Acta Scientific Microbiology (ISSN: 2581-3226)

Volume 9 Issue 8 August 2026

Review Article

Real-Time Smart Surveillance for Neglected Tropical and Parasitic Diseases (NTPDs)

Evelyn Orevaoghene Onosakponome[1]* and Robinson Ndifrekeabasi Itek[2]

[1]Department of Medical Microbiology and Parasitology, Federal University Otuoke, Bayelsa State, Nigeria

[2]Department of Medical Microbiology and Parasitology, Rivers State University, Nigeria

***Corresponding Author:** Evelyn Orevaoghene Onosakponome, Department of Medical Microbiology and Parasitology, Federal University Otuoke, Bayelsa State, Nigeria.

DOI: 10.31080/ASMI.2026.09.1615

Received: June 15, 2026

Published: July 22, 2026

Abstract

Neglected tropical and parasitic diseases (NTPDs) impose a disproportionate burden on populations in low- and middle-income countries, where conventional surveillance infrastructure is too slow, spatially imprecise, and chronically underresourced to detect outbreaks before they spread. Reliance on manual reporting chains and laboratory confirmation generates delays that allow parasitic infections to establish themselves across communities before any coordinated response is mobilised. Advances in artificial intelligence (AI), machine learning (ML), geographic information systems (GIS), global positioning systems (GPS), remote sensing, mobile health (mHealth), and Internet of Things (IoT) technologies have made it technically feasible to construct real-time smart surveillance architectures capable of delivering high-resolution risk maps, automated diagnostics, and predictive alerts. Evidence from infectious disease prediction, environmental monitoring, and digital health implementation supports the position that AI-enabled image analysis, sensor networks, and predictive modelling can substantially shorten outbreak detection timelines and guide targeted interventions in ways conventional systems cannot. Significant obstacles remain, particularly around infrastructure gaps, data governance, trained workforce shortages, and the long-term financial sustainability of digital systems in endemic settings. This review synthesises current literature on the concept, core components, public health applications, advantages, implementation challenges, and future directions of smart surveillance systems for NTPD control, and concludes with practical recommendations for programme adoption.

Keywords: Neglected Tropical Diseases; Parasitic Disease; Smart Surveillance; Artificial Intelligence; Geographic Information Systems

Introduction

More than 1.5 billion people worldwide are affected by NTPDs, a heterogeneous cluster of communicable conditions whose burden falls almost exclusively on impoverished populations in tropical and subtropical settings [1]. The parasitic subset of these diseases, driven by helminths and protozoa with life cycles of considerable biological complexity, is particularly resistant to control. Schistosomiasis, transmitted through freshwater contact with snail intermediate hosts; lymphatic filariasis, caused by filarial nematodes vectored by mosquitoes; and the soiltransmitted helminthiases, caused by *Ascaris lumbricoides*, *Trichuris trichiura*, and hookworm species, each sustain intergenerational cycles of poverty, nutritional deficiency, and impaired cognitive development across hundreds of millions of people [2,3]. Their ecological entanglement with snail intermediate hosts, sandfly and mosquito vectors, and deficient Water, Sanitation, and Hygiene infrastructure means that effective control demands far more than clinical case detection [4]. The WHO's 2030 NTD elimination roadmap has codified this ambition at a global policy level, yet the surveillance infrastructure available to most endemic countries remains structurally misaligned with the pace and precision that elimination programmes require [5].

The problem with conventional surveillance is that field workers collect samples and paper forms that travel through hierarchical administrative chains, routinely arriving at the national level weeks or months after the events they record [6,7]. Underreporting is endemic to this design, diagnostic misclassification adds further distortion, and the epidemiological representation available to programme managers is retrospective by the time it reaches them. These are not failures of individual effort but of systems built for a different era, one in which nearrealtime data transmission was not technically feasible. The consequences for parasitic disease control are concrete: MDA campaigns deployed on outdated prevalence estimates miss transmission hotspots, vector control resources are distributed without spatial evidence, and outbreak signals accumulate undetected until case counts are already high enough to be visible through hospital reporting [8].

The past decade has changed what is technically possible. Geographic information systems and GPS now provide the spatial precision to map transmission hotspots at household and waterbody resolution [9]. AI and ML applied to satellite imagery, climate data, and clinical records generate predictive risk models at subdistrict scale [10]. Remote sensing and UAVs extend ecological monitoring into terrain that ground surveys cannot efficiently reach. mHealth platforms enable community health workers to transmit case data and diagnostic results from remote settings in real time, and IoT sensor networks create continuous environmental monitoring streams that feed into shared analytical platforms [11-13]. The convergence of these technologies has produced a new surveillance architecture, one oriented toward anticipation rather than documentation, and there is now a substantive body of evidence from NTPDendemic settings that these systems can substantially improve outbreak detection speed, intervention targeting, and programme monitoring. What is less clear is the extent to which that evidence base is being translated into sustained operational deployment rather than timelimited pilot programmes, and what conditions favour or obstruct that translation.

This review examines the current state of realtime smart surveillance as applied to NTPDs. Its specific objectives are:

- To define smart surveillance in the NTPD context and distinguish it from conventional surveillance models.
- To review the core technologies enabling smart surveillance and examine their roles in parasitic disease monitoring.
- To present case study evidence from Nigeria, subSaharan Africa, and Asia documenting the application of smart surveillance methods.
- To assess the public health advantages and implementation challenges of these systems.
- To propose future directions and practical recommendations for embedding smart surveillance within national disease control programmes.

Smart surveillance: Concept and components

Definition

In the public health context, smart surveillance refers to the continuous, automated, and realtime collection, integration, analysis, and interpretation of health, ecological, and spatial data for the purpose of detecting, predicting, and responding to disease threats [14]. The defining departure from conventional indicatorbased surveillance is its orientation toward anticipation rather than documentation [14]. Rather than waiting for clinical reports to accumulate and then characterising an outbreak retrospectively, smart surveillance aims to detect anomalies in transmission signals, vector ecology, or environmental conditions before widespread human infection has occurred [14,15]. For parasitic diseases specifically, this means monitoring the full epidemiological triad simultaneously: the human host, the parasitic agent, and the specific environmental or biological vector that enables transmission [16]. The practical realisation of this requires an interconnected network of digital tools operating at different spatial scales and contributing complementary data streams to a shared analytical platform, tools whose individual characteristics and respective contributions are described below [13,17].

Components

Geographic information systems

GIS functions as the spatial architecture that converts diverse epidemiological and ecological datasets into legible, actionable maps [18]. By overlaying population distribution, hydrological features, disease incidence records, and historical vector data, GIS produces risk maps that translate raw field evidence into spatial decision support [19]. For schistosomiasis control, the application is wellestablished: GIS layers human settlement distribution against the freshwater bodies inhabited by *Biomphalaria* and *Bulinus* snail intermediate hosts, identifying transmission hotspots where targeted MDA of praziquantel can be deployed efficiently rather than applied uniformly across entire districts at unnecessary cost [20]. Geospatial analysis has been applied with similar logic to Chagas disease risk mapping, helping authorities allocate healthcare and educational resources toward communities with demonstrable triatomine bug exposure [21]. The broader value of GIS in this context is the precision it introduces into resource allocation: interventions reach the geographies of highest parasitic burden rather than being diffused across administrative units that may span a wide range of actual transmission intensity.

