World Journal of Biology Pharmacy and Health Sciences

eISSN: 2582-5542

Cross Ref DOI: 10.30574/wjbphs

Journal homepage: https://wjbphs.com/

(Review Article)

Artificial intelligence in predicting and mitigating climate-driven infectious disease outbreaks: Implications for community health resilience

Ifeoma Nwamaka Monago [1, *], Joyce Onyinyechi John [2], Blessing Adanna Okonkwo [2], Moyosore Rukayat [3], Bashir Idris [4], Umar Jibril El-Muqaddas [3], Usen Joel Silas [3] and Chizaram Anselm Onyeaghala [5]

[1] *Department of Community Medicine and Primary Health Care, Faculty of Medicine, College of Health Sciences, Nnamdi Azikiwe University, Awka, Nigeria.*

[2] *Department of Public Health and Health Promotion, School of Pharmacy, Applied Sciences and Public Health, Robert Gordon University, Aberdeen, UK.*

[3] *Department of Community Health, Wesley University, Ondo, Nigeria.*

[4] *Department of Community Health Science, Mariam University, Maradi, Niger Republic.*

[5] *Department of Internal Medicine University of Port-Harcourt Teaching Hospital, Port-Harcourt, Nigeria.*

World Journal of Biology Pharmacy and Health Sciences, 2026, 26(01), 221–235

Publication history: Received on 13 March 2026; revised on 20 April 2026; accepted on 23 April 2026

Article DOI: https://doi.org/10.30574/wjbphs.2026.26.1.0210

Abstract

As climate change accelerates the emergence, expansion and intensity of infectious disease outbreaks, conventional surveillance and modelling approaches increasingly struggle to capture the complex, non-linear interactions between environmental drivers and pathogen transmission. This review critically examines the transformative potential of artificial intelligence (AI) in predicting and mitigating climate-driven infectious diseases with particular attention to building community health resilience in vulnerable settings. Drawing on recent advances in machine learning, deep learning and hybrid modelling techniques, the analysis reveals how AI integrates multi-source data from satellite observations and meteorological records to epidemiological surveillance and human mobility patterns to deliver improved outbreak forecasts and support proactive intervention strategies for vector-borne, water-borne and zoonotic diseases. While AI demonstrates clear advantages in early warning, resource optimization and scenario simulation, significant challenges persist which include algorithmic bias, digital divides, data governance concerns and limited evidence of large-scale health impact. The review underscores that meaningful contributions to community resilience will require not only technical refinement but also equitable implementation, co-design with affected populations and deeper integration with existing health systems. Ultimately, responsibly deployed AI offers a powerful instrument for strengthening adaptive capacity and safeguarding public health amid accelerating climatic disruption.

Keywords: Artificial intelligence; Climate change; Infectious disease outbreaks; Disease prediction; Outbreak mitigation; Community health resilience; Early warning systems; Vector-borne diseases

1. Introduction

The accelerating pace of climate change has intensified the re-emergence of infectious diseases, posing unprecedented challenges to global public health systems. Rising temperatures, altered precipitation patterns and extreme weather events create favorable conditions for vector proliferation, pathogen survival and shifts in disease transmission dynamics as well particularly in vulnerable regions. Traditional surveillance and modeling approaches often struggle to capture the complex, non-linear interactions between climatic variables and disease outbreaks. In response, artificial intelligence (AI) has emerged as a promising tool capable of integrating diverse datasets from satellite observations and

* Corresponding author: Ifeoma Nwamaka Monago

meteorological records to epidemiological surveillance to enhance prediction accuracy and support timely mitigation efforts [1][2].

This review examines the role of AI in predicting and mitigating climate-driven infectious disease outbreaks, with a focus on implications for building community health resilience. By synthesizing recent advances, the paper highlights how machine learning and deep learning techniques can address limitations of conventional models while identifying persistent gaps in data availability, model generalizability, as well as equitable implementation especially in low- and middle-income countries.

1.1. Background on the Intersection of Climate Change and Infectious Disease Emergence

Climate change influences infectious disease dynamics through multiple pathways that affect vector biology, pathogen replication rates and human-environment interactions. According to Caminade et al., recent warming has already facilitated the expansion of vector-borne diseases such as malaria and dengue into previously unsuitable highland and temperate regions with projections indicating further geographic shifts under various emission scenarios [3]. Findings from Thomson and Stanberry indicate that changes in temperature and precipitation patterns directly modulate mosquito breeding sites and the extrinsic incubation period of pathogens, thereby altering transmission intensity and seasonality [4].

In many tropical and subtropical areas, extreme events like floods and droughts exacerbate water-borne and vector-borne outbreaks. For instance, increased flooding creates stagnant water pools which is ideal for the breeding of Aedes and Anopheles mosquitoes, while drought can concentrate human and vector populations around limited water sources thereby heightening contact rates. A scoping review by Kulkarni et al. compiled evidence demonstrating clear links between climate-driven rainfall changes and elevated transmission of both malaria and dengue, though effect sizes differ markedly by region and vector species [5].

These environmental shifts disproportionately burden vulnerable communities, where limited infrastructure and adaptive capacity amplify health impacts. Zavaleta-Monestel et al. observed that climate-driven geographic expansion of vectors has intensified disease pressure and co-infection rates in these settings [6]. Overall, the interplay between environmental change and disease ecology demands integrated approaches that move beyond siloed analyses of climate or health data alone.

1.2. Rationale for AI as a Transformative Tool in Prediction and Mitigation

Conventional statistical models frequently rely on linear assumptions and struggle with the high-dimensional, spatio-temporal nature of climate-disease datasets. In contrast, AI techniques excel at uncovering non-linear patterns and handling multi-source inputs effectively. Inam et al. demonstrated in their review that machine learning and deep learning models, including random forests and long short-term memory networks consistently outperform traditional methods in forecasting climate-sensitive outbreaks by integrating real-time climate, surveillance and mobility data [1].

A systematic examination by Villanueva-Miranda et al. revealed that AI-powered early warning systems can improve outbreak detection speed and precision across diseases such as dengue and cholera, leveraging diverse inputs ranging from environmental measurements to digital signals [2]. Farooq et al. applied advanced AI approaches to disentangle eco-climatic drivers of West Nile virus outbreaks, achieving enhanced predictive performance over multi-year datasets [7]. The rationale extends beyond prediction to mitigation, where AI supports optimized resource allocation, targeted interventions and scenario simulations under varying climate projections. Such capabilities enable proactive rather than reactive public health responses, potentially reducing morbidity in climate-vulnerable settings where timely action is critical.

1.3. Scope, Objectives and Significance for Global and Community Health

This review focuses on AI applications in climate-driven infectious diseases, emphasizing vector-borne, water-borne and zoonotic categories, with particular attention to implications for community-level resilience in resource-limited contexts. The primary objectives are to map current AI methodologies, evaluate their predictive and mitigative efficacy based on published evidence, and synthesize challenges alongside pathways toward equitable implementation. The significance lies in informing health policy and practice amid accelerating climate impacts, as frameworks for climate-smart public health increasingly integrate data science to strengthen resilient systems [8].

