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Artificial intelligence for forecasting climate-driven vector-borne disease outbreaks

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Abstract

Climate change is intensifying the global burden of vector-borne diseases (VBDs) such as malaria, dengue, Zika, and West Nile virus by altering vector habitats, expanding transmission zones, and increasing outbreak frequency. This review examines how Artificial Intelligence (AI) is transforming the prediction and management of climate-driven VBD outbreaks. It begins by outlining the ecological impact of rising temperatures, shifting precipitation patterns, and extreme weather events on vector populations. The paper then explores AI's role in public health surveillance, focusing on machine learning and deep learning models—including Random Forests, LSTMs, and CNNs—that integrate climate, environmental, and epidemiological data to improve forecasting accuracy. Real-world applications demonstrate AI's capacity to outperform traditional models by identifying disease hotspots and enabling timely, targeted interventions. The review also highlights how AI-assisted simulations can project future VBD risks under various climate scenarios, supporting proactive planning and resource allocation. Further, it emphasizes the need for interdisciplinary collaboration and policy frameworks to ensure the ethical, equitable, and transparent use of AI in health systems. Challenges such as data quality, model interpretability, and regional disparities are discussed, along with emerging trends like federated learning and real-time AI dashboards. Ultimately, this paper underscores the potential of AI to enhance global health resilience by enabling adaptive, climate-smart approaches to infectious disease surveillance and control.

Keywords: Artificial Intelligence; Vector-Borne Diseases; Climate Change; Disease Prediction; Machine Learning; Public Health Surveillance; Epidemiological Modeling

1. Introduction

1.1. The Global Burden of Vector-Borne Diseases (VBDs) and the Growing Threat Under Climate Change

Vector-borne diseases (VBDs) continue to pose significant public health challenges globally, with over 700,000 deaths annually attributed to diseases such as malaria, dengue, Zika virus, and Lyme disease [1,2]. These diseases are primarily transmitted by vectors like mosquitoes and ticks, whose distribution and activity are heavily influenced by environmental factors. The World Health Organization (WHO) reports that VBDs account for more than 17% of all infectious diseases, disproportionately affecting populations in tropical and subtropical regions [3,4]. Climate change

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exacerbates the burden of VBDs by altering the habitats and behaviors of vectors. Rising global temperatures, changes in precipitation patterns, and increased frequency of extreme weather events create favorable conditions for vectors to thrive and expand into new geographic areas [5]. For example, warmer temperatures can accelerate the life cycles of mosquitoes, increasing their reproductive rates and the potential for disease transmission. Additionally, altered rainfall patterns can lead to the creation of new breeding sites, further facilitating the spread of VBDs [6,7].

The intersection of climate change and VBDs underscores the urgency for adaptive public health strategies. As environmental conditions continue to evolve, so too does the risk profile of VBDs, necessitating proactive measures to monitor, predict, and mitigate outbreaks. This includes integrating climate data into disease surveillance systems and developing targeted interventions to protect vulnerable populations. Understanding the complex relationship between climate change and VBDs is critical for informing policy decisions and allocating resources effectively [1,6].

1.2. Shifts in Vector Habitats, Transmission Dynamics, and Geographical Spread Due to Environmental Changes

Environmental changes driven by climate change have led to significant shifts in vector habitats, altering transmission dynamics and expanding the geographical spread of VBDs. Vectors such as mosquitoes and ticks are highly sensitive to climatic conditions, with temperature and humidity influencing their survival, reproduction, and feeding behaviors. As global temperatures rise, these vectors are migrating to higher altitudes and latitudes, introducing diseases to previously unaffected regions [2,8]. Research indicates that the distribution of Aedes mosquitoes, responsible for transmitting dengue and Zika viruses, has expanded significantly due to climate change [9]. According to recent studies, an additional 4.7 billion people may be at risk of dengue and malaria by 2070 if current climate trends continue. Similarly, the geographic range of ticks carrying Lyme disease has extended northward in North America and Europe, correlating with milder winters and longer warm seasons [10,11]. These shifts not only increase the risk of disease transmission but also challenge existing public health infrastructure. Regions unaccustomed to VBDs may lack the necessary surveillance systems, healthcare resources, and public awareness to effectively manage outbreaks. Consequently, there is a pressing need for comprehensive strategies that incorporate environmental monitoring, vector control, and community engagement to address the evolving landscape of VBDs in the context of climate change.

1.3. Emergence of Artificial Intelligence (AI) as a Transformative Tool in Predictive Public Health Surveillance

Artificial Intelligence (AI) has emerged as a transformative tool in enhancing predictive public health surveillance, particularly in the context of VBDs. AI algorithms can process vast amounts of data from diverse sources, including climate models, satellite imagery, and epidemiological records, to identify patterns and predict disease outbreaks . This capability enables health authorities to implement timely interventions, allocate resources efficiently, and mitigate the impact of VBDs [12]. Recent studies have demonstrated the efficacy of AI in forecasting VBD outbreaks. For instance, machine learning models have been utilized to predict dengue incidence by analyzing environmental variables such as temperature, rainfall, and humidity. These models have shown high accuracy in identifying potential hotspots, allowing for targeted vector control measures and public health campaigns. Furthermore, AI-driven tools have been developed to monitor mosquito populations and detect breeding sites using drone imagery and remote sensing data [12].