Global positioning system

GPS provides the precise coordinate layer on which GIS analysis depends. In field epidemiology, GPSenabled devices allow community health workers (CHWs) to geotag the exact location of each confirmed case, each captured vector specimen, and each household visited during MDA campaigns [22]. For Chagas disease, geotagging the home of a confirmed patient is epidemiologically meaningful because it signals the probable presence of triatomine bug vectors in the immediate domestic environment, justifying targeted entomological assessment and insecticide application at that address [23]. GPS tracking has also been applied to tracking mobile highrisk populations in the Greater Mekong Subregion, where GPSdriven household surveys estimate the size and location of forestgoing and migrant groups, enabling surveillance to follow demographic movement in real time and reduce the risk of drugresistant parasite reintroduction into cleared zones [24]. For snailborne infections, GPS records the precise coordinates of endemic water bodies, supporting correlation analyses between snail intermediate host abundance and proximity to human settlements that directly inform molluscicide deployment [25].

Artificial intelligence

AI, including ML and deep learning methods, functions as both the predictive engine and the diagnostic assistant of any smart surveillance system. On the forecasting side, deep learning architectures, particularly Long ShortTerm Memory networks designed to process timeseries data, ingest historical incidence records alongside realtime climate variables such as rainfall, temperature, and humidity to generate early warnings for vectorborne disease transmission [26]. Kraemer., *et al*. [27], in a comprehensive perspective published in *Nature*, detail how AI systems that combine ML, computational statistics, and information retrieval are now capable of addressing key epidemiological questions at a scale and speed that conventional modelling cannot match. For Chagas disease, De Rose Ghilardi., *et al*. [28] demonstrated that ML algorithms trained on sociodemographic and environmental datasets could predict *Trypanosoma cruzi* infection in rural Brazilian populations with meaningful discriminative accuracy, establishing proof of concept for AIdriven prescreening that could guide targeted serological testing and reduce mass testing costs by over twenty percent. On the diagnostic side, AIpowered microscopy systems that run on midrange smartphones without internet connectivity now detect and quantify microfilariae species in real time, effectively replicating the diagnostic workflow of an expert microscopist in settings where no such expert is available [29].

Remote sensing and satellite imaging

Remote sensing uses satellite imagery and airborne sensors to gather physical and biological environmental data at spatial scales that ground surveys cannot replicate. Most tropical parasites and their vectors depend on specific ecological conditions, and the ability to measure soil moisture, vegetation density, surface water extent, and land surface temperature (LST) from orbit directly characterises habitat suitability for *Anopheles* mosquito breeding, phlebotomine sandfly populations, and freshwater snail intermediate hosts [30]. Combining satellitederived metrics into composite indices, such as the Mosquito Habitat Suitability Index built from Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index, and LST values, generates granular malaria risk maps at a fraction of the cost of equivalent ground survey efforts [31]. Highresolution orbital imagery also enables continuous temporal tracking of landuse change, flood dynamics, and livestock distribution across large territories. Xue., *et al*. [32] developed deep learning semantic segmentation models applied to highresolution satellite imagery to automatically identify and monitor livestock bovine distribution, the primary animal reservoir for *Schistosoma japonicum* in China, achieving recognition ratios above 84% across island beaches and grassland environments. This approach provides continuous, automated surveillance of animal reservoirs that would otherwise require exhaustive and expensive ground enumeration, and illustrates a broadening application of satellite imaging from habitat characterisation toward direct infectious source monitoring.

Mobile health technologies

mHealth includes the use of smartphones, tablets, and dedicated applications by frontline health workers for clinical reporting and data collection at the point of care. Its role in smart surveillance is to serve as the fieldlevel data entry layer that connects remote communities to centralised national databases. CHWs performing Rapid Diagnostic Tests (RDTs) for malaria log results directly into mobile applications, transmitting structured data to district and national surveillance platforms in real time. O'Brien., *et al*. [33] documented that digital health technologies have substantially improved healthcare data generation across subSaharan Africa, particularly in settings where paperbased systems generated monthslong delays before data reached any level capable of acting on it. The offline functionality of welldesigned mHealth platforms, synchronising data to central servers when connectivity is restored, is especially important for maintaining surveillance visibility over offgrid populations where parasitic burdens tend to be heaviest. This design principle directly addresses the equity problem in conventional surveillance, where communities furthest from formal health infrastructure are simultaneously the most affected and the least visible to national monitoring systems.

Now, taken individually, each of these components offers a meaningful improvement over conventional surveillance methods. Their value is multiplied, though, when they are integrated into a unified platform where spatial data, predictive models, field case reports, and ecological sensor outputs inform each other in real time. That integration is the technical and governance challenge that determines whether smart surveillance delivers its potential in operational practice.

Principles of realtime surveillance

Smart surveillance systems, to be effective in NTPD settings, must embody a set of operational principles that collectively define what distinguishes them from conventional approaches. These principles are not independent design choices but interconnected requirements: a system that achieves spatial precision without timeliness cannot prevent an outbreak; one that achieves timeliness without equity of reach will systematically miss the populations most at risk [34]. Timeliness is the most fundamental requirement as *Plasmodium falciparum* can achieve high transmission intensity within weeks of favourable *Anopheles* breeding conditions [35]. A surveillance system that captures and transmits epidemiological signals near instantaneously allows health authorities to deploy chemoprevention or vector control before localised infection crosses the threshold into community wide transmission. Integrating RDT results directly into digital surveillance networks eliminates the critical lag of paper based clinic reporting; the combination of real time syndromic data and diagnostic results enables pre epidemic response that no retrospective system can match [36].

Spatial precision is equally nonnegotiable, because parasitic diseases are focally distributed and tied to specific ecological microniches. Uniform distribution of limited resources across administrative districts, without geospatial evidence of where transmission is actually occurring, wastes intervention capacity and leaves true hotspots underserved. GIS and GPS together allow epidemiologists to map vulnerability at household or waterbody resolution, ensuring that indoor residual spraying, MDA, and mollusciciding reach the right locations [37]. In settings where every vial of praziquantel or litre of molluscicide represents a constrained budget, this spatial precision is not merely a technical refinement but a determinant of programmatic effectiveness. Interoperability across data types prevents smart surveillance from reproducing the siloed fragmentation of conventional systems. Entomological counts, clinical incidence records, and satellite environmental data must flow into a single integrated platform that can crossreference these streams in real time. Evaluations of subnational malaria intervention tailoring have demonstrated that successfully localising disease responses requires platforms, such as the District Health Information Software 2 (DHIS2), capable of synthesising clinical and vector ecology data simultaneously [38]. Without interoperability, the predictive and spatial capabilities of individual components cannot be fully realised, because each operates on only a fragment of the epidemiological picture.

ML algorithms applied to historical transmission data and realtime environmental variables detect early warning signals, localised shifts in temperature and humidity that favour triatomine bug or *Anopheles* breeding, enabling preventive action before any human case presents clinically [28]. This anticipatory capacity represents a categorical shift from what any accumulationanddetect approach can offer, and it is what distinguishes smart surveillance as a genuinely different model rather than merely a faster version of the old one. NTPDs are concentrated precisely in communities furthest from formal healthcare, and surveillance architectures that only capture cases presenting at health facilities will systematically undercount the most affected populations. mHealth applications with offline capability, communitybased reporting platforms, and crowdsourced case identification are the mechanisms that extend surveillance visibility into marginalised settings, ensuring that vulnerable, offgrid populations remain visible to national elimination programmes [39]. Equity is not an aspirational addon to these systems; it is a validity criterion for any surveillance claiming to monitor NTD burden accurately.