By centering community resilience, this paper addresses equity concerns such as digital divides and algorithmic bias that could otherwise widen health disparities. Borham et al. noted the growing adoption of AI in epidemic surveillance, yet stressed the need for context-specific adaptations to maximize benefits in diverse geographic and socio-economic settings [9].

1.4. Overview of Review Methodology and Paper Structure

The review draws on peer-reviewed literature published primarily between 2018 and 2025, sourced through systematic searches in databases such as PubMed, Google Scholar, and Scopus. Keywords combined terms related to artificial intelligence, climate change, infectious diseases, prediction, mitigation, and resilience. Inclusion criteria prioritized empirical studies, systematic reviews, and modeling papers that reported verifiable performance metrics or mechanistic insights; exclusion criteria applied to works published before 2018 (during which much things have not been studied about AI) and non-peer-reviewed sources.

The paper proceeds with a detailed examination of climate-disease dynamics in Section 2, followed by AI methodologies in Section 3, specific applications in prediction in Section 4, mitigation in Section 5, implications for community resilience in Section 6 and then a concluding synthesis with forward-looking recommendations in Section 7.

2. Climate Change and the Dynamics of Infectious Disease Outbreaks

Climate change is reshaping the environmental conditions that govern the ecology and transmission of many infectious pathogens. Through alterations in temperature, precipitation, humidity, and the frequency of extreme events, it creates new opportunities for disease emergence, range expansion, and intensified outbreaks. These effects operate across multiple biological scales from vector physiology to human exposure patterns and often interact with socio-economic vulnerabilities. Traditional models have struggled to fully capture these non-stationary and synergistic processes, highlighting the value of detailed mechanistic understanding [4][11].

2.1. Mechanisms Linking Climate Variables to Disease Transmission

Temperature acts as a key driver by influencing vector development, survival, and the rate at which pathogens mature inside them. According to Caminade et al., even modest warming can shorten the extrinsic incubation period of malaria parasites and dengue virus within mosquitoes, thereby extending transmission windows and enabling establishment in previously marginal areas [3]. Findings from Thomson and Stanberry indicate that rising temperatures accelerate mosquito larval growth and increase adult biting rates, while also modulating pathogen replication dynamics [4]. Precipitation variability further modulates these risks by determining the availability and quality of breeding habitats. A scoping review by Kulkarni et al. compiled evidence demonstrating clear links between climate-driven rainfall changes and elevated transmission of both malaria and dengue, though effect sizes differ markedly by region and vector species [5]. de Souza et al. emphasized that climate change impacts on vector-borne diseases can be multifaceted and complex, sometimes producing ambiguous or opposing consequences depending on local conditions [10].

Additional factors such as humidity and extreme weather events introduce further complexity. Flooding not only expands breeding sites but can also disrupt sanitation systems, promoting water-borne spread. Mora et al. provided a broad synthesis showing that climatic hazards have already aggravated 58% (218 out of 375) of known human pathogenic diseases through over 1,000 unique pathways [11]. Rocklöv and Dubrow described climate change as an enduring challenge for vector-borne disease prevention and control, noting how these stressors interact with ecological and social pathways to amplify pathogen survival and host exposure [12].

2.2. Key Disease Categories Affected by Climate Change

Vector-borne diseases remain among the most climate-sensitive. Malaria and dengue have shown measurable range shifts and seasonal changes in response to warming and altered rainfall. Klepac et al., in their scoping review, explored effects of climate change on malaria and neglected tropical diseases, highlighting that amplitude and direction of impacts vary by disease and location and are often non-linear [13]. Franklinos et al. examined the effect of global change on mosquito-borne disease, underscoring expanded risks under future scenarios [14].

Water-borne illnesses, notably cholera, exhibit strong associations with climatic extremes. Flood events facilitate contamination of water sources, while drought can heighten exposure through reliance on unsafe supplies. These patterns illustrate how different disease categories respond to overlapping but distinct climatic influences.

2.3. Global and Regional Patterns with Emphasis on Vulnerable Populations

The burden of climate-influenced diseases falls disproportionately on low- and middle-income countries in tropical and subtropical zones. Sub-Saharan Africa, South and Southeast Asia, and parts of Latin America face compounded risks due to favorable baseline climates for vectors combined with constraints in health infrastructure. Zavaleta-Monestel et al. documented how vector expansion has heightened disease pressure and co-infection rates in these settings [6].

In temperate and highland regions, new transmission foci have appeared during anomalously warm periods, often catching surveillance systems off guard. Such incursions highlight the shifting geographic patterns driven by progressive warming. Socio-economic and environmental inequities amplify these patterns. Populations with inadequate housing, limited access to clean water, and weak health services experience more severe outcomes. Such disparities call for resilience strategies that explicitly address structural vulnerabilities alongside environmental drivers.

2.4. Gaps in Traditional Epidemiological Modeling

Many conventional epidemiological approaches rely on assumptions of linearity and environmental stationarity that do not hold under accelerating climate change. They often have difficulty integrating heterogeneous spatio-temporal data or accounting for threshold effects, lagged responses, and interactions with non-climatic factors such as land-use change and mobility. As a result, forecasts may under- or over-estimate risks in dynamic settings [3][10].

Surveillance gaps in high-burden regions compound these modeling challenges. Long-term, fine-resolution climatic and disease data remain scarce in many vulnerable areas, limiting model calibration and validation. Alcayna et al. emphasized the importance of recognizing both climatic and non-climatic drivers when assessing climate sensitivity of infectious diseases, pointing to the need for more integrative frameworks [15]. Overall, these limitations reduce confidence in projections and hinder timely public health responses.

3. Artificial Intelligence Methodologies for Disease Prediction and Mitigation

Artificial intelligence has become a critical set of tools for addressing the complex, non-linear relationships between climate variables and infectious disease transmission. These methodologies integrate diverse data streams, including meteorological observations, satellite imagery, epidemiological reports, and human mobility patterns, to generate insights that conventional approaches often cannot achieve. By moving beyond linear assumptions, AI techniques support both prediction of outbreak risks and optimization of mitigation strategies under changing climatic conditions. Their application continues to expand as public health systems seek more responsive and data-driven solutions [16].

3.1. Overview of Core AI Techniques

Machine learning algorithms such as support vector machines and random forests remain widely applied because they handle high-dimensional data effectively and provide stable performance even when some observations are missing. Inam et al. showed that these ensemble methods consistently outperform traditional statistical models when forecasting climate-sensitive outbreaks by capturing interactions among environmental and epidemiological variables [1].

Deep learning architectures add further capability for modelling temporal and spatial patterns. Long short-term memory (LSTM) networks are particularly useful for time-series forecasting, while convolutional neural networks excel at extracting spatial features from environmental data. Villanueva-Miranda et al., in their systematic review of early warning systems, found that deep learning approaches improve detection speed and precision for diseases such as dengue and cholera when combined with multi-source inputs [2]. Hybrid models that combine classical machine learning with deep learning components have gained attention for balancing interpretability and predictive power. These systems often integrate tree-based methods with recurrent networks to simultaneously address static risk factors and dynamic climate trends. Such combinations have shown promise in producing more reliable outputs across varying geographic and seasonal contexts [18].