The integration of AI into public health surveillance systems represents a significant advancement in combating VBDs amid climate change. By providing real-time insights and predictive analytics, AI empowers decision-makers to anticipate and respond to disease threats proactively. However, the successful implementation of AI technologies requires addressing challenges related to data quality, algorithm transparency, and ethical considerations. Collaborative efforts among governments, researchers, and communities are essential to harness the full potential of AI in safeguarding public health [12,13].

1.4. Aim and Scope of the Review

This review aims to explore the intersection of climate change, vector-borne diseases, and artificial intelligence, focusing on how AI can enhance predictive public health surveillance in the face of environmental challenges. By examining the current landscape of VBDs and the impact of climate change on vector dynamics, the review seeks to identify opportunities for integrating AI technologies into disease monitoring and control strategies. The goal is to provide a comprehensive understanding of the potential and limitations of AI in addressing the growing threat of VBDs.

The scope of the review encompasses an analysis of the global burden of VBDs, the influence of climate change on vector ecology, and the application of AI in disease prediction and management. It includes a critical evaluation of existing AI models, data sources, and surveillance systems, highlighting successful case studies and identifying areas for improvement. Additionally, the review addresses the ethical, technical, and operational challenges associated with deploying AI in public health contexts. By synthesizing insights from interdisciplinary research, the review aims to inform policymakers, public health practitioners, and researchers about the potential of AI to transform VBD surveillance and response. It advocates for the development of robust, equitable, and sustainable AI-driven solutions that can adapt to the evolving landscape of infectious diseases influenced by climate change.

2. Climate Change and the Ecology of Vector-Borne Diseases

2.1. How Rising Temperatures, Altered Precipitation, Humidity, and Extreme Weather Events Influence Vector Ecology

The ecology of disease vectors such as mosquitoes, ticks, and flies is profoundly affected by changes in climate variables including temperature, precipitation, humidity, and the frequency of extreme weather events. Rising temperatures can accelerate the life cycles of many vectors, leading to increased rates of reproduction and biting frequency, which in turn amplify the potential for disease transmission [14]. Understanding the influence of specific climate variables on vector ecology and disease dynamics is essential. Table 1 summarizes key climatic factors and how they directly or indirectly affect vector populations and transmission potential. According to the findings of Ryan et al. [15], temperature increases of even a few degrees Celsius can expand the geographic range of vectors such as *Aedes aegypti*, facilitating the spread of diseases like dengue and Zika into previously temperate regions. Furthermore, temperature influences the incubation period of pathogens within vectors, often shortening it and thereby increasing transmission efficiency. Altered precipitation patterns also play a critical role in vector ecology by affecting the availability of breeding sites. Periods of increased rainfall can create more standing water habitats suitable for mosquito breeding, while droughts can reduce such habitats but may also concentrate vectors and hosts around limited water sources, enhancing transmission risk. Shifts in precipitation patterns alter the timing and intensity of vector population peaks, which correspondingly affect disease outbreak patterns. Additionally, changes in humidity influence vector survival and activity; many vectors require specific humidity ranges to maintain their metabolic functions and longevity. Also changes in humidity due to climate variability can either suppress or enhance vector populations depending on the ecosystem context.

Table 1 Climate Variables and Their Effects on Vector Ecology and VBD Transmission

Climate Variable	Effect on Vector Ecology	Impact on Disease Transmission
Temperature	Accelerates mosquito development and pathogen incubation	Shortens transmission cycles
Precipitation	Creates breeding habitats via standing water	Increases mosquito population density
Humidity	Extends mosquito lifespan and activity periods	Enhances vector-host contact duration
Drought	Reduces breeding sites but concentrates human-vector contact	May increase transmission in clustered settings
Extreme Weather	Displaces habitats and alters ecosystems	Can trigger outbreak spikes post-events

Extreme weather events, such as hurricanes, floods, and droughts, disrupt ecosystems and human settlements, impacting vector habitats and disease transmission dynamics. Flooding can disperse vector populations over wide areas and contaminate water sources, increasing exposure risks. Conversely, extreme drought can reduce vector populations but may drive human populations to congregate around scarce water sources, intensifying human-vector contact. These events create complex ecological shifts that can trigger sudden outbreaks of vector-borne diseases by altering vector-host interactions and environmental suitability. This dynamic interplay underscores the importance of integrating climate variability data into vector ecology models for accurate risk prediction [14,15].