Role of smart technologies in NTPD surveillance

GPSbased disease and vector tracking

The focal, ecologicallydetermined nature of parasitic disease transmission gives GPSenabled spatial epidemiology a specificity advantage that aggregate populationlevel data simply cannot provide. Among the clearest operational demonstrations is the application to mobile highrisk populations in the Greater Mekong Subregion, where eliminating *Plasmodium falciparum* by 2030 is complicated by the constant movement of forest workers and migrants who may acquire and reintroduce drugresistant parasites [40]. GPSdriven household surveys have been used to estimate the size and spatial distribution of these groups, allowing surveillance networks to track demographic shifts in real time rather than operating on fixed administrative assumptions about where people live [24]. For schistosomiasis, GPS allows the precise geotagging of endemic freshwater sites; by correlating the abundance of *Bulinus* and *Biomphalaria* snail hosts with the GPS coordinates of nearby settlements, researchers can direct molluscicide applications and MDA campaigns to the water bodies actually driving human infection rather than applying them across all accessible water surfaces [25]. In both cases, the epidemiological value is specificity: resources reach the right place because GPS evidence, rather than administrative assumption, defines where the right place is.

AIBased prediction and diagnostics

The chronic shortage of trained parasitologists across much of subSaharan Africa and South Asia is one of the most durable structural weaknesses in NTD diagnostic capacity, and AIpowered microscopy is now making a substantive impact on this gap. Autonomous microscopy platforms, including the Octopi system and the Noul miLab device, identify and quantify *Plasmodium* species in digitised blood smears within minutes without manual staining or slide preparation [41]. More significantly, the integration of Vision Transformers and Gradientweighted Class Activation Mapping (GradCAM) introduces a degree of diagnostic explainability that earlier blackbox classifiers lacked: health workers can see precisely which morphological features of the analysed red blood cell triggered the positive diagnosis, which supports clinical trust and enables quality assurance in lowresource settings [42]. Lin., *et al*. [29] extended this capability further with an edge AI system that detects and quantifies four microfilariae species, *Loa loa*, *Mansonella perstans*, *Wuchereria bancrofti*, and *Brugia malayi*, using a smartphone camera aligned with an optical microscope, operating entirely offline without internet connectivity. That a system of this power can now run on a midrange smartphone is a meaningful development for lymphatic filariasis and onchocerciasis programmes operating in settings where laboratory infrastructure is essentially absent. At the epidemiological level, ML frameworks trained on climatic and environmental inputs now issue early warnings for vectorborne transmission surges weeks before they manifest in clinical case counts, providing the preepidemic lead time that allows preemptive resource allocation rather than reactive emergency response [27].

Remote sensing for environmental monitoring

Tracking environmental conditions over the vast and often inaccessible territories where NTPD vectors breed is one of the clearest areas where satellite remote sensing outperforms any groundbased alternative on both cost and coverage. Highresolution satellite data tracking water level fluctuations, LST, and NDVI allow epidemiologists to map the spatial risk of schistosomiasis transmission across wetland systems that would take years to survey on foot, identifying where snail population expansions are likely before human exposure increases [25]. For SoilTransmitted Helminths (STHs) such as *A. lumbricoides* and hookworm species, remote sensors measuring soil moisture determine how long infectious larvae and eggs can persist in the environment, which directly informs the scheduling of seasonal deworming campaigns to coincide with periods of maximum transmission risk rather than arbitrary calendar dates [43]. Drone surveillance adds a loweraltitude layer to this ecological monitoring: UAVs can survey urban water containers, agricultural ditches, and floodprone settlement perimeters at the fine resolution needed for larval source identification in malaria control, and the same methodology is being extended to schistosomiasis snail habitat mapping [44]. The costeffectiveness argument for remote sensing as a surveillance input is strong; it replaces repeated, expensive ground surveys with continuous automated data streams and does so at a spatial scale that ground methods cannot match even with unlimited resources.

mHealth reporting systems

The transformation that mHealth has brought to communitylevel NTD surveillance is best understood by considering the baseline it replaced. CHWs performing RDTs in remote villages historically completed paper ledgers that took months to reach central health ministries, generating an epidemiological record that was useless for realtime decisionmaking. Mobile reporting applications have replaced this with reporting timelines measured in minutes, enabling district authorities to investigate sudden spikes in RDT positivity and assess service delivery concerns within hours of their occurrence [45]. The data quality improvement is as important as the speed gain: mobile reporting eliminates the transcription errors that accumulate through hierarchical paperbased chains and transmits structured, queryable data directly into national databases. The further capability of mHealth platforms to digitise results from pointofcare biosensors and lateral flow assays prevents the underreporting that has historically characterised endoparasitic infections, particularly in settings where patients present infrequently or formal diagnoses are rarely completed.

Data integration and visualisation

The full analytical value of smart surveillance materialises only when GPS coordinates, AI forecasts, remote sensing outputs, and mHealth case reports are synthesised into a unified operational interface. According to Akpan., *et al*. [46], in many endemic countries, mobile field data now flows directly into DHIS2 platforms, allowing health ministries to track case locations through integrated GIS displays and maintain reporting rates above 90%. The consequence is a form of operational intelligence that conventional surveillance architectures cannot produce. When AI analysis of satellite remote sensing data predicts an imminent malaria transmission surge based on observed increases in standing water, and DHIS2 dashboards simultaneously show depletion of antimalarial commodity stocks in the affected districts, programme managers can reroute supplies to the GPS coordinates of atrisk clinics before a logistical failure compounds the epidemiological risk. That kind of crossdomain synthesis, closing the loop between environmental prediction, clinical monitoring, and supply chain management, is what distinguishes integrated smart surveillance from the sum of its component parts.

Public health applications

Early outbreak detection

Conventional surveillance systems characteristically identify outbreaks only after widespread transmission has already occurred, by which point the window for containment has substantially narrowed. The operational advantage of realtime smart surveillance lies precisely in its capacity to compress this detection lag [47]. By continuously analysing epidemiological, environmental, climatic, and entomological data through AIdriven predictive models, smart surveillance generates outbreak signals weeks before they appear in clinical case counts. Khew., *et al*. [48] argue that ML algorithms analysing rainfall variability, humidity, vegetation change, and population movement patterns can predict outbreaks of vectorborne diseases such as malaria and lymphatic filariasis with enough lead time for preemptive vector control campaigns, MDA deployment, and environmental sanitation, converting what would have been an emergency response into a planned prevention activity.

The expanding geographic distribution of NTPD vectors driven by climate change, urbanisation, and deforestation makes this predictive capacity increasingly indispensable. Kraemer., *et al*. [27] review a range of AI architectures now applied to infectious disease epidemiology, including systems capable of processing hospital records, climate sensor outputs, and genomic databases simultaneously to identify transmission trends at a scope and speed that no conventional analytical method could approach. Automated digital alerts generated by these platforms allow ministries of health and international partners to coordinate responses far more rapidly than paperbased notification chains permit, and live epidemiological dashboards provide continuously updated situational awareness of incidence, transmission hotspots, and vector density that fundamentally changes the information environment in which outbreak responses are planned.

Vector habitat mapping

GIS, remote sensing, drone surveillance, and satellite imaging are now used operationally to monitor the ecological conditions associated with parasite transmission, generating dynamic risk maps that spatially prioritise intervention [49]. For schistosomiasis, satellite imaging identifies freshwater snail habitat characteristics with enough resolution to guide targeted mollusciciding without the cost of field surveys across entire river systems or lake shores [50]. For human African trypanosomiasis, remote sensing characterises tsetse fly breeding zones within specific woodland and riverine vegetation profiles [51]. For leishmaniasis, multispectral data identifies the soil moisture and vegetation profiles that favour phlebotomine sandfly habitat [52]. In each case, the output is a spatial prioritisation layer that concentrates insecticide programmes, environmental sanitation, and MDA precisely where transmission risk is highest rather than distributing them uniformly across administrative boundaries that bear no relation to the ecology of transmission [53]. IoTenabled vector surveillance is adding a continuous, automated dimension to this ecological monitoring. Smart mosquito traps integrated with ML classification algorithms automatically identify vector species and transmit surveillance data directly to centralised dashboards, replacing the periodic trapchecking that characterised earlier entomological monitoring and creating realtime visibility of vector density changes that can trigger preemptive control responses [48,54]. Environmental sensors tracking water quality, temperature, and vegetation density contribute further continuous data streams, collectively producing an ecological situational picture that was simply not available to NTPD programme managers a decade ago.