Table 1 summarizes key AI methodologies applied to climate-driven infectious disease prediction and mitigation. It details core techniques, integrated data sources, targeted diseases, reported performance improvements, and advantages over conventional statistical models, illustrating how these approaches effectively capture complex non-linear climate-disease interactions [1][2]

Table 1 AI Methodologies for Climate-Driven Infectious Disease Prediction and Mitigation: Techniques, Data Sources, Performance, and Advantages

Ai technique category	Specific models/ Architectures	Key data sources integrated	Disease categories targeted	Reported performance metrics / improvements	Advantages over conventional models	Key references
Machine learning (ensemble)	Random Forests, Support Vector Machines, XGBoost	Meteorological records, satellite observations, epidemiological surveillance, socio-environmental factors	Vector-borne (malaria, dengue), water-borne	AUC 0.85–0.92; 10–25% accuracy gains in multi-country evaluations	Handles high-dimensional non-linear interactions and missing data effectively; robust in data-sparse LMIC settings	Inam et al. [1]; Villanueva-Miranda et al. [2]; Farooq et al. [7]
Deep learning	Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNN)	Time-series climate data, satellite imagery for breeding sites, human mobility patterns	Dengue, cholera, vector-borne diseases	Improved detection speed and precision; strong performance in provincial incidence forecasting	Captures lagged effects of rainfall/temperature and spatial patterns from remote sensing; outperforms traditional time-series approaches	Villanueva-Miranda et al. [2]; Inam et al. [1]; Nguyen et al. [26]
Hybrid models	Tree-ensemble + Recurrent Networks; Mechanistic-epidemiological + AI	Climate projections, surveillance, genomic and mobility data	Vector-borne, water-borne, zoonotic under climate scenarios	Enhanced reliability across geographic and seasonal contexts; better scenario simulation	Balances interpretability with predictive power; maintains biological plausibility under uncertain climate projections	Inam et al. [1]; Chen and Moraga [18][30]; Pley et al. [35]
Explainable ai (xai)	SHAP values combined with tree-based or deep models	Climatic variables (temperature, humidity, rainfall), sociodemographic and landscape features	Dengue, malaria, climate-sensitive outbreaks	Reveals dominant drivers (e.g., temperature and humidity); increases model trust and adoption	Improves interpretability of complex models; aligns predictions with known climate-disease mechanisms	Rahman et al. [27]; Inam et al. [1]; Villanueva-Miranda et al. [2]
Early warning & decision-support	Ensemble ML with optimization; Reinforcement learning elements	Multi-source real-time climate, mobility, and surveillance data	Dengue, cholera, malaria resurgence	1–3 month lead times; graded risk levels; shortened response times in pilots	Enables proactive rather than reactive interventions; supports optimized resource allocation	Inam et al. [1]; Villanueva-Miranda et al. [2]; Rahman et al. [27]

ML, Machine Learning; LMIC,; Low- and Middle-Income Countries; AUC, Area Under Curve

Then figure 1 illustrates a conceptual depiction of the AI/ML modeling process applied to climate-infectious disease linkages, highlighting the steps from defining analysis objectives through data integration and model outputs. This framework underscores how AI moves beyond traditional approaches by enabling precise, multi-source predictive analytics

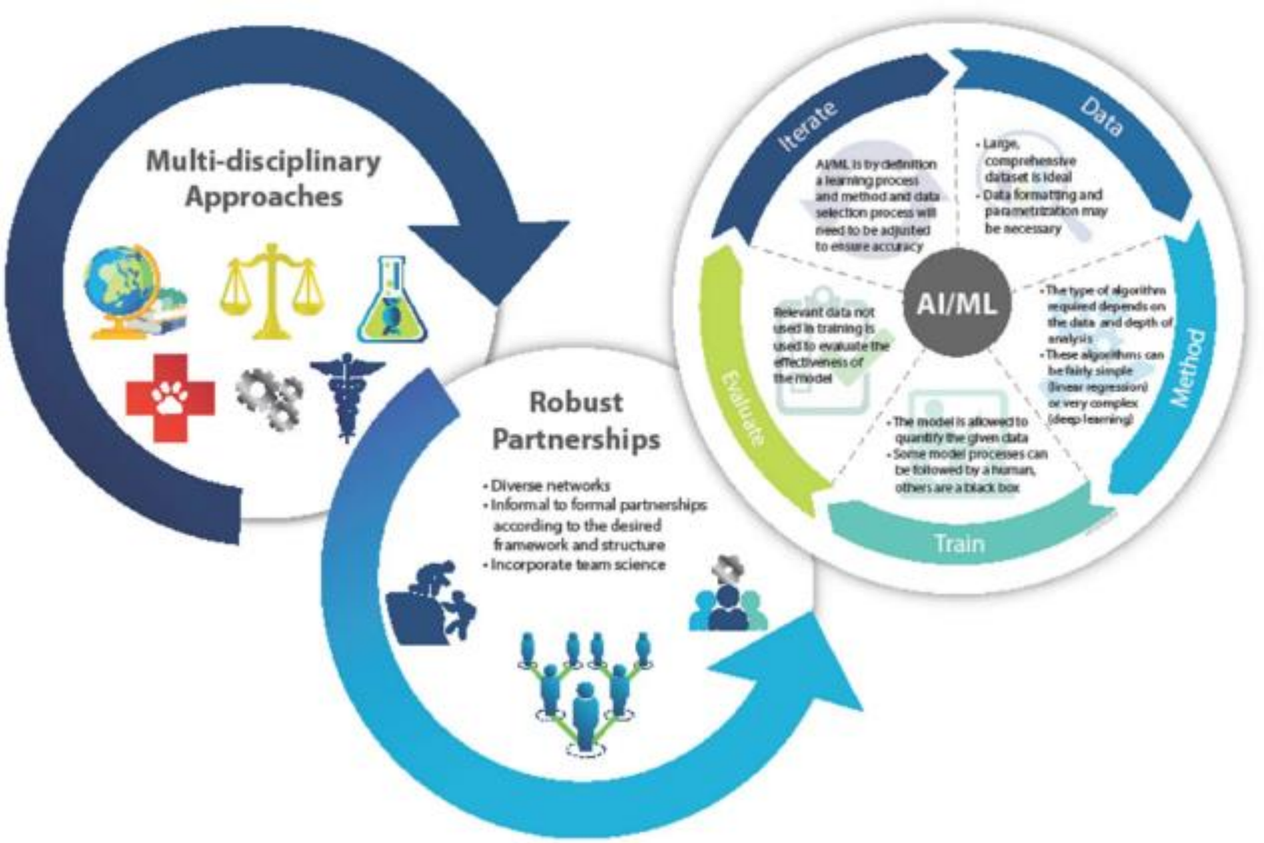

Figure 1 Conceptual Framework for AI/ML in Linking Climate Change and Infectious Diseases [58]

3.2. Data Sources, Preprocessing, and Model Evaluation Metrics

Successful AI applications depend on the quality and integration of multiple data types, ranging from ground weather stations and remote sensing products to health surveillance records and genomic information. Preprocessing typically involves normalization, imputation of missing values, and careful feature engineering to reduce noise and multicollinearity. Studies applying random forest-based techniques have demonstrated the value of such imputation when working with global climatic and disease datasets that frequently contain gaps [19].