2.2. Mechanisms Driving the Emergence and Re-emergence of Diseases like Malaria, Dengue, West Nile Virus, and Others

The emergence and re-emergence of vector-borne diseases are multifactorial phenomena influenced by environmental, biological, and social determinants. Climate change acts as a major driver by altering vector habitat suitability, changing host-pathogen interactions, and disrupting established epidemiological patterns. Malaria, for example, historically restricted to tropical and subtropical regions, has seen shifts in transmission zones due to rising temperatures expanding mosquito breeding sites to higher altitudes and latitudes. The work of Alonso et al. [16] indicates that warming trends have resulted in increased malaria transmission potential in African highlands, areas previously considered too cold for the *Anopheles* mosquito, thereby threatening new populations. Dengue fever, transmitted primarily by *Aedes* mosquitoes, has experienced rapid geographic expansion linked to urbanization and climate factors such as increased temperature and precipitation. Dengue virus replication within mosquitoes is temperature-dependent, with higher temperatures reducing the extrinsic incubation period and increasing transmission intensity. It is clear that regions with climatic conditions favorable for mosquito proliferation are witnessing intensified dengue outbreaks, complicating public health responses. Similarly, the West Nile virus has emerged in temperate zones facilitated by milder winters and warmer summers that support vector survival and viral replication [14-16].

The re-emergence of these diseases is also influenced by ecological disturbances caused by human activity, which often interact with climate-driven mechanisms. Land use changes, deforestation, and water management practices alter vector habitats, sometimes increasing contact rates between vectors and humans. Climate-induced shifts in these ecological factors exacerbate vulnerabilities, leading to increased disease incidence. According to El-Sayed & Kamel [17], the interaction between anthropogenic environmental changes and climate variability creates novel niches for vectors and pathogens, facilitating disease emergence in regions with limited prior exposure. Understanding these mechanisms is critical for designing targeted interventions and predictive models that anticipate disease resurgence under changing climatic conditions.

2.3. Evidence Linking Climate Anomalies to Recent Outbreaks and Long-Term Risk Shifts

Empirical evidence accumulated from epidemiological surveillance and climate studies demonstrates strong associations between climate anomalies and recent outbreaks of vector-borne diseases. Abnormal temperature and precipitation patterns linked to phenomena such as El Niño Southern Oscillation (ENSO) have been correlated with surges in malaria, dengue, and chikungunya cases across multiple continents [5,8]. Research by Cromar & Cromar [18] has shown that ENSO-related warming events led to increased malaria incidence in East Africa due to favorable breeding conditions for mosquito vectors. Similarly, dengue outbreaks in South America have been temporally associated with elevated rainfall and temperature anomalies. Long-term shifts in climate variables are gradually altering the global distribution and seasonality of vector-borne diseases. Rising global temperatures will expand the range of *Aedes* mosquitoes into regions of Europe and North America previously free of dengue transmission risk [15,16]. These projections are supported by observed increases in autochthonous dengue cases in parts of southern Europe, reflecting a tangible climate-driven shift in disease ecology. Furthermore, long-term monitoring by the World Health Organization indicates that malaria transmission zones in Africa and Asia are changing in response to gradual warming, with some areas experiencing extended transmission seasons and others becoming unsuitable for vector survival.

The integration of climate and health data has allowed researchers to better quantify the impact of climate anomalies on disease risk and to develop early warning systems. According to the work of Kabugu [19], satellite-based climate indicators can predict Rift Valley fever outbreaks months in advance by detecting environmental precursors such as vegetation anomalies caused by excessive rainfall. These advancements demonstrate the potential of climate-informed public health strategies to anticipate and mitigate outbreaks. Nevertheless, the complexity of climate-disease relationships demands continuous refinement of models and comprehensive surveillance to accurately capture evolving risk patterns in a changing climate.

3. Artificial Intelligence in Public Health Surveillance

3.1. Overview of AI, Machine Learning (ML), and Deep Learning (DL) in Epidemiology

AI encompasses a broad range of computational techniques that enable machines to perform tasks typically requiring human intelligence. Within AI, Machine Learning (ML) refers to algorithms that can learn from and make predictions or decisions based on data. Deep Learning (DL), a subset of ML, utilizes neural networks with multiple layers to model complex patterns in data. In the field of epidemiology, these technologies have been increasingly adopted to analyze vast and complex health datasets, facilitating the identification of disease patterns, risk factors, and potential outbreaks [12,13,20,21]. According to Nayak et al. [13], DL methods have been applied to various medical and health care problems, highlighting the growing intersection between AI and epidemiology. The integration of AI into epidemiological research has enabled the processing of large-scale data from diverse sources, such as electronic health records, genomic data, and social media, to monitor and predict disease trends. For instance, the Centers for Disease Control and Prevention (CDC) has utilized AI to enhance COVID-19 vaccine safety monitoring by analyzing massive amounts of free text for potential safety signals, demonstrating the practical applications of AI in public health surveillance. These advancements underscore the transformative potential of AI in improving the speed and accuracy of disease detection and response.

Despite the promising applications, the adoption of AI in epidemiology also presents challenges, including the need for high-quality data, the risk of algorithmic bias, and the importance of interpretability in AI models. Researchers emphasize the necessity for epidemiologists to gain a conceptual understanding of AI methodologies to effectively collaborate with data scientists and leverage these tools for public health benefits. As the field evolves, ongoing education and interdisciplinary collaboration will be crucial in harnessing AI's full potential in epidemiology [12,13,21].