Monitoring treatment programmes

According to Smits [55], MDA programmes remain the primary control modality for schistosomiasis, lymphatic filariasis, onchocerciasis, and STHs, and monitoring their coverage, therapeutic outcomes, adherence, and logistics has historically been among the most difficult operational challenges in NTD control. Digital surveillance now enables realtime tracking of MDA activities through electronic reporting platforms, mobile applications, and cloudbased databases, allowing health authorities to identify underserved populations, assess adherence, and evaluate programme effectiveness far more efficiently than periodic paperbased coverage surveys permit [56]. Realtime treatment monitoring also improves transparency and operational accountability within national disease control programmes, which is important for both domestic governance and donor reporting requirements.

AIassisted diagnostics are transforming laboratory response capacity in ways directly relevant to treatment programme monitoring. Lin., *et al*. [29] developed an edge AI system running on a standard smartphone attached to an optical microscope that detects and quantifies four microfilariae species in real time, without internet connectivity, achieving diagnostic performance comparable to expert microscopists. The system operates offline, which matters enormously for lymphatic filariasis and loiasis control programmes working in remote settings where laboratory infrastructure is absent. By enabling diagnosis at the point of care and feeding results into national databases through mHealth platforms, this kind of tool directly supports both case confirmation and posttreatment assessment in the field.

CommunityBased surveillance

Sustainable NTD control ultimately depends on community participation, and smart surveillance technologies have created practical mechanisms through which local populations can contribute meaningfully to disease detection. Chukwuocha., *et* *al*. [39] conducted a crowdsourced, imagebased surveillance pilot across 45 communities in three Nigerian states, covering a population of 477,138 people. Community members selfreported suspected NTD symptoms by photographing and transmitting skin and eye manifestations via digital platforms to an expert review panel, which confirmed 75.4% of the 512 submitted images as showing genuine NTD signs. Community focal points facilitated over 80% of all submissions, illustrating that the system functioned not as a passive digital tool but as an active, communityintegrated reporting network. The result was a set of morbidity hotspot maps for the study states that would have required substantially greater resources to generate through conventional active case search. This is, in practical terms, a demonstration that surveillance capacity can be extended into settings with no laboratory infrastructure provided community members have access to basic smartphone technology and a structured submission platform.

The applicability of this model extends beyond contexts with functioning health systems as observed in conflict zones, refugee settlements, and geographically isolated communities where formal surveillance infrastructure is frequently absent or disrupted, and communitybased digital surveillance may represent the only available source of epidemiological intelligence. Participatory reporting of vector infestations, environmental hazards, and unusual disease clustering strengthens the grassroots data layer on which national surveillance platforms depend, and the bidirectional nature of digital communication platforms, disseminating public health information back to communities as well as collecting data from them, supports the behavioural changes and early careseeking that reduce onward transmission [56].

Case studies: Published evidence from Nigeria, SubSaharan Africa, and Asia

Nigeria

Nigeria carries one of the highest NTD burdens globally, with schistosomiasis, lymphatic filariasis, onchocerciasis, and STHs each contributing substantially to national morbidity [57]. Smart surveillance efforts in the country have yielded a body of evidence illustrating the feasibility of GISbased risk mapping, crowdsourced digital reporting, and AIassisted diagnostics. Ekpo., *et al*. [58] produced the first comprehensive national GISbased risk maps for *Schistosoma haematobium* and *S. mansoni* using Bayesian geospatial modelling of compiled survey data, providing subnational transmission risk estimates that guided MDA targeting. However, the reliance on historical prevalence surveys limits the temporal resolution, and the models have not been systematically validated with postMDA data. A communitybased digital platform deployed across 45 communities in three Nigerian states [39] demonstrated that crowdsourced imagebased reporting can generate validated NTD morbidity hotspot maps, with an expert panel confirming 75.4% of submitted images as genuine NTD signs. This approach illustrates the potential to extend surveillance beyond facilitybased reporting, though its scalability and sustained community engagement remain uncertain. Geospatial modelling of secondary malaria vector species using field entomological data from 20 states [59] integrated remote sensing and climate variables to predict vector distribution, offering a valuable tool for targeting control measures, yet the study's predictions require field validation over multiple transmission seasons. The application of dronebased deep learning for *Anopheles* breeding habitat identification in Côte d'Ivoire and Burkina Faso [60] establishes a transferable methodology for larval source mapping, but its operational integration into routine malaria control programmes has not been demonstrated. For lymphatic filariasis, a quasiexperimental evaluation of an AIassisted microscopy device (AiDx Assist) used by community health workers in Nigeria [61] reported 85.7% sensitivity and 82.5% specificity for microfilaria detection, suggesting that taskshifting with AI support can expand diagnostic capacity; however, the small sample and singlesite design limit generalisability. Finally, a systematic review and metaanalysis of STH prevalence across Nigeria [62] constructed GISbased risk zone maps, yet the underlying data were heterogeneous and largely predated current MDA intensification. Collectively, these studies demonstrate a range of technological feasibility, but the transition from individual research initiatives to integrated, nationally scaled surveillance systems remains unrealised.

SubSaharan Africa

Across subSaharan Africa, smart surveillance studies have addressed schistosomiasis snail habitat prediction, onchocerciasis programme monitoring, trypanosomiasis elimination modelling, UAV applications, and STH programme evaluation. Tabo., *et al*. [63] applied random forest machine learning to climate and soil data to predict the occurrence of *Biomphalaria* and *Bulinus* intermediate hosts across East Africa, generating a spatial framework for targeted snail control; however, the model's reliance on presenceonly data and limited snail survey coverage may inflate predicted habitat suitability. In Cameroon, a communitydirected ivermectin distribution programme augmented with digital data collection improved treatment coverage monitoring [64], but the study's short time frame and lack of control group preclude causal attribution. For gambiense human African trypanosomiasis in the Democratic Republic of Congo, Crump., *et al*. [65] used mathematical modelling across 168 health zones to evaluate screening and vector control strategies, projecting that only 98 zones were on track for elimination; the model provided valuable spatial prioritisation but was sensitive to assumptions about diagnostic sensitivity and passive reporting rates. A systematic review of UAV applications for malaria vector surveillance [66] documented growing evidence that drones can identify breeding habitats and deliver larvicides at fine spatial scales, yet operational costs, regulatory hurdles, and the lack of standardised protocols constrain widespread uptake. In Ethiopia, Maddren., *et al*. [67] conducted a systematic review of two decades of STH and schistosomiasis data, revealing that despite MDA, prevalence remained high in many regions with significant surveillance gaps, underscoring the need for improved digital reporting integration in national programmes. The studies from the region collectively show that while smart tools can enhance surveillance precision, their effectiveness is compromised by fragmented implementation, limited longitudinal validation, and insufficient integration with routine health systems.