Model performance is commonly assessed using metrics such as the area under the receiver operating characteristic curve, root mean square error and F1-score. Many studies report AUC values between 0.85 and 0.92 for short- to medium-term predictions, although accuracy tends to decrease when models are tested in new regions or under extreme climate scenarios. These metrics help quantify improvements over baseline statistical models but must be interpreted alongside external validation results [16][20].

3.3. Advantages Over Conventional Statistical Models

Conventional epidemiological models frequently rely on assumptions of linearity and environmental stationarity that do not hold well under climate change. In contrast, AI techniques discover complex, non-linear patterns without requiring strong prior specifications. Inam highlighted that machine learning and deep learning models capture real-time climate-disease interactions more effectively than traditional time-series methods, particularly for vector-borne and water-borne diseases [1].

Pley et al. observed that digital innovations, including AI algorithms, enable faster processing of large datasets and yield higher detection accuracy for climate-driven vector-borne outbreaks compared with conventional surveillance approaches [15]. Tree-ensemble and recurrent network methods have repeatedly demonstrated superior classification and forecasting performance in multi-country evaluations [21].

Hybrid architectures further extend these advantages by allowing mechanistic knowledge to be combined with data-driven learning. This integration helps maintain biological plausibility while improving predictive skill under uncertain future climate projections [18].

3.4. Ethical and Technical Considerations

Despite clear performance gains, AI methodologies raise important technical and ethical challenges. Models trained on data from well-monitored regions may perform poorly when applied to low-resource settings where surveillance is sparse, leading to potential bias and reduced generalizability. Researchers have stressed the need for careful validation across diverse socio-economic and climatic contexts to avoid exacerbating existing health inequities [19][22].

Explainability remains a central concern for adoption in public health decision-making. Tools such as SHAP (SHapley Additive exPlanations) values (an explainable AI (XAI) technique used to interpret complex machine learning models) help reveal the contribution of individual features, including specific climatic variables, to model predictions. Studies applying SHAP to dengue and other climate-sensitive diseases have shown that temperature and humidity often emerge as dominant drivers, increasing trust when results align with domain knowledge [23].

Responsible deployment also requires attention to data privacy, governance frameworks and interdisciplinary collaboration. Without transparent processes and external validation, even high-performing models risk limited uptake by health authorities. Addressing these issues through explainable AI and federated learning approaches represents an important direction for future methodological development [17][24].

4. AI-Driven Prediction of Climate-Driven Infectious Disease Outbreaks

Artificial intelligence models have demonstrated growing potential to forecast climate-influenced infectious disease outbreaks by integrating environmental, climatic, and epidemiological data streams. These approaches capture non-linear and spatio-temporal relationships that traditional statistical methods frequently overlook. In practice, many models deliver useful lead times for public health decision-making, though their performance depends heavily on data availability, regional context, and the specific forecast horizon chosen. This section reviews documented applications, integration strategies, performance indicators, and persistent limitations reported in the literature [1][2].

4.1. Applications in Forecasting Vector-Borne Diseases

Vector-borne diseases such as malaria and dengue have attracted substantial AI modelling efforts due to their well-documented sensitivity to temperature, rainfall, and humidity. Inam et al. described how machine learning early warning systems in sub-Saharan Africa combine climate variables with health records to anticipate malaria resurgence periods [1].

For dengue fever, several studies report encouraging lead times of one to two months. An AI-based early-warning system developed for India uses meteorological and health data to predict outbreaks approximately two months in advance, potentially allowing health officials more time to prepare interventions [25]. In Vietnam, deep learning models incorporating multiple climate factors have been tested for forecasting dengue incidence, with LSTM-based architectures showing competitive performance across provinces [26].

Explainable tree-based models have also been applied successfully in Bangladesh. Rahman et al. constructed an interpretable machine learning framework using climatic, sociodemographic, and landscape features to generate dengue risk predictions and outbreak alerts [27]. These examples highlight how AI can support both seasonal risk mapping and localized hotspot identification in regions where climate variability drives transmission intensity.

4.2. Applications in Water-Borne and Zoonotic Outbreaks

Water-borne diseases such as cholera show clear associations with extreme rainfall and flooding that facilitate pathogen dissemination through contaminated water sources. AI frameworks have been explored for cholera prediction by fusing spatio-temporal climate data with socio-environmental indicators. One approach combined ensemble machine learning with long short-term memory networks, identifying rainfall patterns and sanitation coverage as influential predictors [28].

Zoonotic diseases receive comparatively less dedicated climate-AI modelling, yet some studies incorporate habitat shifts and surveillance data to estimate spillover risks. Overall, the literature indicates that data fusion strategies developed for vector-borne diseases often transfer usefully to water-borne contexts when near-real-time inputs are accessible [4][29].

4.3. Spatio-Temporal Modeling, Early Warning Indicators, and Performance Benchmarks

Spatio-temporal modelling forms a core component of many AI prediction systems, generating risk maps and early warning signals at district or provincial scales. Convolutional and recurrent neural network architectures help capture both spatial distribution of breeding sites and lagged effects of rainfall events. Reported performance frequently includes area under the curve values above 0.85 for short-term forecasts, with some models showing accuracy gains of 10–25% over conventional time-series baselines [17][30].

Lead time remains an important practical benchmark. Models capable of one- to three-month forecasts are viewed as particularly valuable for operational planning, such as vector control or public messaging campaigns. However, predictive skill commonly declines with longer horizons or when models are applied to new geographic areas without local recalibration [31][32].

Integration of satellite observations and electronic health records has been shown to strengthen hotspot detection in several pilot systems. These multi-source approaches can flag emerging risks before routine surveillance registers sharp case increases [20][33].

4.4. Limitations Observed in Existing Models

Despite notable advances, published AI prediction studies consistently identify several limitations. Data scarcity in many low-resource settings restricts robust training and external validation, often reducing model generalizability when transferred beyond well-monitored regions [1][34]. Overfitting remains a concern, particularly when historical training data do not adequately represent extreme climate events. Even statistically strong models may see performance drops under novel conditions [35].

Translating predictions into timely public health action poses another practical challenge. Outputs that lack sufficient interpretability or fail to align with local decision-making workflows tend to see limited adoption by health authorities [27][36]. Algorithmic bias linked to uneven data representation across populations can further undermine equitable use of these tools. These constraints underscore the importance of continued focus on domain adaptation, rigorous external validation, and sustained collaboration between modellers and frontline public health teams.

5. AI Strategies for Mitigating Climate-Driven Infectious Disease Outbreaks

Artificial intelligence is increasingly applied not only to predict climate-driven infectious disease outbreaks but also to support targeted mitigation efforts that reduce transmission and lessen health impacts. These strategies focus on optimizing resource allocation, timing interventions, and simulating response scenarios under different climate conditions. By processing real-time and projected data, AI tools help public health authorities move from reactive to proactive measures, particularly in resource-limited settings where timely decisions are critical. This section examines documented AI applications in mitigation, their integration into early warning and decision-support systems, and evidence of outcomes from published studies [1][2].

5.1. AI-Optimized Interventions and Resource Allocation

AI techniques assist in prioritizing interventions such as vector control, vaccination campaigns, and public health messaging by identifying high-risk locations and time periods. Inam et al. noted that machine learning models can recommend optimal allocation of limited insecticide or bed-net resources based on predicted outbreak hotspots, improving cost-effectiveness in malaria-endemic areas [1][6].