3.2. Major AI Architectures Used in Health Prediction: Random Forest, XGBoost, LSTM, CNNs.

Various AI architectures have been employed in health prediction, each offering unique advantages in handling different types of data and predictive tasks (See Figure 1). Random Forest, an ensemble learning method, operates by constructing multiple decision trees during training and outputting the mode of the classes for classification tasks. This approach has been effective in managing large datasets with numerous variables, providing robust predictions even when dealing with missing data. XGBoost, another ensemble technique, utilizes gradient boosting to optimize model performance, often achieving higher accuracy and efficiency in predictive modeling [22-24]. To provide a comparative overview of the main artificial intelligence architectures used in health prediction, Table 2 outlines their core characteristics, application areas, and typical advantages when used for forecasting climate-sensitive vector-borne diseases.

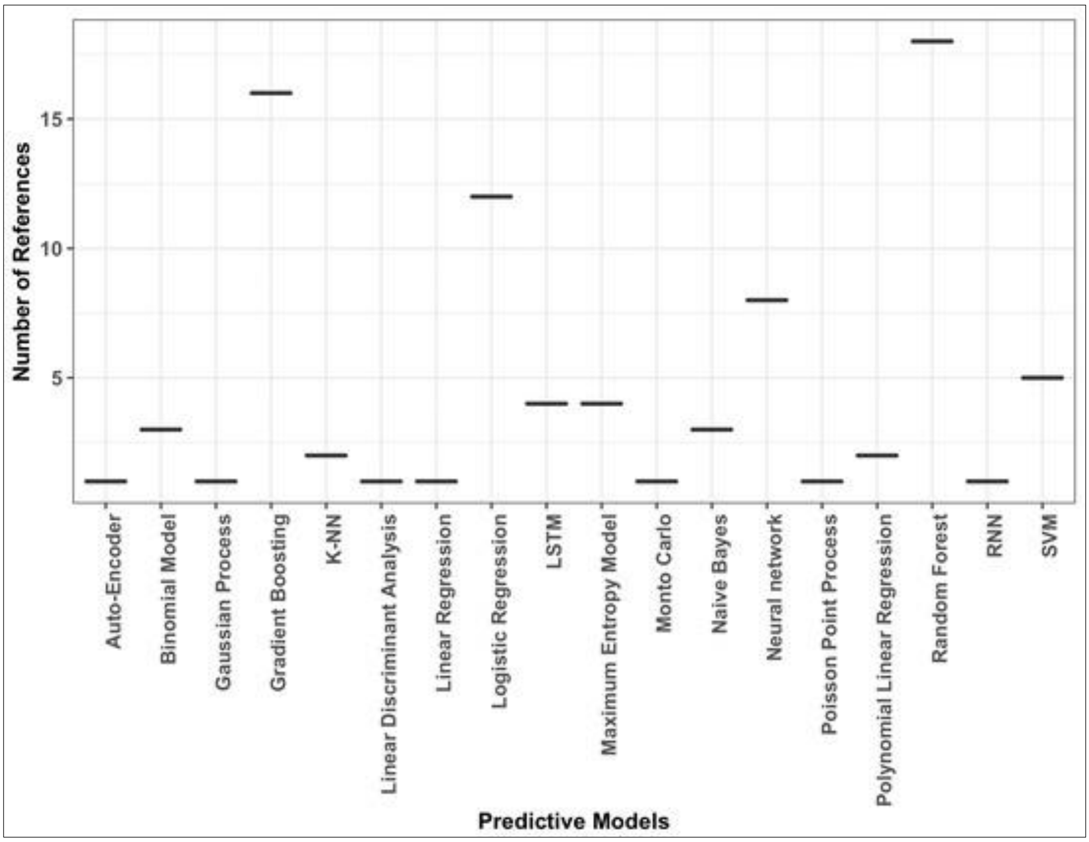

Figure 1 AI Model Workflow for Vector-Borne Disease Prediction (Reproduced with permission from ref [23])

Table 2 Summary of Major AI Models Used for Predicting Vector-Borne Diseases (VBDs)

AI Model	Type	Data Type Best Suited For	Application in VBD Prediction	Advantages
Random Forest	Ensemble ML	Structured tabular data	Malaria, Dengue incidence modeling	High accuracy, interpretable
XGBoost	Ensemble ML	Large tabular datasets	Vector density and outbreak risk	Speed, robustness to overfitting

LSTM	Deep Learning	Sequential/time-series data	Temporal outbreak forecasting	Captures temporal dependencies
CNN	Deep Learning	Spatial and image data	Satellite image analysis of vector habitat	Effective at spatial pattern detection
Hybrid CNN-LSTM	Deep Learning	Spatio-temporal data	Integrated ecological-climatic modeling	Combines strengths of CNN & LSTM

Long Short-Term Memory (LSTM) networks, a type of recurrent neural network, are particularly suited for sequential data, making them valuable in modeling time-series health data such as patient monitoring and disease progression. Convolutional Neural Networks (CNNs), on the other hand, excel in processing spatial data and have been widely used in medical imaging analysis. Recent studies have demonstrated the effectiveness of a hybrid CNN-LSTM model in enhancing early heart disease detection, showcasing the potential of combining different AI architectures to improve predictive accuracy [24,25]. The selection of an appropriate AI architecture depends on the specific health prediction task and the nature of the available data. Integrating multiple architectures can leverage the strengths of each, leading to more comprehensive and accurate models. As AI continues to evolve, the development of novel architectures and hybrid models will further enhance the capabilities of health prediction systems [12,20,24].