Asia and global evidence

The Asian and global evidence base features some of the most technically sophisticated integrations of remote sensing and deep learning for schistosomiasis, as well as broader AI applications. In China, Zhang., *et al*. [68] demonstrated that AIsupported GIS models integrating satellite environmental data improved prediction of *Schistosoma japonicum* transmission risk zones, strengthening the environmental surveillance framework for the national elimination programme. The subsequent development of deep learning models for highresolution satellite imagery [32] enabled automatic recognition of bovine reservoir distribution with 84–90% accuracy, allowing infectious source monitoring without ground enumeration. These advances, while impressive, are embedded in China's strong surveillance infrastructure and may not be directly transferable to resourceconstrained African settings. A hybrid deep learning system for trypanosome species identification from microscopy images [69] achieved superior accuracy and could be deployed on standard oilimmersion microscopes, but its realworld field validation in endemic countries is pending. AIsupported predictive mapping in Southeast Asia [70] improved identification of malaria mosquito breeding habitats and generated seasonal outbreak forecasts, contributing evidence for preemptive interventions; nonetheless, the reliance on highquality entomological and climate data inputs poses challenges in settings with sparse monitoring networks. Globally, Khew., *et al*. [48] reviewed the application of machine learning to NTD surveillance, finding that while AI can enhance outbreak prediction, risk mapping, and treatment monitoring, data scarcity, model generalisability, and implementation gaps in lowincome settings remain critical barriers. The reviewed evidence highlights that without sustained investment in data infrastructure and local capacity, even the most advanced algorithmic tools risk remaining academic exercises.

Advantages of smart surveillance

Realtime data availability

Conventional NTD surveillance systems have operated on reporting cycles measured in weeks or months, generating a systematic lag between epidemiological event and programmatic response. Smart surveillance collapses this timeline by transmitting field data instantaneously through mobile applications, electronic health records, SMS platforms, and cloudbased systems, creating a continuously updated picture of disease activity that programme managers can act on in nearrealtime [71,72]. IoTenabled devices extend this capacity to remote endemic areas where reliable connectivity is absent, maintaining data flow through intermittent connections and synchronising on schedule. Talo., *et al*. [73], in a systematic review of AI and IoT in infectious disease monitoring, found that this combination accelerated diagnostic turnaround, improved public health response, and facilitated remote patient monitoring, with the most pronounced benefits in hardtoreach areas where conventional infrastructure is weakest. The implication for NTPD programmes is direct: surveillance that was previously blind to communitylevel transmission events during interreporting periods can now maintain continuous visibility.

Improved decisionmaking

The analytical foundation of smart surveillance is the capacity to synthesise large and diverse data streams into actionable intelligence at the speed of disease transmission rather than at the speed of administrative process. When AI, GIS, IoT, and ML operate together on shared data platforms, health authorities can analyse epidemiological evidence at a resolution and pace that paperbased and fragmented digital systems cannot approach [74]. Decisions on resource allocation, MDA scheduling, vector control deployment, and health worker distribution shift from being based on historical aggregates to being grounded in current, spatially precise evidence. This is the basic requirement for any surveillance system that aspires to prevent rather than merely document disease, and the integrated nature of smart surveillance is what makes it achievable.

Costeffective intervention planning

The upfront investment in smart surveillance infrastructure is nontrivial, but the downstream operational savings across programme lifetimes are substantial. Satellite ecological monitoring replaces repeated expensive ground surveys. AI diagnostic assistance reduces the personnel costs of microscopy at scale. Geospatially guided MDA and insecticide campaigns deliver interventions to hightransmission zones rather than distributing them uniformly across districts where much of the coverage would reach lowrisk populations. Chukwuocha., *et al*. [39] have demonstrated this in their study where they reported that crowdsourced imagebased digital reporting can generate meaningful epidemiological intelligence at relatively low operational cost in Nigeria, illustrating the broader principle that welldesigned smart surveillance systems extend reach without proportional cost escalation. Over a programme cycle, the cost of an undetected outbreak, in treatment costs, lost productivity, and programme setbacks, is far greater than the investment required to prevent it through timely detection.

Improved prevention strategies

The cumulative effect of realtime data, spatial precision, and predictive modelling is a fundamental shift from reactive containment toward proactive prevention. When satellite remote sensing detects ecological conditions favouring elevated vector breeding weeks before human cases present, health systems can initiate targeted vector control, preposition treatments at atrisk facilities, and mobilise CHWs before a transmission peak occurs. This lead time is not a marginal improvement over conventional approaches; it represents a different category of intervention, one that acts on transmission conditions rather than on cases already established in a community. The evidence that AI models trained on climatic and environmental data can generate reliable early warnings for diseases including malaria, schistosomiasis, and Chagas disease [27,28] provides the empirical basis for this shift from surveillanceasdocumentation to surveillanceasprevention.

Challenges of smart surveillance implementation

Infrastructure and connectivity gaps

Many communities where NTPDs are endemic lack the electricity supply, mobile network coverage, functioning hardware, and technical maintenance capacity that smart surveillance systems require. AI and IoTbased surveillance depend on reliable connectivity and operational devices; where these are absent or intermittent, even welldesigned systems fail to deliver their intended function. Talo., *et al*. [73] identify inadequate infrastructure as one of the primary barriers to effective AI and IoTbased surveillance deployment in developing countries, a finding consistent with implementation experience across multiple endemic regions. Connectivity and infrastructure are not independent problems: poor internet access disrupts realtime data synchronisation, cloudbased analytics, and platform interoperability, and in rural tropical regions with low bandwidth and limited mobile coverage, these disruptions occur precisely where the public health need for responsive surveillance is most acute. Offlinecapable mHealth applications and scheduled synchronisation protocols partially mitigate this, but they do not resolve it. Addressing these constraints requires treating basic digital infrastructure as a precondition for effective surveillance deployment rather than an aspirational parallel investment.

Shortage of trained personnel

Operating, maintaining, and interpreting smart surveillance systems requires competencies in data science, AI, epidemiology, bioinformatics, GIS, and digital health system administration. These skills are in short supply across most NTDendemic countries, and healthcare workers in rural settings frequently have limited digital literacy even with standard electronic reporting tools [75]. The consequence is that technically sophisticated surveillance architectures can be deployed and produce data that is neither adequately analysed nor translated into operational decisions, because no one with the relevant skills is positioned to do so [76]. Capacity building cannot be treated as a postdeployment activity; it must be integrated into system design from the outset, with sustained investment in training that outlasts the implementation period of any individual grant or project.

Sustainability and funding dependence

Many digital surveillance systems in endemic settings are initiated through international donor funding, nongovernmental organisation support, or timelimited research grants, and when external support ends, the responsibility for maintaining equipment, software licences, internet services, technical staff, and operational coordination falls to health systems that frequently lack the domestic budget to sustain them. The result is a recurring pattern in which pilot programmes generate genuine public health value and then cease functioning after the funding period, leaving communities without either the old or the new system operating effectively. WorsleyTonks., *et al*. [77] identify this fragmentation of surveillance infrastructure as one of the central structural weaknesses of global health security in low and middleincome countries. Sustainable implementation requires that governments integrate smart surveillance into national healthcare budgets and governance frameworks, allocating stable domestic funding rather than treating these systems as donordependent supplements that exist only as long as external money flows.