For dengue control, optimization algorithms have been used to guide targeted larviciding and adulticiding operations. Studies show that AI-supported scheduling can reduce vector density more efficiently than uniform application strategies, especially when climate forecasts indicate elevated transmission risk [37]. In water-borne disease response, AI has helped model the impact of sanitation improvements and water treatment interventions under varying rainfall scenarios, allowing authorities to focus efforts where contamination risk is highest [28][38].

Table 2 presents documented AI applications across major climate-driven disease categories, including specific approaches, performance outcomes, supported mitigation strategies, and implications for community health resilience in vulnerable settings [35].

Table 2 AI Applications in Prediction and Mitigation of Climate-Driven Infectious Diseases: Approaches, Performance, Mitigation Strategies, and Resilience Implications

Disease category	Geographic/settings focus	Ai approaches used	Key inputs & lead time	Performance highlights / outcomes	Mitigation strategies supported	Community resilience implications	Key references
Vector-borne (malaria & dengue)	Sub-Saharan Africa, India, Vietnam, Bangladesh	Random Forests, LSTM, Interpretable tree-based models	Meteorological data, satellite observations, health surveillance, mobility; 1–2 months	AUC >0.85; 10–25% improvement over baselines; better hotspot and seasonal risk mapping	Optimized vector control (insecticides, bed-nets); targeted interventions during high-risk periods	Strengthens early warning and localized preparedness in climate-vulnerable communities	Inam et al. [1]; Rahman et al. [27]; Nguyen et al. [26]
Water-borne (cholera)	Flood-prone regions (e.g., Nigeria and similar settings)	Ensemble ML combined with LSTM hybrids	Spatio-temporal rainfall, sanitation indicators, climate data	Improved outbreak detection; rainfall and sanitation identified as strong predictors	Prioritization of sanitation and water treatment under varying climate scenarios	Reduces impact of extreme weather events (floods/droughts) on vulnerable populations	Villanueva-Miranda et al. [2]; Inam et al. [1]; Kulkarni et al. [5]
Vector-borne (west nile & general)	Temperate/highland regions with range expansion	Advanced AI for eco-climatic driver analysis	Climate variables, vector habitat data, environmental records	Enhanced predictive performance; better disentanglement of climate drivers	Scenario simulations for intervention planning under future climate projections	Supports adaptive capacity as disease ranges shift due to warming	Farooq et al. [7]; Thomson and Stanberry [4]; Rocklöv and Dubrow [12]
General climate-sensitive outbreaks	LMIC pilots in Southeast Asia and Africa	AI-powered early warning platforms and decision-support tools	Multi-source climate, mobility, and surveillance data	Shorter response times; modest reductions in seasonal case peaks; graded risk alerts	Optimized resource allocation and "what-if" climate scenario testing	Facilitates community mobilization and equity-focused responses in resource-limited settings	Inam et al. [1]; Pley et al. [35]; Rahman et al. [44]

Zoonotic & broader risks	Global projections with habitat shifts	Hybrid mechanistic-AI models	Environmental, genomic, and mobility data	Improved spillover risk estimation under uncertain climate conditions	Targeted surveillance and adaptation measures (e.g., urban planning)	Promotes One Health integration and equitable implementation across diverse populations	Inam et al. [1]; de Souza et al. [10]; Alcayna et al. [15]

5.2. Role in Early Warning Systems and Decision-Support

Early warning systems enhanced by AI provide actionable alerts that trigger mitigation activities before cases surge. It has also been highlighted by researchers that AI-powered platforms integrate climate, mobility, and surveillance data to generate graded risk levels, enabling timely deployment of response teams [17].

Decision-support tools built on reinforcement learning or optimization frameworks simulate multiple intervention scenarios under projected climate conditions. These systems help planners evaluate trade-offs between different mitigation options, such as the balance between vector control intensity and vaccination coverage [39]. Real-world pilots have demonstrated that AI-driven alerts can shorten response times and contribute to lower case numbers when linked directly to operational protocols [35][40].

Figure 2 presents an AI agents-driven closed-loop framework that integrates surveillance, risk evaluation, early warning, and decision support. Such architectures can be adapted for climate-driven outbreaks, enabling real-time data fusion and optimized mitigation responses under varying environmental conditions

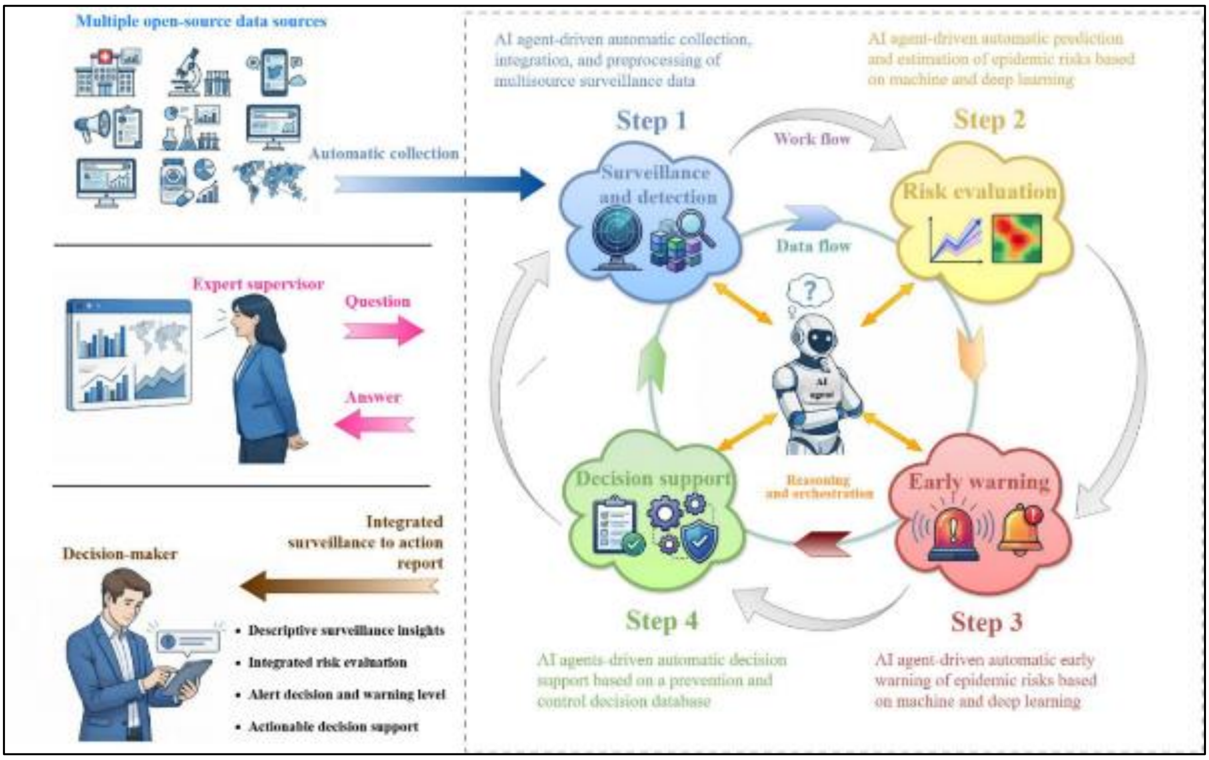

Figure 2 AI Agents-Driven Closed-Loop Framework for Epidemic Intelligence [59]

5.3. Hybrid AI Approaches for Simulation of Mitigation Scenarios

Hybrid models that combine mechanistic epidemiological knowledge with data-driven AI are particularly useful for simulating mitigation under future climate projections. These approaches allow testing of “what-if” scenarios, such as the effect of shifting rainfall patterns on the effectiveness of current vector control measures [31][41].

