost) combined with SHAP for fine-scale dengue risk linked to land use, transport infrastructure, and urbanisation [14]; random forest (RF) and XGBoost models for imported malaria risk using cases, mobility and socioeconomic indicators [15].

The practical value of these models lies in supporting stratified public health decisions. Risk maps would become useful when they support differentiated surveillance and intervention priorities. High environmental suitability does not always imply the same intervention priority, because dynamic at-risk population presence, vulnerability, accessibility, and health-system capacity can modify risk [16]. Risk stratification therefore requires expert-guided variable selection and local calibration. However, models trained in one region may not transfer to another, because ecological conditions, mobility networks and surveillance conditions differ.

5. Forecasting and Early Warning: From Point Predictions to Calibrated Triggers

Predictive studies have increasingly progressed toward ensemble frameworks that integrate multi-source data such as epidemiological, environmental, and population data. Comparative dengue forecasting work shows that no single algorithm or feature set performs best across settings, reinforcing the need for locally calibrated model selection and continuous recalibration [17]. Explainable AI (XAI) methods can improve model interpretability by quantifying the relative contributions of climate, population density, land use, and other drivers to epidemic dynamics [18]. Recent progress on large language models and other foundation-model approaches have begun to reformulate epidemic prediction as a multimodal reasoning task that can incorporate contextual text, spatial information, genomic surveillance, and time-series data, with outputs such as risk categories and confidence scores [19,20]. However, large language models may generate false information, commonly referred to as LLM hallucinations, which could pose risks when their outputs inform infectious disease forecasting and early warning, including VBD applications. Such errors could distort surveillance summaries or signal interpretation and lead to misleading forecasts or alerts.

Environmental and population change complicate VBD prediction because both the numerator and denominator can move. Case counts change with transmission and reporting, while exposed populations change with daily mobility, rural-urban migration, displacement, tourism, and settlement expansion [21]. For VBD early warning, AI should estimate risk in relation to dynamic at-risk populations, not only administrative case totals [22]. In practice, programmes using the framework could first combine geocoded case and vector-surveillance data with a gridded residential population baseline. Privacy-preserving aggregated mobility data or population dynamic index, derived from mobile phones, social media apps, public transport records or surveys, could then estimate population presence or seasonal re-distribution by location and over time. These estimates should be weighted, where data permit, by vector distribution or abundance, biting period, exposure setting and susceptibility to derive a time-varying, exposure-weighted population at risk. Resident-based and exposure-adjusted indicators can be compared at the spatial unit and time interval at which exposure can reasonably be attributed and action can be delivered. Because notification location may differ from infection location and digital mobility sources may under-represent some groups, coverage adjustments, sensitivity analyses and validation against surveys or administrative counts are also required.

Uncertainty in population presence and exposure weights should be further propagated into generating location-specific risk estimates and alert thresholds. Ensemble methods can address model uncertainty by promoting model diversity in nowcasting and forecasting, Bayesian approaches can address parameter and latent-state uncertainty when surveillance data are incomplete or noisy, and conformal prediction can quantify predictive uncertainty [8]. In this framework, a calibrated trigger refers to a decision rule that maps an estimated exceedance probability and its uncertainty to an operational threshold chosen with explicit consideration of false-alarm and missed-outbreak costs, available response capacity and the consequences of delayed detection.

6. Intervention Decision Support: Translating Evidence into Operational Choices

The most important test of AI is whether it improves VBD control decisions and helps translate risk identification and early warning into actionable interventions. UAV-based identification help localize breeding sites and support community-scale prioritization [12]. GeoXAI can guide urban targeting by identifying prevention and control zones that require different strategies [13,14]. In low-transmission or near-elimination malaria settings, models that incorporate population dynamics and environmental data can help identify high-risk importation routes that may trigger local, seasonal transmission [15]; in high-burden settings, they can support more timely resource allocation and targeted interventions under constrained conditions [23].