Data privacy and ethical governance

The collection of geotagged patient data, crowdsourced health images, and behavioural tracking information raises legitimate data privacy concerns that must be addressed at the system design stage, not managed retrospectively [21]. Patients in marginalised communities are not always positioned to exercise meaningfully informed consent over how their health data is stored, shared across platforms, or used for model training. AI systems trained on datasets derived from specific endemic populations also carry the risk of encoding existing health inequities into predictive outputs if dataset representativeness is not actively monitored and corrected. Olawade., *et al*. [78] emphasise that ethical AI frameworks specifically adapted to lowresource health contexts are necessary because governance capacity in many endemic settings is insufficient to independently audit algorithmic outputs, enforce data protection standards, or hold system developers accountable for model failures. These are not hypothetical risks; they are design constraints that must be built into smart surveillance architectures from the outset if these systems are to be equitable as well as technically effective.

Future perspectives

Big data and advanced machine learning

The trajectory of AI application in NTPD surveillance points toward increasingly integrated systems that fuse clinical, environmental, spatial, and socioeconomic data into realtime transmission models. Kraemer., *et al*. [27] outline a nearfuture in which AI systems combining ML, computational statistics, and genomic data simultaneously forecast disease spread, identify emerging antimicrobial and antiparasitic resistance, and generate spatially precise risk maps, capabilities already being tested in pilot form for malaria that have clear extensions to schistosomiasis, leishmaniasis, and Chagas disease. Digital epidemiology approaches that use mobile phone data, social media signals, and internet search patterns as proxies for disease activity complement these structured data streams, enabling affordable early warning in settings where formal surveillance infrastructure is sparse [79]. The challenge ahead is not primarily one of technical capability, which is advancing rapidly, but of building the governance, interoperability, and training infrastructure that allows these methods to function in operational endemiccountry settings rather than only in wellresourced research contexts.

Drones and robotics in vector surveillance

UAVs are moving from experimental application toward operational use in vector surveillance. Fedra Trujillano., *et al*. [60] document that dronebased habitat mapping linked to deep learning classification models can substantially improve the targeting of larval source management in malaria control, and that the same principle applies to emerging zoonotic disease monitoring more broadly. The extension of this methodology to snail habitat mapping for schistosomiasis control, vector density estimation for lymphatic filariasis, and sandfly habitat characterisation for leishmaniasis represents a natural next step, given the ecological mapping requirements these diseases share with malaria. The ability of UAVs to survey water bodies, agricultural drainage systems, and periurban settlement perimeters at the fine spatial resolution required for source identification, without the cost and logistics of ground surveys in difficult terrain, makes them a practically attractive component of future integrated surveillance systems.

Integration into national health information systems

Technical surveillance capabilities will only produce sustained public health impact when they are embedded within national health information systems rather than operated as parallel, externallyfunded project structures. WorsleyTonks., *et al*. [77] argue that sustainable disease surveillance in low and middleincome countries requires opensource databases, interoperable platforms, and One Health frameworks that integrate animal, human, and environmental monitoring under unified governance. Manyazewal., *et al*. [80], reviewing digital health implementation in Ethiopia, found that isolated digital tools consistently fail to generate systemic impact unless they are connected to broader health information architectures with stable political and financial support. The implication for NTPD smart surveillance is clear: systems must be designed from the outset with national integration as the endpoint, not as a hopedfor outcome of a successful pilot.

Global collaboration and equity

Technically sophisticated surveillance systems deliver limited public health value if they are accessible only to wellresourced countries or deployed exclusively in the research contexts that generate academic publications. Achieving the WHO 2030 NTD targets requires smart surveillance capacity to be built equitably, with specific attention to the lowestincome endemic countries where parasitic burdens are highest and conventional surveillance is weakest. This requires investment in digital infrastructure, sustained workforce training, opensource platform development, and ethical AI governance frameworks accessible to countries without large domestic regulatory capacity. Kostkova., *et al*. [81] stress that digital surveillance systems must be linked to actionable public health response and operated within official surveillance governance structures rather than as standalone innovation demonstrations. Regional platforms for tool development, implementation evidence sharing, and crosscountry evaluation represent the most practical available mechanism for accelerating equitable access to smart surveillance capability at the speed the 2030 roadmap requires.

Recommendations

To build a resilient and forwardlooking approach to NTPD surveillance, national ministries of health must first prioritize structural investments in AI and ML capacity. This requires establishing dedicated internal teams that blend expertise in machine learning, geospatial analysis, and epidemiology. Rather than operating in isolation, these units should leverage targeted training partnerships with universities and international research institutions to continuously sharpen their capabilities [77].

Crucially, the analytical insights generated by these teams depend heavily on the quality of the underlying data architecture. National health authorities need to develop or strengthen integrated digital surveillance platforms that seamlessly merge routine NTPD case data with broader environmental, vector, and mHealth data streams. Enforcing explicit interoperability standards across national health information systems is essential here, as it allows public health officials to crossreference clinical data with realtime ecological shifts [79,81]. Within this integrated ecosystem, innovative technologies like drone and remote sensingbased vector and snail habitat mapping should be systematically piloted in highrisk environments. By linking these aerial observations with deep learning classification models, programs can precisely prioritize larval source management and target environmental interventions for diseases like malaria and schistosomiasis [44].

However, highlevel data models are only as good as the information flowing into them from the field, which underscores the urgent need to fortify digital infrastructure and mHealth tool access for frontline CHWs and endemic populations. Strengthening this localized access is a fundamental prerequisite for reliable, realtime case reporting and treatment followup; furthermore, developers must treat offlinecapable applications as a nonnegotiable design standard to ensure these systems remain functional for offgrid communities [80].

To ensure longterm sustainability, these smart surveillance systems cannot exist as adhoc projects; they must be explicitly woven into national digital health strategies and overarching One Health policies from their very inception. This proactive policy alignment means that governance frameworks, datasharing protocols, and ethical AI guidelines, specifically addressing data privacy, algorithmic representativeness, and model accountability, are hardcoded into the system design rather than patched on retrospectively [77,78]. Finally, because infectious diseases ignore borders, local and national efforts must be anchored in robust regional and global collaboration. By actively participating in international digital health initiatives, codeveloping opensource platforms, and systematically trading implementation evidence and evaluation frameworks, the global health community can ensure that equity of access to these lifesaving digital tools remains an explicit, nonnegotiable target [80,81].

Conclusion

The evidence reviewed in this paper establishes that realtime smart surveillance is not a speculative proposition for NTPD control but a technically validated and increasingly operationally deployed approach that outperforms conventional surveillance on every criterion that matters for elimination: detection speed, spatial precision, predictive capacity, and community reach. AIpowered microscopy, GPSguided MDA targeting, satellite habitat mapping, and mHealthbased community reporting have each been demonstrated to work in endemic settings, including in lowincome contexts where conventional surveillance infrastructure is weakest. The gap that remains is not primarily technical but operational and institutional: translating validated components into integrated, sustained surveillance systems embedded within national health information architectures, funded by stable domestic budgets, and staffed by trained local personnel. The WHO 2030 NTD roadmap sets elimination and control targets that cannot be reached through the surveillance models currently predominant in most endemic countries. The research synthesised here provides a credible evidence base for what a different model looks like and what it requires. Realising it demands coordinated investment across digital infrastructure, workforce training, data governance, and international technical collaboration, none of which is a question of technological feasibility but of political commitment and sustained funding prioritisation. The 2030 deadline is close enough that the window for investing in smart surveillance as a prevention infrastructure, rather than as a response to an alreadyestablished crisis, is narrowing.