By incorporating uncertainty estimates, hybrid systems generate probabilistic outputs that support more robust planning. Researchers have applied such models to evaluate long-term adaptation strategies, including changes in urban design or community-based surveillance that could buffer against climate-amplified outbreaks [42]. Performance evaluations often show that hybrid AI frameworks provide more realistic projections of intervention impact than purely statistical or purely mechanistic models alone [43].

5.4. Real-World Implementations and Evidence of Reduced Morbidity

Several field implementations have begun to link AI mitigation tools with measurable health outcomes. In parts of Southeast Asia and Africa, AI-supported early warning systems have been associated with faster deployment of control measures and modest reductions in reported cases during seasonal peaks [44].

However, evidence of large-scale impact remains emerging rather than definitive. Most published evaluations rely on retrospective analysis or small-scale pilots, with calls for more rigorous prospective studies to quantify reductions in morbidity and mortality [45][46]. Challenges in scaling these systems include limited integration with existing health infrastructure and the need for continuous model updating as climate patterns evolve. Addressing these barriers through sustained stakeholder collaboration remains essential for translating AI mitigation strategies into sustained public health gains [36][47].

6. Implications for Community Health Resilience

Artificial intelligence holds significant promise for strengthening community health resilience against climate-driven infectious disease outbreaks by enhancing adaptive capacity at the local level. It can support localized surveillance, equitable resource distribution, and community-informed decision-making while addressing structural vulnerabilities in low- and middle-income settings. However, realizing these benefits requires careful attention to equity, data governance, and integration with existing community structures. This section explores how AI contributes to adaptive capacity, key challenges and barriers, case examples, and recommendations for scalable, community-centred frameworks [8].

6.1. How AI Enhances Adaptive Capacity at Community Levels

AI applications can improve community-level surveillance by integrating local environmental data with broader climate projections to generate actionable risk information. Golden et al. described climate-smart public health frameworks that leverage data science and AI to build resilience by guiding adaptation strategies tailored to local contexts [8][48].

At the community scale, AI tools support equity-focused interventions by identifying vulnerable subpopulations and prioritizing support for those with limited access to health services. Federated learning approaches allow models to be trained across decentralized datasets without centralizing sensitive information, preserving privacy while enabling broader participation [49].

Community health workers can benefit from AI-assisted decision tools that provide real-time guidance on outbreak risks and intervention timing. Such tools have the potential to strengthen local response capacity when designed with input from end-users and aligned with existing health system workflows [50].

6.2. Challenges and Barriers: Data Governance, Algorithmic Bias, and Digital Divides

Despite its potential, AI deployment faces substantial barriers that can undermine community resilience. Algorithmic bias arises when training data under-represent marginalized populations or regions, leading to less accurate predictions for the very communities that face the highest risks [23][51].

The digital divide remains a critical obstacle, as many vulnerable communities lack reliable internet access, devices, or digital literacy required to engage with AI-supported systems. This gap risks widening existing health inequities rather than narrowing them [52]. Data governance issues, including concerns around ownership, privacy, and consent, further complicate implementation in community settings. Without transparent and participatory governance frameworks, trust in AI tools may erode, limiting their adoption and effectiveness [53].

6.3. Case Examples of Resilience-Building in Urban/Rural and LMIC Settings

In urban and rural settings across low- and middle-income countries, pilot initiatives have begun demonstrating how AI can support localized resilience. Some AI-enhanced early warning platforms in Southeast Asia and sub-Saharan Africa have helped communities prepare for dengue and malaria surges linked to seasonal climate patterns, leading to faster community mobilization [27][44].

In rural areas with limited health infrastructure, mobile-based AI tools have assisted community health workers in prioritizing outreach and education efforts during climate-related risk periods. These examples illustrate the value of context-specific adaptations that combine technological solutions with local knowledge [54]. However, scaling such initiatives remains challenging. Successful cases often involve strong partnerships between technologists, local health authorities, and community representatives to ensure tools are culturally appropriate and practically usable [55].

6.4. Recommendations for Scalable Frameworks and Future Policy Directions

To advance equitable resilience, future frameworks should prioritize co-design processes that involve affected communities from the outset. Federated and edge-computing approaches can reduce reliance on centralized infrastructure while addressing privacy concerns [49][56].

Policy recommendations include investment in digital infrastructure in vulnerable regions, development of bias-auditing standards for health AI, and integration of AI tools into national adaptation plans for climate-sensitive diseases. Interdisciplinary collaboration between data scientists, public health practitioners, and social scientists will be essential to translate technical capabilities into sustainable community benefits [50][57]. Overall, AI can contribute meaningfully to community health resilience only when deployed as part of broader efforts to address structural inequities and strengthen local health systems.

7. Conclusion

Climate change is intensifying the emergence and spread of infectious diseases, challenging traditional public health approaches. This review has synthesized the role of artificial intelligence in predicting and mitigating climate-driven outbreaks, with emphasis on implications for community health resilience. AI techniques, including machine learning and hybrid models, have demonstrated superiority over conventional methods by capturing complex climate-disease interactions and supporting timely forecasting and intervention. Applications in prediction and mitigation show promising lead times, hotspot identification, and optimized resource allocation, particularly for vector-borne and water-borne diseases. At the community level, AI offers potential to enhance adaptive capacity through localized surveillance and equity-focused decision support. However, persistent barriers such as algorithmic bias, digital divides, and weak health system integration continue to limit impact. Future progress depends on co-design with communities, bias mitigation, privacy-preserving methods, and stronger alignment with national adaptation plans. When implemented responsibly and equitably, artificial intelligence can serve as a valuable tool for strengthening community resilience amid accelerating climate change.

Compliance with ethical standards

Acknowledgments

The authors recognize the hard work of all the scholars and colleagues who together wrote and refined this review paper. The team carried out this work with their intellectual and academic efforts, without any aid or funding from outside sources like individuals, institutions, or organizations.

Disclosure of conflict of interest

The authors confirm they have no financial interests or personal connections that might have affected the research shared in this paper.

References

[1] Inam SA. A review of artificial intelligence for predicting climate driven infectious disease outbreaks to enhance global health resilience. Discover Public Health. 2025;22(1):738. https://doi.org/10.1186/s12982-025-01167-4

[2] Villanueva-Miranda I, Xiao G, Xie Y. Artificial intelligence in early warning systems for infectious disease surveillance: a systematic review. Frontiers in public health. 2025;13:1609615. https://doi.org/10.3389/fpubh.2025.1609615

[3] Caminade C, McIntyre KM, Jones AE. Impact of recent and future climate change on vector-borne diseases. Annals of the New York Academy of Sciences. 2019;1436(1):157-73. https://doi.org/10.1111/nyas.13950

[4] Thomson MC, Stanberry LR. Climate change and vectorborne diseases. New England Journal of Medicine. 2022;387(21):1969-78. https://doi.org/10.1056/NEJMra2200092

[5] Kulkarni MA, Duguay C, Ost K. Charting the evidence for climate change impacts on the global spread of malaria and dengue and adaptive responses: a scoping review of reviews. Globalization and health. 2022;18(1):1. https://doi.org/10.1186/s12992-021-00793-2

[6] Zavaleta-Monestel E, Rojas-Chinchilla C, Molina-Sojo P, Murillo-Castro MF, Rojas-Molina JP, Martínez-Vargas E, et al. Impact of climate change on the global dynamics of vector-borne infectious diseases: a narrative review. Cureus. 2025;17(1).