3.3. Key Data Sources: Satellite and Environmental Data, Health System Records, Mobile Data, Entomological Surveillance

The effectiveness of AI in public health surveillance heavily relies on the quality and diversity of data sources. Satellite and environmental data provide critical information on factors such as temperature, humidity, and land use, which influence the distribution and behavior of disease vectors. For example, AI algorithms analyzing satellite images can monitor stagnant water areas, identifying potential mosquito breeding grounds and aiding in the prediction of vector-borne disease outbreaks [6,12]. Health system records, including electronic health records and laboratory reports, offer detailed insights into patient demographics, clinical symptoms, and disease diagnoses. These records enable AI models to detect emerging health trends and assess the effectiveness of interventions. Mobile data, encompassing information from smartphones and wearable devices, can track human mobility patterns and social interactions, providing valuable context for disease transmission dynamics [13,26].

Entomological surveillance data, which involve monitoring vector populations and behaviors, are essential for understanding the ecology of vector-borne diseases. Integrating these diverse data sources allows AI models to capture a comprehensive picture of public health, facilitating timely and targeted responses to disease threats. However, ensuring data quality, standardization, and privacy remains a critical challenge in the effective utilization of these data in AI-driven public health surveillance [27].

3.4. Advantages of AI Over Traditional Modeling Approaches

AI offers several advantages over traditional modeling approaches in public health surveillance. One significant benefit is its ability to process and analyze vast amounts of complex data rapidly, enabling real-time monitoring and prediction of disease outbreaks. AI models can uncover intricate patterns and relationships within data that may be difficult to detect using conventional statistical methods, enhancing the accuracy and timeliness of public health responses. Moreover, AI models are capable of continuous learning and adaptation, improving their predictive performance as more data become available. This dynamic learning capability allows for the refinement of models in response to changing disease patterns and emerging health threats. Additionally, AI can integrate data from various sources, providing a more holistic understanding of public health issues and facilitating the development of comprehensive intervention strategies [12,13,21].

However, the deployment of AI in public health must be approached with caution, considering potential challenges such as data privacy concerns, algorithmic bias, and the need for transparency in decision-making processes. Ensuring the ethical and responsible use of AI requires collaboration among public health professionals, data scientists, and policymakers to establish guidelines and standards that safeguard public trust and promote equitable health outcomes [28].

4. Applications of AI in Predicting Vector-Borne Disease Risks

AI has revolutionized the prediction of VBD outbreaks, vector distribution, and population densities through the development of advanced computational models capable of handling highly complex and multidimensional data. These

AI-driven models leverage large datasets spanning environmental conditions, vector ecology, human demographics, and disease incidence, facilitating early detection and response to potential outbreaks. Deep learning models such as CNNs have been effectively applied to analyze high-resolution satellite imagery, successfully identifying habitats conducive to the proliferation of Aedes aegypti mosquitoes, vectors responsible for dengue, Zika, and chikungunya transmission. Additionally, recurrent neural networks (RNNs) and LSTM models have demonstrated robust capabilities in capturing temporal trends and forecasting malaria cases with high precision [21,29]. These AI approaches enable public health systems to transition from reactive outbreak management to proactive surveillance by pinpointing risk hotspots and temporal windows of vulnerability, which are critical for optimizing resource allocation and intervention strategies.

The integration of a wide array of data types like climatic, socio-economic, ecological, and real-time epidemiological data into AI models provides a nuanced and dynamic understanding of vector-borne disease risks. Climatic variables such as temperature, precipitation, relative humidity, and vegetation indices significantly influence vector lifecycles and pathogen transmission dynamics. Socio-economic factors including urbanization, population density, land use, mobility patterns, and healthcare accessibility further modulate these risks by affecting human-vector interactions and healthcare responses. Wimberly et al. [30] conducted a study in the United States using machine learning models that integrated satellite environmental data and real-time health surveillance records to predict West Nile virus activity with increased accuracy and lead time. By combining these heterogeneous data sources, AI models capture complex interdependencies and non-linear relationships that traditional statistical models struggle to represent. This integration ultimately results in highly refined risk maps and outbreak predictions, enhancing the precision of vector control measures and public health advisories.