Bibliography

1. World Health Organization. "Neglected tropical diseases". Geneva: WHO (2023).
2. Guido G., *et al*. "Prevalence of neglected tropical diseases among migrants living in Europe: A systematic review and meta analysis". *Travel Medicine and Infectious Disease* 64 (2025): 102823.
3. Famakinde DO. "Tackling the menace of schistosomiasis: Successes and the way forward". *Tropical Medicine and Infectious Disease* 3.1 (2018): 30.
4. Hotez PJ. "The neglected tropical diseases and the neglected infections of poverty: overview of their common features, global disease burden and distribution, new control tools, and prospects for disease elimination". In: Institute of Medicine (US) Forum on Microbial Threats. Washington (DC): National Academies Press (US); (2011).
5. World Health Organization. "Global report on neglected tropical diseases 2023". Geneva: WHO; (2023).
6. Mugasha R., *et al*. "Scaling up and enhancing the functionality of the electronic integrated diseases surveillance and response system in Uganda, 2020 2022: description of the journey, challenges, and lessons learned". *JMIR Public Health Surveillance* 11 (2025): e59783.
7. Siddig EE., *et al*. "Epidemiological trend of leprosy in Sudan, 2017 2020: a retrospective national analysis". *Frontiers in Tropical Disease* 7 (2026): 1793089.
8. Amanyi Enegela JA., *et al*. "Community feedback on mass medicines administration for neglected tropical diseases in Federal Capital Territory, Abuja, Nigeria". *Tropical Medicine and Infectious Disease* 9.6 (2024): 126.
9. Kala AK., *et al*. "A comparison of least squares regression and geographically weighted regression modeling of West Nile virus risk based on environmental parameters". *Peer Journal* 5 (2017): e3070.
10. Vidal Durango JV., *et al*. "The role of big data in developing innovative predictive learning models for neglected tropical diseases within the new generation of the evidence based medicine pyramid". *InfezMed* 33.4 (2025): 355-369.
11. Odendaal WA., *et al*. "Health workers' perceptions and experiences of using mHealth technologies to deliver primary healthcare services: a qualitative evidence synthesis". *Cochrane Database Systematic Review* 3 (2020): CD011942.
12. Oswald WE., *et al*. "Development and application of an electronic treatment register: a system for enumerating populations and monitoring treatment during mass drug administration". *Global Health Action* 13.1 (2020): 1785146.
13. Muraro M., *et al*. "How technologies are driving digital innovation in mosquito surveillance systems: a global scoping review over the past decade". *BMJ Public Health* 4.2 (2026): e003145.

14. Taiwo AE., *et al*. "Smart health risk monitoring framework using AI for predicting epidemic trends and resource planning". *Global Multidisciplinary Perspectives Journal* 1.4 (2024): 21-33.

15. Ikechukwu GC., *et al*. "Artificial intelligence for public health surveillance: promises, pitfalls, and an ethics equity roadmap for deployment". *Disease Prevention Epidemiology* 1.1 (2026): 22-39.

16. van Seventer JM and Hochberg NS. "Principles of infectious diseases: transmission, diagnosis, prevention, and control". *International Encyclopedia of Public Health* 1 (2017): 22-39.

17. Saeed MA and Jabbar A. "Smart diagnosis" of parasitic diseases by use of smartphones". *Journal of Clinical Microbiology* 56.1 (2018): e01469-1417.

18. Belizario VY., *et al*. "The use of geographic information system as a tool for schistosomiasis surveillance in the province of Davao del Norte, the Philippines". *Geospat Health* 12.2 (2017): 540.

19. Deka MA. "Predictive risk mapping of schistosomiasis in Madagascar using ecological niche modeling and precision mapping". *Tropical Medicine and Infectious Disease* 7.2 (2022): 15.

20. Brooker S., *et al*. "Rapid mapping of schistosomiasis and other neglected tropical diseases in the context of integrated control programmes in Africa". *Parasitology* 136.13 (2009): 1707-1718.

21. Pacheco GJ., *et al*. "Geospatial analysis as a tool to identify target areas for Chagas disease education for healthcare providers". *BMC Infectious Disease* 22 (2022): 607.

22. Tanser FC and le Sueur D. "The application of geographical information systems to important public health problems in Africa". *International Journal of Health Geographics* 1.1 (2002): 4.

23. Vazquez Prokopec GM., *et al*. "Cost effectiveness of Chagas disease vector control strategies in northwestern Argentina". *PLOS Neglected Tropical Diseases* 3.1 (2009): e363.

24. Topali S., *et al*. "Estimating the size of populations at high risk of malaria in two operational districts in Cambodia: household based survey". *JMIR Public Health Surveillance* 10 (2024): e58584.

25. Anagbogu IN., *et al*. "Abundance and seasonal variations of snail intermediate hosts of schistosomiasis in the Federal Capital Territory, Abuja, Nigeria". *International Journal of Environmental Research and Public Health* 23.3 (2026): 384.

26. Chen X and Moraga P. "Dengue forecasting and outbreak detection in Brazil using LSTM: integrating human mobility and climate factors". *Infectious Disease Model* 11.1 (2026): 338-354.

27. Kraemer MUG., *et al*. "Artificial intelligence for modelling infectious disease epidemics". *Nature* 638.8051 (2025): 623-635.

28. De Rose Ghilardi F., *et al*. "Machine learning for predicting Chagas disease infection in rural areas of Brazil". *PLOS Neglected Tropical Diseases* 18.4 (2024): e0012026.

29. Lin L., *et al*. "Edge artificial intelligence for real time automatic quantification of filariasis in mobile microscopy". *PLOS Neglected Tropical Diseases* 18.4 (2024): e0012117.

30. Simoonga C., *et al*. "Remote sensing, geographical information system and spatial analysis for schistosomiasis epidemiology and ecology in Africa". *Parasitology* 136.13 (2009): 1683-1693.

31. Daulay NA., *et al*. "Optimizing malaria control: granular and cost effective mosquito habitat index in endemic areas through satellite imagery". *Knowledge Engineering in Data Science* 7.1 (2024): 40-57.

32. Xue J B., *et al*. "Recognizing and monitoring infectious sources of schistosomiasis by developing deep learning models with high resolution remote sensing images". *Infectious Diseases of Poverty* 12.1 (2023): 6.

33. O'Brien N., *et al*. "Strengths, weaknesses, opportunities, and threats analysis of the use of digital health technologies in primary health care in sub Saharan Africa: qualitative study". *Journal of Medical Internet Research* 25 (2023): e45224.

34. Maddah N., *et al*. "Effectiveness of public health digital surveillance systems for infectious disease prevention and control at mass gatherings: a systematic review". *Journal of Medical Internet Research* 25 (2023): e44649.

35. Savi MK. "An overview of malaria transmission mechanisms, control, and modeling". *Medical Science* 11.1 (2022): 3.

36. Fallatah DI., *et al*. "Digital epidemiology: harnessing big data for early detection and monitoring of viral outbreaks". *Infection Prevention in Practice* 6.3 (2024): 100382.

37. Banti AD., *et al*. “Modelling malaria vulnerability hotspot by using geospatial techniques: the case of Kindo Koysha Woreda, Wolaita Zone, Ethiopia”. *Geocarto International* 39.1 (2024): 2326003.

38. The Global Fund to Fight AIDS, Tuberculosis and Malaria. “Independent evaluation of capacity, quality and decision making in sub national tailoring of malaria interventions”. Geneva: The Global Fund (2025).

39. Chukwuocha UM., *et al*. “Crowdsourced surveillance for neglected tropical diseases, Nigeria”. *Bulletin of the World Health Organization* 103.12 (2025): 757-765.

40. Cui L., *et al*. “Multidisciplinary investigations of sustained malaria transmission in the Greater Mekong Subregion”. *American Journal of Tropical Medicine and Hygiene* 107 (2022): 138.

41. Martín Ramírez A., *et al*. “Automated microscopy for malaria diagnosis in a reference laboratory in nonendemic settings”. *Parasites and Vectors* 19.1 (2026): 325.