[7] Farooq Z, Rocklöv J, Wallin J, Abiri N, Sewe MO, Sjödin H, et al. Artificial intelligence to predict West Nile virus outbreaks with eco-climatic drivers. The Lancet Regional Health–Europe. 2022;17. https://doi.org/10.1016/j.lanepe.2022.100393

[8] Golden CD, Childs ML, Mudele OE, Andriamizarasoa FA, Bouley TA, De Nicola G, et al. Climate-smart public health for global health resilience. The Lancet Planetary Health. 2025;9(8).

[9] Borham A, Kamal LT, Chun S. Artificial intelligence in epidemic watch: revolutionizing infectious diseases surveillance. Frontiers in Digital Health. 2025;7:1692617. https://doi.org/10.3389/fdgth.2025.1692617

[10] De Souza WM, Weaver SC. Effects of climate change and human activities on vector-borne diseases. Nature reviews microbiology. 2024;22(8):476-91. https://doi.org/10.1038/s41579-024-01043-5

[11] Mora C, McKenzie T, Gaw IM, Dean JM, Von Hammerstein H, Knudson TA, et al. Over half of known human pathogenic diseases can be aggravated by climate change. Nature climate change. 2022;12(9):869-75. https://doi.org/10.1038/s41558-022-01426-1

[12] Rocklöv J, Dubrow R. Climate change: an enduring challenge for vector-borne disease prevention and control. Nature immunology. 2020;21(5):479-83. https://doi.org/10.1038/s41590-020-0648-y

[13] Klepac P, Hsieh JL, Ducker CL, Assoum M, Booth M, Byrne I, et al. Climate change, malaria and neglected tropical diseases: a scoping review. Transactions of The Royal Society of Tropical Medicine and Hygiene. 2024;118(9):561-79. https://doi.org/10.1093/trstmh/trae026

[14] Franklinos LH, Jones KE, Redding DW, Abubakar I. The effect of global change on mosquito-borne disease. The Lancet infectious diseases. 2019;19(9):e302-12. https://doi.org/10.1016/S1473-3099(19)30161-6

[15] Alcayna T, Fletcher I, Gibb R, Tremblay L, Funk S, Rao B, et al. Climate-sensitive disease outbreaks in the aftermath of extreme climatic events: A scoping review. One Earth. 2022;5(4):336-50. https://doi.org/10.1016/j.oneear.2022.03.007

[16] El Morr C, Ozdemir D, Asdaah Y, Saab A, El-Lahib Y, Sokhn ES, et al. AI-based epidemic and pandemic early warning systems: A systematic scoping review. Health Informatics Journal. 2024;30(3):14604582241275844. https://doi.org/10.1177/14604582241275844

[17] Mendes VI, Mendes BM, Moura RP, Lourenço IM, Oliveira MF, Ng KL, et al. Harnessing artificial intelligence for enhanced public health surveillance: a narrative review. Frontiers in Public Health. 2025;13:1601151. https://doi.org/10.3389/fpubh.2025.1601151

[18] Chen X, Moraga P. Dengue forecasting and outbreak detection in Brazil using LSTM: integrating human mobility and climate factors. Infectious Disease Modelling. 2025.

[19] Rahman MS, Shiddik MA. Leveraging explainable artificial intelligence and spatial analysis for communicable diseases in Asia (2000–2022) based on health, climate, and socioeconomic factors. International Journal of Health Geographics. 2025;24(1):45.

[20] Haque S, Mengersen K, Barr I, Wang L, Yang W, Vardoulakis S, et al. Towards development of functional climate-driven early warning systems for climate-sensitive infectious diseases: Statistical models and recommendations. Environmental Research. 2024;249:118568. https://doi.org/10.1016/j.envres.2024.118568

[21] Ssebyala SN, Kintu TM, Muganzi DJ, Dresser C, Demetres MR, Lai Y, et al. Use of machine learning tools to predict health risks from climate-sensitive extreme weather events: A scoping review. PLoS Climate. 2024;3(1):e0000338. https://doi.org/10.1371/journal.pclm.0000338

[22] Pennisi F, Pinto A, Borgonovo F, Scaglione G, Ligresti R, Santangelo OE, et al. Artificial Intelligence Models for Forecasting Mosquito-Borne Viral Diseases in Human Populations: A Global Systematic Review and Comparative Performance Analysis. Machine Learning and Knowledge Extraction. 2026;8(1):15. https://doi.org/10.3390/make8010015

[23] Cao Y, Lancaster E, Lee J, Wu J. Integrating explainable AI and One Health: a new frontier in combating infectious diseases. EBioMedicine. 2026;126.

[24] Odone A, Barbati C, Amadasi S, Schultz T, Resnik DB. Artificial intelligence and infectious diseases: an evidence-driven conceptual framework for research, public health, and clinical practice. The Lancet Infectious Diseases. 2026;26(3):e152-67.

[25] Bagwe P, Vijayanand S, Gaur A. Vaccines as Prophylactics and Therapeutics. InApproved: The Life Cycle of Drug Development 2025 (pp. 35-91). Cham: Springer Nature Switzerland.

[26] Nguyen VH, Tuyet-Hanh TT, Mulhall J, Minh HV, Duong TQ, Chien NV, et al. Deep learning models for forecasting dengue fever based on climate data in Vietnam. PLoS Neglected Tropical Diseases. 2022;16(6):e0010509. https://doi.org/10.1371/journal.pntd.0010509

[27] Rahman MS, Amrin M, Bokkor Shiddik MA. Dengue Early Warning System and Outbreak Prediction Tool in Bangladesh Using Interpretable Tree-Based Machine Learning Model. Health Science Reports. 2025;8(5):e70726. https://doi.org/10.1002/hsr2.70726

[28] Ibrahim AM, Ahmed MM, Musa SS, Haruna UA, Hamid MR, Okesanya OJ, et al. Leveraging AI for early cholera detection and response: Transforming public health surveillance in Nigeria. Exploration of Digital Health Technologies. 2025;3:101140. https://doi.org/10.37349/edht.2025.101140

[29] Zhou HY, Li Y, Li JY, Meng J, Wu A. Harnessing the power of artificial intelligence to combat infectious diseases: Progress, challenges, and future outlook. The Innovation Medicine. 2024;2(4):100091-. https://doi.org/10.59717/j.xinn-med.2024.100091

[30] Chen X, Moraga P. Forecasting dengue across Brazil with LSTM neural networks and SHAP-driven lagged climate and spatial effects. BMC public health. 2025;25(1):973.