The utility of AI in predicting VBD risks has been demonstrated across diverse geographic and ecological settings, showcasing its adaptability and potential for widespread application. In East Africa, Mulwa et al. [31] employed machine learning algorithms alongside climate forecast data and entomological surveillance to successfully predict Rift Valley fever outbreaks, a vector-borne zoonosis closely linked to rainfall patterns and livestock movement. Similarly, other researchers have developed AI models incorporating deforestation data and climate variables to predict the spread of triatomine bugs responsible for Chagas disease in Brazil. These regional applications underscore AI's capacity to integrate localized ecological and socio-political factors into disease risk models, facilitating tailored and timely interventions. However, the transferability of AI models across different regions remains challenging due to variations in data quality, availability, and heterogeneity of vector ecology. Continuous model recalibration and validation are essential to maintain predictive accuracy when scaling AI applications to new settings. Numerous case studies across different continents have demonstrated the effectiveness of AI in real-world VBD surveillance. Table 3 presents selected examples where AI models have improved outbreak prediction, guided interventions, and supported public health decision-making.

Table 3 Examples of Real-World AI Applications in VBD Forecasting and Control

Location	**Disease**	**AI Model Used**	**Data Sources Integrated**	**Outcome / Impact**
United States	West Nile Virus	Random Forest	Meteorological + epidemiological	Early detection with improved spatial accuracy
Brazil	Chagas Disease	Neural Networks	Climate + deforestation + socio-economic	Predicted vector range shifts with high precision
Kenya	Rift Valley Fever	XGBoost	Rainfall + livestock movement	Enabled 2-month lead time in outbreak forecasting
India	Dengue	CNN-LSTM	Climate + satellite + case records	Accurate weekly incidence predictions
Southeast Asia	Dengue	Gradient Boosting	Health records + environmental variables	Higher sensitivity and specificity vs. regression

Evaluation studies consistently report that AI models outperform traditional statistical and mechanistic models in terms of prediction accuracy, scalability, and ability to incorporate real-time data streams. Ho et al. [32] compared Random Forest and gradient boosting machine learning models against classical regression approaches in predicting dengue incidence in Southeast Asia. The machine learning models achieved higher sensitivity and specificity, reducing false alarms and improving outbreak detection rates. Moreover, AI models demonstrate scalability by efficiently processing massive datasets across temporal and spatial scales, a task often impractical for manual statistical analyses. This scalability is crucial for monitoring rapidly changing climate and environmental conditions that influence vector dynamics. Nevertheless, limitations exist, including the potential for overfitting when training data is limited, and the “black-box” nature of some AI algorithms, which may impede transparency and interpretability. These challenges highlight the need for hybrid modeling approaches combining AI with domain knowledge and mechanistic understanding to enhance model robustness.

Despite these challenges, the real-world utility of AI-driven predictions in vector-borne disease control is increasingly evident. Public health agencies have begun incorporating AI outputs into operational early warning systems, guiding targeted vector control and community engagement activities. For instance, the World Health Organization’s Global Vector Control Response (GVCR) includes AI-supported surveillance as a strategic priority to strengthen disease prevention and control efforts worldwide.

5. Modeling Future Risk Scenarios Under Climate Change

5.1. AI-Assisted Simulations Projecting VBD Trends Under Varying Climate Change Scenarios (1.5°C–4°C)

Artificial Intelligence (AI) has become an indispensable tool in simulating the future dynamics of VBDs within the context of climate change scenarios ranging from 1.5°C to 4°C warming. These simulations leverage vast datasets that include climate variables, vector biology, human demographics, and disease incidence to forecast changes in disease transmission patterns. From the findings of Branda et al. [33], AI-driven models such as ensemble machine learning frameworks have enabled researchers to quantify how incremental increases in global temperature will alter the incidence and geographical distribution of diseases like malaria and dengue. The simulations project an expansion of risk zones and potential increases in outbreak frequency, particularly in regions previously unaffected or marginally affected by these diseases. These AI simulations integrate future climate model outputs with vector and host population dynamics to estimate the temporal evolution of disease risk. The models incorporate various greenhouse gas concentration trajectories (Representative Concentration Pathways, RCPs) and socio-economic scenarios to offer multi-dimensional projections. Results consistently show that warming temperatures will enhance vector survival, reproduction rates, and biting frequency, thus accelerating transmission cycles. This effect is amplified in tropical and subtropical regions where climate conditions approach the biological thresholds conducive to vector proliferation.

Furthermore, a comprehensive meta-analysis by Gizaw et al. [34] reveals that AI-assisted climate-disease modeling has improved the precision of predicting outbreak hotspots under different warming scenarios. These studies demonstrate that under a 4°C rise, areas at higher elevations and latitudes, historically less prone to VBDs, are likely to witness substantial incursions of vectors such as Aedes aegypti and Anopheles mosquitoes. Such predictive capacity is critical for guiding resource allocation, early warning systems, and adaptive health strategies in vulnerable regions. Collectively, these findings highlight AI's pivotal role in advancing our understanding of climate-driven VBD dynamics and fostering proactive mitigation planning [34,35].