42. Band SS., *et al*. “Application of explainable artificial intelligence in medical health: a systematic review of interpretability methods”. *Informatics in Medicine Unlocked* 40 (2023): 101286.

43. Mengistu B., *et al*. “Trends in the prevalence and intensity of soil transmitted helminth (STH) infection in Ethiopia 2000 to 2023: a systematic review”. *Parasites and Vectors* 18.1 (2025): 269.

44. Zhang L., *et al*. “Modern technologies and solutions to enhance surveillance and response systems for emerging zoonotic diseases”. *Science One Health* 3 (2024): 100061.

45. Breakthrough ACTION. “Malaria service delivery assessment tool: four steps to identify challenges and opportunities”. Baltimore: Johns Hopkins Center for Communication Programs; (2024).

46. Akpan GU., *et al*. “Conclusions of the African Regional GIS Summit (2019): using geographic information systems for public health decision making”. *BMC Proceeding* 16 (2022): 1.

47. Meckawy R., *et al*. “Effectiveness of early warning systems in the detection of infectious diseases outbreaks: a systematic review”. *BMC Public Health* 22.1 (2022): 2216.

48. Khew CY., *et al*. “Progress and challenges for the application of machine learning for neglected tropical diseases”. arXiv (2022): 2212.01027.

49. Beck LR. “Remote sensing and human health: new sensors and new opportunities”. *Emergency Infectious Disease* 6.3 (2000): 217-227.

50. Gong Y F., *et al*. “Identification of the high risk area for schistosomiasis transmission in China based on information value and machine learning: a newly data driven modeling attempt”. *Infectious Diseases of Poverty* 10.1 (2021): 88.

51. Rogers DJ and Robinson TP. “Tsetse distribution”. In: The trypanosomiases. Wallingford: CABI (2004): 139-179.

52. Elamin E., *et al*. “Visceral Leishmaniasis/HIV co infection in Sudan: isolation of parasites from peripheral blood and documentation of 7 cases”. *Indian Journal of Medical Microbiology* 55 (2025): 100832.

53. Weatherhead JE., *et al*. “The global state of helminth control and elimination in children”. *Pediatric Clinics of North America* 64.4 (2017): 867-877.

54. Obradović Z., *et al*. “A literature review on vector borne diseases”. *International Journal of Medical Reviews and Case Reports* 6 (2022): 1-1.

55. Smits HL. “Prospects for the control of neglected tropical diseases by mass drug administration”. *Expert Review of Anti-infective Therapy* 7.1 (2009): 37-56.

56. World Health Organization. “Ending the neglect to attain the Sustainable Development Goals: a road map for neglected tropical diseases 2021 2030”. Geneva: WHO (2021).

57. Hotez PJ., *et al*. “Nigeria: “Ground Zero” for the high prevalence neglected tropical diseases”. *PLOS Neglected Tropical Diseases* 6.7 (2012): e1600.

58. Ekpo UF., *et al*. “Mapping and prediction of schistosomiasis in Nigeria using compiled survey data and Bayesian geospatial modelling”. *Geospat Health* 7.2 (2013): 355-366.

59. Adeogun AO., *et al*. “Spatial distribution and geospatial modeling of potential spread of secondary malaria vectors species in Nigeria using recently collected empirical data”. *PLoS One* 20.4 (2025): e0320531.

60. Trujillano F., *et al*. “Mapping malaria vector habitats in West Africa: drone imagery and deep learning analysis for targeted vector surveillance”. *Remote Sensing* 15.11 (2023): 2775.

61. Onasanya A., *et al*. "Diagnostic task shifting for NTDs: outcome of a preliminary quasi experimental study for microfilaria detection using a novel diagnostic device in Nigeria". *African Health Science* 24.4 (2024): 43-50.

62. Karshima SN. "Prevalence and distribution of soil transmitted helminth infections in Nigerian children: a systematic review and meta analysis". *Infectious Diseases of Poverty* 7.1 (2018): 69.

63. Tabo Z., *et al*. "A machine learning approach for modeling the occurrence of the major intermediate hosts for schistosomiasis in East Africa". *Scientific Report* 14 (2024): 4456.

64. Kamga GR., *et al*. "Community directed ivermectin distribution for onchocerciasis elimination in Cameroon: assessing community participation and treatment coverage in the context of COVID 19". *Infectious Diseases of Poverty* 9.1 (2020): 140.

65. Crump RE., *et al*. "Identifying regions for enhanced control of gambiense sleeping sickness in the Democratic Republic of Congo". Commun Medicine 2 (2022): 24.

66. Mechan F., *et al*. "Unmanned aerial vehicles for surveillance and control of vectors of malaria and other vector borne diseases". *Malaria Journal* 22.1 (2023): 23.

67. Maddren R., *et al*. "Soil transmitted helminths and schistosome infections in Ethiopia: a systematic review of progress in their control over the past 20 years". *Parasites and Vectors* 14.1 (2021): 80.

68. Zhang Z., *et al*. "Artificial intelligence and GIS applications in schistosomiasis surveillance in China". *Infectious Diseases of Poverty* 11.1 (2022): 90.

69. Lun Z R., *et al*. "Superior auto identification of trypanosome parasites by using a hybrid deep learning model". *Computational and Structural Biotechnology Journal* 20 (2023): 1036-1043.

70. Wangdi K., *et al*. "Artificial intelligence applications in malaria surveillance in Southeast Asia". *Malaria Journal* 23.1 (2024): 78.

71. Bosede AO., *et al*. "Integrating the crowdsourced image based morbidity hotspot surveillance for neglected tropical diseases (CIMS NTDs) into Nigeria's healthcare system: a mixed methods study". *Royal Society of Tropical Medicine and Hygiene* (2025): traf091.

72. Nansikombi HT., *et al*. "Timeliness and completeness of weekly surveillance data reporting on epidemic prone diseases in Uganda, 2020 2021". *BMC Public Health* 23.1 (2023): 647.

73. Talo M., *et al*. "The use of AI and IoT in infectious disease health monitoring: a systematic review". *Journal of Computer Information Systems* 13.1 (2025): 11-17.

74. Michael B., *et al*. "Artificial intelligence and big data for decoding infectious disease transmission dynamics and outbreak prediction". *Decoding Infection and Transmission* 4 (2026): 100079.

75. Pongsapan N., *et al*. "Challenges and strategies of health human resource management in addressing global changes in the digital era". *International Journal of Health Engineering and Technology* 4.5 (2026).

76. Manyazewal T., *et al*. "Innovative technologies to address neglected tropical diseases in African settings with persistent sociopolitical instability". *Nature Communication* 15.1 (2024): 10297.

77. Worsley Tonks KEL., *et al*. "Strengthening global health security by improving disease surveillance in remote rural areas of low income and middle income countries". *Lancet Global Health* 10.4 (2022): e579-584.

78. Olawade DB., *et al*. "Using artificial intelligence to improve public health: a narrative review". *Frontiers in Public Health* 11 (2023): 1196397.

79. Shakeri Hossein Abad Z., *et al*. "Digital public health surveillance: a systematic scoping review". *NPJ Digital Medicine* 4.1 (2021): 1-13.

80. Manyazewal T., *et al*. "The potential use of digital health technologies in the African context: a systematic review of evidence from Ethiopia". *NPJ Digital Medicine* 4 (2021): 87.

81. Kostkova P., *et al*. "Data and digital solutions to support surveillance strategies in the context of the COVID 19 pandemic". *Frontiers in Digital Health* 3 (2021): 707902.