[31] Cheng Y, Cheng R, Xu T, Tan X, Bai Y. Dengue fever prediction based on meteorological features and deep learning models. Infectious Disease Modelling. 2025.

[32] Schneider R, Sebastianelli A, Spiller D, Wheeler J, Carmo R, Nowakowski A, et al. Climate-based ensemble machine learning model to forecast dengue epidemics. InICML 2021 Workshop on tackling climate change with machine learning 2021.

[33] El Morr C, Ozdemir D, Asdaah Y, Saab A, El-Lahib Y, Sokhn ES, et al. AI-based epidemic and pandemic early warning systems: A systematic scoping review. Health Informatics Journal. 2024;30(3):14604582241275844. https://doi.org/10.1177/14604582241275844

[34] Alcayna T, Rao VB, Lowe R. Identifying the climate sensitivity of infectious diseases: a conceptual framework. The Lancet Planetary Health. 2025;9(8).

[35] Pley C, Evans M, Lowe R, Montgomery H, Yacoub S. Digital and technological innovation in vector-borne disease surveillance to predict, detect, and control climate-driven outbreaks. The Lancet Planetary Health. 2021;5(10):e739-45. https://doi.org/10.1016/S2542-5196(21)00250-5

[36] Tiggeloven T, Pfeiffer S, Matanó A, Van Den Homberg M, Thalheimer L, Reichstein M, et al. The role of artificial intelligence for early warning systems: Status, applicability, guardrails, and ways forward. Iscience. 2025;28(11).

[37] Cheong KH, Li K, Yu D, Zhao X. Forecasting dengue cases through time-series modeling with Google Trends and deep neural networks. Chaos, Solitons & Fractals. 2025;201:117290. https://doi.org/10.1016/j.chaos.2025.117290

[38] Magers B, Brumfield KD, Colwell RR, Jutla AS. Evaluation of a novel climate-driven SIR model for cholera prediction. GeoHealth. 2026;10(4):e2025GH001437. https://doi.org/10.1029/2025GH001437

[39] Mustapha AY, Ikhalea N, Chianumba EC, Forkuo AY. A model for integrating AI and big data to predict epidemic outbreaks. Journal of Frontiers in Multidisciplinary Research. 2023;4(1):157-76.

[40] Kang L, Hu J, Cai K, Jing W, Liu M, Liang W, et al. The intelligent infectious disease active surveillance and early warning system in China: an application of dengue prevention and control. Global Transitions. 2024;6:249-55

[41] Cheng Y, Cheng R, Xu T, Tan X, Bai Y, Yang J, et al. Integrating meteorological data and hybrid intelligent models for dengue fever prediction. BMC public health. 2025;25(1):1516.

[42] Liu Q, Liu M, Liu J. Climate-sensitive infectious diseases under global climate change. Biomedical and Environmental Sciences. 2025;38(9):1129-41.

[43] Liscano Y, Anillo Arrieta LA, Montenegro JF, Prieto-Alvarado D, Ordoñez J. Early warning of infectious disease outbreaks using social media and digital data: A scoping review. International journal of environmental research and public health. 2025;22(7):1104. https://doi.org/10.3390/ijerph22071104

[44] Rahman MS, Shiddik MA. Explainable artificial intelligence for predicting dengue outbreaks in Bangladesh using eco-climatic triggers. Global Epidemiology. 2025;10:100210. https://doi.org/10.1016/j.gloepi.2025.100210

[45] Liu B, Hossain MF, Hossain S. A comparative evaluation of multiple machine learning approaches for forecasting dengue outbreaks in Bangladesh. Scientific Reports. 2025;15(1):35931.

[46] Boudreault J, Lamothe F, Campagna C, Chebana F. Machine learning for modelling the health impacts of extreme heat: A comprehensive literature review. Environment International. 2025;109965. https://doi.org/10.1016/j.envint.2025.109965

[47] Idahor CO, Esomu EJ, Ogbonna N, Momoh Z, Ogbeide OA, Ikhu-Omoregbe O, et al. Infectious Disease Surveillance in the Era of Big Data and AI: Opportunities and Pitfalls. Cureus. 2025;17(10).

[48] Xia A, Xu JJ, Shang W, Wei X, Zhao D, Ma C, et al. Health GeoAI beyond algorithms: Embedding equity, accountability, and environmental responsibility. Geography and Sustainability. 2026;100445. https://doi.org/10.1016/j.geosus.2026.100445

[49] Fortnam M, Hailey P, Witter S, Balfour N. Resilience in interconnected community and formal health (and connected) systems. SSM-Health Systems. 2024;3:100027. https://doi.org/10.1016/j.ssmhs.2024.100027

[50] Song P, Jiang D, Zhou J, Zhu Y, Manaf RA, Bojude DA, et al. Research priorities for data science and artificial intelligence in global health: an international consensus exercise. The Lancet Global Health. 2026;14(3):e455-65.

[51] Kaur J, Butt ZA. AI-driven epidemic intelligence: the future of outbreak detection and response. Frontiers in Artificial Intelligence. 2025;8:1645467. https://doi.org/10.3389/frai.2025.1645467

[52] Brownstein JS, Rader B, Astley CM, Tian H. Advances in artificial intelligence for infectious-disease surveillance. New England Journal of Medicine. 2023;388(17):1597-607. https://doi.org/10.1056/NEJMra2215675

[53] Shiddik MA, Toshi FZ, Yesmin S, Rahman MS. District-Level Dengue Early Warning Prediction System in Bangladesh Using Hybrid Explainable AI and Bayesian Deep Learning. Tropical Medicine and Infectious Disease. 2026;11(3):73. https://doi.org/10.3390/tropicalmed11030073

[54] Ye Y, Pandey A, Bawden C, Sumsuzzman DM, Rajput R, Shoukat A, et al. Integrating artificial intelligence with mechanistic epidemiological modeling: a scoping review of opportunities and challenges. Nature Communications. 2025;16(1):581.

[55] Kim C, Austin R, Wurtz R, Delaney CW, Rajamani S. Applications of Artificial Intelligence in the Control of Infectious Diseases in the Post-COVID Era: Scoping Review. JMIR nursing. 2025;8:e84242. https://doi.org/10.2196/84242

[56] Li JH, Tseng YJ, Chen SH, Chen KF. Artificial Intelligence in Infection Surveillance: Data Integration, Applications and Future Directions. Biomedical Journal. 2025;100929. https://doi.org/10.1016/j.bj.2025.100929

[57] Çeleğen İ, Sarıöz A. Climate-driven infectious disease risks: a global scoping review of epidemiological patterns, methodological gaps, and policy imperatives. BMC Infectious Diseases. 2025;25(1):1770.

[58] Yeh KB, Parekh FK, Mombo I, Leimer J, Hewson R, Olinger G, et al. Climate change and infectious disease: A prologue on multidisciplinary cooperation and predictive analytics. Frontiers in Public Health. 2023;11:1018293. https://doi.org/10.3389/fpubh.2023.1018293

[59] Yang L, Shan L, Cao X, Cui J, Tong M, Niu Y, et al. AI Agents and Epidemic Intelligence on Respiratory Infectious Diseases: Toward a Conceptual Framework Integrating Decision Support. Journal of Medical Internet Research. 2026;28:e86936. https://doi.org/10.2196/86936