For VBD control programmes, AI decision support should compare feasible action packages rather than produce a single risk score. The 2025 Foshan chikungunya response provides a concrete context in which case surveillance was combined with breeding site removal, adult mosquito control, community mobilization and household protection [24]. The cited case did not describe the use of AI in the outbreak response. If an AI decision-support framework had been available in this case, it could have supported comparison of feasible intervention packages under the real-world constraints described below. AI could combine available epidemiological and intervention records with data describing feasible alternative packages. It could estimate the expected epidemiological impact and resource requirements of each package, apply constraints related to cost, workforce availability and response timing, and generate comparisons and rankings based on intervention intensity, duration, equity and social acceptability. Experts would define the criteria and local priorities, validate the data and assumptions, assess context-specific feasibility, and approve, modify or reject the recommended intervention packages before implementation. Observed coverage, costs, adverse effects and epidemiological and entomological outcomes would then support prospective evaluation and model updating. Evaluation should extend beyond Root Mean Squared Error (RMSE) or short-term forecast error. More relevant metrics include whether AI improves targeting, timeliness, and intervention coverage [9]. AI systems should be embedded in operational workflows that support resource allocation and threshold-based action triggers, rather than being evaluated as isolated predictive models. Across these four stages, AI contributes different forms of decision value, requires different data streams, and depends on distinct expert roles for interpretation, validation, and action (Table 1).

Table 1. Human-AI decision points for VBD control under environmental and population change.

Decision Point	Typical Data	Useful AI Approaches	AI-Added Decision Value	Main Limitations	Expert Roles	Key References
Surveillance and detection	Vector images, trap counts, UAV imagery, remote sensing, land cover, meteorology, human activity patterns	CNNs, object detection, UAV vision, multimodal learning, GeoXAI	Automate recognition of vectors and breeding sites; improve surveillance coverage; link vector signals with human presence and operational risk	Validation-heavy evidence; limited operational testing; mosquito-centred datasets; weak transfer across settings	Define surveillance design; verify field signals; interpret anomalous detections	[11–13]
Risk assessment and stratification	Cases, land use, climate, transport, mobility, socioeconomic indicators, dynamic at-risk population estimates, health-system capacity	RF, XGBoost, SHAP	Identifie high-risk areas, dynamic exposure settings, and differentiated intervention priorities	Regional heterogeneity; denominator uncertainty; limited transferability across ecological and surveillance settings	Select variables; calibrate local meaning of risk; translate maps into intervention priorities	[14–16]
Forecasting and early warning	Case time series, environmental and population data,mobility, genomic signals, contextual text, spatial information	Ensemble forecasting, XAI, foundation models, conformal prediction	Support threshold-based alerts and intervention decisions for changing at-risk populations	Non-stationarity; uncertainty communication; false-alarm trade-offs; transferability across settings	Set action thresholds; interpret uncertainty; judge when to investigate or intervene	[8,17–22]
Intervention decision support	Risk maps, vector-control resources, accessibility, intervention history, population dynamics, environmental data, operational constraints	Optimisation, simulation, GeoXAI, hybrid mechanistic-AI models	Guide targeting, resource allocation, and differentiated strategies; support threshold-based action triggers	Limited real-world evaluation; weak integration with operational workflows; accountability concerns	Assess feasibility, equity, acceptability, and policy consequences; feed outcomes back into models	[9,12–15,23]

Abbreviations: AI = artificial intelligence; VBDs = vector-borne diseases; CNN = convolutional neural network; UAV = unmanned aerial vehicle; XGBoost = extreme gradient boosting; SHAP = Shapley additive explanations; RF = random forest; XAI = explainable artificial intelligence; GeoXAI = geospatial explainable artificial intelligence.

7. The Necessity of Human-AI Collaboration for VBD Control

Human-AI collaboration is necessary because VBD control decision-making can be both data intensive and context dependent. VBD intervention strategy design has long relied on local experience and interdisciplinary expertise. The integrated vector management (IVM), promoted by WHO, is an evidence-informed process grounded in local ecology, resource constraints, multisectoral coordination, and programme capacity [25]. For instance, Delphi approaches can aggregate expert judgements on the effectiveness, applicability, and relative importance of malaria vector control tools under routine and emergency settings [26]. Expert experience is limited by the scale and speed of information processing, while purely AI-based approaches can suffer from limited interpretability, low transparency, and decision uncertainty [27]. Human teams often cannot continuously process large-scale multimodal data in real time, and AI systems can overfit historical correlations and obscure uncertainty when presented as black-box outputs [28,29].