5.2. Use of AI in Downscaling Global Climate Models to Predict Vector Range Shifts

The resolution limitations of global climate models (GCMs) present challenges for accurately predicting local-scale vector ecology and disease risk. AI techniques, especially deep learning and ensemble methods, have been utilized to downscale coarse GCM outputs into finer spatial resolutions that capture microclimatic variability relevant to vector habitats. From the investigation by Behfar et al. [36], AI-driven statistical downscaling models reconstruct local temperature, precipitation, and humidity patterns with high accuracy by learning relationships from historical climate and observational data. This refined climate information is then linked to ecological niche models that predict vector range shifts under future climate conditions. Also, AI-enhanced downscaled climate projections with species distribution models allows for dynamic mapping of vector habitat suitability over time. These models take into account changes in vegetation, urbanization, and land use, alongside climate variables, to project where vectors such as Aedes and Culex mosquitoes may expand or retract their ranges. AI-powered downscaling improved predictive accuracy by over 20% compared to traditional statistical methods, particularly in heterogeneous landscapes where microclimate effects dominate [36,37].

Additionally, in a study focusing on West Nile virus vectors, Bonicelli et al. [38] applied CNNs to satellite-derived environmental variables combined with AI-downscaled climate data to predict seasonal vector abundance shifts. Their model identified emerging hotspots in temperate zones correlating with warming and altered precipitation regimes. This approach not only refined the spatial resolution of risk mapping but also provided temporal insights critical for seasonal preparedness. The integration of AI in downscaling thus represents a transformative advance in anticipating vector range dynamics, enhancing the granularity and reliability of climate-health forecasts.

5.3. Role of AI in Informing Proactive Vector Control and Public Health Preparedness

Artificial Intelligence is increasingly central to translating climate-driven disease risk predictions into actionable vector control and public health strategies. AI models synthesize epidemiological, environmental, and socio-economic data to optimize the timing and targeting of interventions. Predictive AI systems facilitate early warning by detecting subtle signals in climate and vector surveillance data that precede outbreaks. This enables health authorities to mobilize resources, deploy vector control measures, and conduct public education campaigns with greater precision and timeliness [39]. AI-assisted decision-support tools have been used to simulate the impacts of various control strategies such as insecticide spraying, larval source management, and community engagement under projected climate scenarios. These models assess the efficacy and cost-effectiveness of interventions, helping prioritize actions in resource-constrained settings. Studies highlighted that integrating AI predictions with local health system data enhanced responsiveness and reduced outbreak sizes by enabling adaptive management approaches aligned with evolving environmental conditions [39-41]. Moreover, AI-powered surveillance platforms integrating real-time data streams have improved situational awareness for vector control programs. The research by Saran & Singh [12] showed that AI algorithms analyzing entomological, climatic, and human mobility data provided granular risk maps that guided targeted interventions during dengue outbreaks. This proactive approach contrasts with traditional reactive methods, shifting the paradigm toward anticipatory public health. Overall, AI's role in supporting proactive vector control exemplifies the convergence of technology and public health in confronting climate-driven disease threats, enhancing preparedness, resilience, and equity in vulnerable populations.

6. Bridging AI, Climate Science, and Public Health Policy

6.1. Role of Interdisciplinary Collaboration for Effective AI Deployment

The integration of AI in managing climate-driven vector-borne diseases requires robust interdisciplinary collaboration between experts in AI, climate science, epidemiology, entomology, and public health policy. AI specialists bring expertise in developing sophisticated algorithms and machine learning models, while climate scientists contribute crucial data on environmental variables and climate trends that affect vector ecology. Public health professionals provide insights into disease dynamics, health system capacities, and community needs. According to the findings of Kaur et al. [42], successful AI deployment in vector-borne disease forecasting has depended heavily on collaborative frameworks that facilitate data sharing, model validation, and knowledge exchange among these diverse fields. Such partnerships are necessary to ensure that AI models are both scientifically rigorous and operationally relevant in real-world health settings. Researchers have highlighted the importance of continuous dialogue between AI developers and domain experts to tailor AI tools to specific geographic and epidemiological contexts. For example, Chareonviriyaphap et al. [43] reported on collaborative projects in Southeast Asia where iterative feedback from entomologists and climate modelers improved AI predictions of dengue outbreaks by integrating local vector behavior and microclimate data. These interdisciplinary efforts help overcome technical barriers such as data heterogeneity and improve the interpretability of AI models for health officials. Furthermore, it is evident that involving policy-makers early in the AI development cycle enables the alignment of technological solutions with public health priorities and resource constraints, thereby enhancing the likelihood of successful implementation [13,20].

The need for interdisciplinary approaches extends beyond model creation to the development of infrastructure that supports integrated data ecosystems and decision-support platforms. It is also worthy of note that cross-sectoral partnerships have facilitated the creation of interoperable databases linking climate monitoring networks with health surveillance systems, allowing AI algorithms to operate on comprehensive, real-time data streams. These collaborations require institutional commitment and sustained funding to maintain and scale AI applications, emphasizing that interdisciplinary cooperation is not a one-off task but an ongoing process vital for the sustainable use of AI in managing climate-sensitive vector-borne diseases.