The relevant human-AI collaboration design principle is role allocation. Human experts should review data quality and AI outputs at each stage of this decision-support chain, identify potential errors and prevent unverified outputs from informing action. In surveillance and detection, they define surveillance strategies and data standards, and validate surveillance results through data quality checks and field confirmation. In risk assessment, stratification and forecasting, experts provide insights for distinguishing decision-relevant covariates from primarily predictive covariates. Decision-relevant covariates include household water storage, vector distribution and abundance, population mobility and vector-control coverage. These variables can identify intervention targets, locations or timing, and also be used in predictive models. Meteorological conditions and broader climatic suitability are used primarily as predictive covariates.

Covariates can further become more actionable when their spatial and temporal resolution matches a specific intervention unit and response cycle. For example, household water storage and vector abundance data available at household or block level within a daily or weekly response cycle may guide local surveillance and intervention. At the district level, population mobility and vector-control coverage data may support prioritization of surveillance and control activities across areas. Experts should therefore assess spatial and temporal alignment, measurement error, data leakage, transportability and whether each variable can alter a feasible decision.

In intervention decision support, experts evaluate recommendations generated by AI for feasibility, cost, workforce availability, timing, equity and acceptability, and then approve, modify or override them before implementation. After implementation, experts use observed field outcomes to monitor model performance and determine whether recalibration or revalidation is needed. Evidence from human-in-the-loop machine learning also supports expert-guided model development, while chimeric forecasting shows that combining computational models with human judgement can improve forecasts in some settings [30,31]. For VBD control, collaboration should be designed into the workflow from problem formulation to deployment, monitoring, and revision. Table 2 uses dengue as an example to further illustrate these role-allocation ideas in a peri-urban dengue early warning workflow from signal acquisition to feedback.

Table 2. Illustrative Human-AI workflow for supporting dengue early warning and response in a peri-urban setting.

Decision Stage	Data, AI Task and Output	Human Decision and Evaluation Checkpoint
Surveillance and detection	AI integrates geocoded cases, mosquito traps, vector images, weather, land cover and reports of water-storage or breeding sites, and support vector or breeding-site classification, while flagging anomalies and coverage gaps.	Staff verify anomalous signals, assess data completeness and representativeness, and confirm surveillance gaps across formal and informal settlements.
Dynamic exposure and risk assessment	AI combines validated signals with residential populations and aggregate mobility or time-use data to estimate local risk and the dynamic population at risk, including commuters and seasonal migrants.	Epidemiologists and demographers review exposure assumptions, denominator bias, uncertainty and differences between resident-based and exposure-adjusted risk.
Forecasting and early warning	AI estimates the probability that cases or vector indicators will exceed a locally defined threshold within a specified period and location.	Experts consider calibration, lead time, false alerts, available response capacity and uncertainty before confirming an alert, and judge when investigation or action is warranted.
Intervention decision support and feedback	For a confirmed alert, AI compares and ranks feasible response packages, such as source reduction, insecticide spraying and community mobilization, under workforce, cost, access and equity constraints. It records implementation and outcomes for model updating.	Programme teams approve, modify or override recommendations, prioritise accessible and underserved locations, verify outcomes and decide whether the system requires recalibration or revalidation.

8. Implementation Challenges and Ethical Considerations

Several barriers limit the translation of AI-assisted tools from technical demonstration to operational VBD control. The first is non-stationarity. Climate change, vector abundance, pathogen dynamics, host immunity, human behaviour, environmental conditions, reporting systems, interventions, and population redistribution can all destabilize the patterns on which models were trained [3]. The feedback makes VBD systems difficult to simulate and can reduce the reliability of models transferred across seasons, cities, diseases, or surveillance regimes [8,20,32]. Model development should therefore prioritise shift detection, uncertainty calibration, and closer integration with mechanistic models, causal inference, or digital-twin approaches where these are feasible [20,32].

The denominator problem adds a distinct source of error. Static census or administrative denominators may be adequate for some annual planning tasks, but they are poorly aligned with daily mobility, seasonal labour circulation, temporary displacement, tourism, and informal peri-urban growth [16,22]. For VBDs, denominator error can distort incidence, mislead prioritization, and obscure where service demand and exposure are becoming misaligned. A rise in reported incidence may reflect increased transmission, improved detection, population inflow, or a shrinking denominator, and these mechanisms imply different responses. To ensure that changes in rates can be accurately attributed to the numerator or denominator, programmes should report the denominator used alongside each indicator, and calculate key indicators under both residential-based and exposure-adjusted denominators, treating their discrepancies as a signal warranting further investigation. Mobility-derived estimates should be benchmarked against censuses, surveys, transport counts or other administrative data, with sensitivity analyses for groups poorly represented in digital sources and privacy-preserving aggregation for small areas. Because VBD exposure occurs where people actually spend time rather than where they are registered, analysis also needs to redirect attention toward high-exposure, low-registration settings such as workplaces, schools, transport hubs, informal settlements, and seasonal labour sites.

Data quality and availability remain major constraints. Public health, entomological, meteorological, remote-sensing, mobility, genomic, demographic, and intervention data are often fragmented across agencies and spatial scales. Many datasets lack consistent geocoding, time stamps, metadata on surveillance effort, or records of interventions. These gaps limit large-scale data integration, model pre-training, reproducible evaluation, and cross-setting comparison [10]. Studies on AI and infectious disease surveillance highlight that open data, shared metadata, interoperability standards, and responsible location-data governance are prerequisites for reusable and transferable public health infrastructure [20,32,33]. Shared data assets should follow findable, accessible, interoperable, and reusable (FAIR) principles and the Locus Charter principles for responsible use of location data [34].

Equity, trust, and governmental accountability are also central implementation issues. The locations with the highest disease burden and greatest potential for benefit from AI tools, particularly low- and middle-income countries often have the most restricted data and deployment capacity [35]. Investment in interoperable surveillance systems, local analytic capacity, and locally owned model evaluation is as important as algorithm development. High-resolution spatial data from mobile phones, wearables, social media, and household-level surveillance can strengthen early warning, but they can also create risks related to consent, privacy, location-based stigmatization of neighbourhoods or mobile groups, and misuse. Algorithmic bias, insufficient transparency, unclear responsibility for model errors, and weak post-deployment monitoring remain core ethical concerns in health AI [36,37]. Privacy-preserving methods like federated learning, differential privacy, and synthetic data can reduce some privacy and data-scarcity constraints, but technical safeguards do not replace governance. Therefore, public health AI requires auditability, human oversight, transparent reporting, and mechanisms for contesting or revising model-informed decisions before they shape actions.

9. Future Priorities for AI-Enabled VBD Control

AI-enabled VBD control requires multimodal data ecosystems that connect case reports, vector monitoring data, remote sensing imagery, street-level environmental observations, meteorological inputs, gridded population estimates, human mobility patterns, pathogen genomics, health-system capacity, and intervention records. These systems should be interoperable, routinely updated, and locally governed. Emerging AI-derived geospatial embeddings (e.g., AlphaEarth, available online: https://deepmind.google/blog/alphaearth-foundations-helps-map-our-planet-in-unprecedented-detail/ (accessed on 30 July 2025) and PDFM embeddings, available online: https://research.google/blog/insights-into-population-dynamics-a-foundation-model-for-geospatial-inference/ (accessed on 14 November 2024)) may support feature extraction in data-sparse settings, but their spatial bias, scale dependence, and transferability require local validation before operational use. AI should also be coupled with mechanistic and causal models. Mechanistic constraints on vector-host-pathogen interactions can improve extrapolation beyond observed conditions and strengthen causal interpretation [32]. Machine learning can capture high-dimensional spatial and environmental patterns, but hybrid approaches are more likely to remain useful under environmental and population change than purely statistical models trained on historical regularities [32].

The preceding description of multimodal data integration and hybrid mechanistic-AI modelling is based mostly on findings from mosquito-borne systems, whereas the framework's components differ in how easily they transfer to other vector-borne diseases and this requires further clarification. Framework elements concerned with multimodal data integration, hybrid mechanistic-AI modeling, uncertainty quantification, phased human review, governance and outcome-based evaluation are not inherently mosquito-specific and can be adapted across vector systems. Therefore, they are applicable to ticks, fleas, mites, triatomine bugs and sandflies as well as mosquitoes that transmit different pathogens. By contrast, the biological and operational modules, such as surveillance design, relevant reservoirs and hosts, spatial and temporal resolution, exposure definition and available interventions, must reflect vector ecology. Tick surveillance, for example, relies less on trap-based counts and more on fine-scale microclimate and vegetation covariates linked to ambush questing behaviour and multi-year life cycles [38]. Triatomine bug distribution models ought to incorporate housing quality and household survey data because transmission cycles shift between sylvatic and domiciliary settings [39,40]. Sandfly vectors of leishmaniasis generate abundance data that are sparse and heavily skewed toward zero, which often confines modelling to the genus rather than the species level [41]. Evidence on flea- and mite-borne systems remains comparatively limited, so their at-risk population classifications and surveillance inputs will require local validation before the framework can be used confidently.

Dynamic at-risk populations should be estimated using combinations of census data, settlement layers, mobility proxies, night-time lights, remote sensing, displacement records, and local knowledge. Programmes need interpretable probability intervals, risk classifications, and trigger thresholds that make false-alarm and missed-outbreak trade-offs explicit. Foundation models and few-shot transfer learning may help identify shared transmission dynamics across settings with limited data, but their public health use requires external validation, uncertainty reporting, and safeguards against overconfident outputs [20].

Multi-agent AI systems may support complex workflows if they remain accountable. VBD control involves a sequential chain of activities spanning surveillance review, data modelling, spatial analysis, evidence synthesis, visualisation, report generation, and decision documentation. Task-specific agents could support these functions, while a supervisory layer checks evidence quality, consistency, uncertainty, and ethical constraints. Emerging geospatial multi-agent architectures provide one possible template, but public health deployment requires stronger validation and governance than generic analytical automation [42]. Safeguards for LLM-enable workflows are also required to defend against the risks connected manufactured evidence, incorrect interpretation of surveillance signals or misleading intervention recommendations that may occur during LLM use. Retrieval-augmented generation is limited to pre-curated corpora, including surveillance databases, guidelines and program documents. To avoid self-generated interpolation, alert summaries and epidemic bulletins should follow restricted-use templates with numerical fields pulled directly from databases. Human review needs to be also strengthened across each stage, with experts examining critical judgements and issuing approval or rejection decisions. Establishing a stable feedback mechanism between practitioners and the AI system helps calibrate model performance and reduce the risk of hallucination. Any LLM output must retain the prompt, retrieved evidence and model version so that experts can render a final judgement and take corresponding responsibility.

Real-world evaluation should assess both whether AI improves immediate public health operational practice and whether these improvements translate into sustained population health gains over the longer term. Short-term operational outcomes include data completeness, alert calibration, lead time, surveillance-to-action intervals, intervention coverage, workload, and efficiency of resource allocation. Longer-term epidemiological and health outcomes include reductions in disease incidence and seroincidence, severe cases and deaths, and epidemic size and duration, as well as disability-adjusted life years (DALYs) averted and broader indirect economic and societal benefits. These outcomes should be assessed alongside conventional predictive metrics.

Lastly, AI can contribute to VBD control only when it is integrated into accountable public health practice. The priority is a human-AI workflow that links surveillance, dynamic at-risk population intelligence, risk stratification, early warning, intervention, and feedback. Such a workflow should make uncertainty explicit, preserve expert and community judgement, support equitable resource allocation, and learn from implementation outcomes. Under environmental and population change, AI should help public health systems detect shifting exposure earlier, target interventions more accurately, communicate uncertainty more clearly, and evaluate whether decisions improved coverage, timeliness, and equity.

Author Contributions

S.L.: writing—original draft, writing—review & editing, conceptualization, funding acquisition, supervision; T.C.: writing—original draft, writing—review & editing, conceptualization, supervision; Z.Z.: writing—original draft, writing—review & editing, conceptualization, methodology; J.X.: writing—original draft, writing—review & editing, visualization; H.L.: writing—original draft, writing—review & editing, visualization. All authors have read and agreed to the published version of the manuscript.

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No new data were generated or analyzed in support of this research.

Conflicts of Interest

The authors declare no conflict of interest. The funders had no role in study design, data collection, data analysis, data interpretation or writing of the paper.

Use of AI and AI-Assisted Technologies

During the preparation of this work, the authors used ChatGPT-5.6-luna to check grammar. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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