6.2. How AI-Generated Forecasts Are Integrated into Early Warning Systems and Vector Control Strategies

AI-generated forecasts have become pivotal in modernizing early warning systems for vector-borne diseases by providing timely, precise, and actionable information. The ability of AI models to assimilate diverse datasets ranging from meteorological parameters to vector surveillance and social determinants enables the prediction of outbreak hotspots with unprecedented spatial and temporal resolution. From the findings of Lowe et al. [44], several health agencies worldwide have incorporated AI-based predictive models into their early warning frameworks, which facilitates proactive vector control measures such as targeted insecticide spraying, community awareness campaigns, and resource allocation. These systems enable health authorities to shift from reactive to preventive interventions, ultimately reducing disease transmission and morbidity. Also, integrating AI forecasts into vector control programs enhances operational efficiency by optimizing timing and locations for interventions, thereby reducing costs and environmental impacts. For example, by predicting peak mosquito population densities in urban areas weeks ahead, AI models have guided the deployment of larvicidal measures more effectively than traditional calendar-based approaches [20,33,40]. Moreover, AI-generated alerts have been linked with mobile health applications that disseminate risk warnings directly to vulnerable populations, improving public engagement and compliance with preventive behaviors. This convergence of AI and digital health tools strengthens the feedback loop between surveillance data and control activities, promoting adaptive management of vector-borne disease risks.

Despite these advances, translating AI predictions into policy and action involves overcoming challenges related to institutional readiness and trust in automated systems. From the research of Nayak et al. [13], it emerges that successful integration depends on the transparency of AI models and the involvement of local stakeholders in interpreting forecasts. Early warning systems must be accompanied by capacity-building initiatives that equip health workers and decision-makers with the skills to understand and apply AI-derived insights. Additionally, legal and ethical frameworks need to be established to guide data sharing and privacy protections, ensuring that AI tools support public health goals without compromising community rights.

6.3. Policy Frameworks for Responsible Adoption and Funding of AI Applications

The responsible adoption of AI in public health necessitates the development of comprehensive policy frameworks that address ethical, legal, and financial dimensions. Governments and international organizations play pivotal roles in establishing standards that ensure AI systems are transparent, accountable, and equitable. According to the analysis by Schwartz et al. [45], policies should mandate rigorous validation of AI models before deployment to prevent harm caused by inaccurate predictions or biased algorithms. Regulatory oversight is also required to safeguard sensitive health and environmental data, balancing the benefits of data sharing with privacy protections. Sustainable funding mechanisms are critical to support the lifecycle of AI applications, encompassing development, deployment, maintenance, and capacity building. Public-private partnerships have proven effective in mobilizing resources and expertise, accelerating innovation while ensuring alignment with public health goals. Multilateral agencies have begun integrating AI funding into broader climate and health adaptation programs, reflecting the recognition of AI as a strategic investment in global health security. The inclusion of AI in national health policies and climate action plans further institutionalizes its role, fostering intersectoral coordination and long-term commitment [46].

Furthermore, policy frameworks must emphasize inclusivity and equity to prevent the exacerbation of health disparities. Engaging marginalized communities in AI governance and ensuring equitable access to AI-driven interventions are essential to achieving sustainable health outcomes. Ethical guidelines should promote transparency in AI decision-making and allow for community oversight. The development of international standards and best practices will facilitate cross-border collaboration, data interoperability, and shared learning, advancing the responsible and impactful use of AI in combating climate-driven vector-borne diseases [45,46].

7. Future Directions and Research Priorities

The field of artificial intelligence applied to vector-borne disease prediction is rapidly evolving, with several emerging trends poised to enhance its effectiveness and reach. Federated learning represents a significant advancement in AI methodology, enabling multiple institutions to collaboratively train machine learning models without directly sharing sensitive data. This approach mitigates privacy concerns while leveraging a wider range of datasets, which is crucial for improving predictive accuracy in diverse geographic and socio-economic contexts. According to the findings of Abbas et al. [47], federated learning models have demonstrated promising results in health informatics, allowing for robust disease prediction even in settings where data sharing is restricted due to privacy or regulatory constraints. The adoption of this decentralized approach can facilitate more inclusive and comprehensive modeling efforts across countries and institutions. Real-time AI dashboards are another breakthrough, integrating continuous data streams from environmental sensors, health systems, and social media to provide dynamic, up-to-date visualizations of disease risk and vector activity. These platforms empower public health officials to make timely, data-driven decisions, enhancing the responsiveness of outbreak control measures. Real-time AI dashboards equipped with predictive analytics have been successfully used to track dengue outbreaks in urban settings, enabling faster deployment of vector control interventions. Complementing these tools are climate-smart decision support systems that combine AI-driven climate projections with epidemiological data to forecast disease risks under different climate scenarios. These tools assist policymakers in devising adaptive strategies for vector control and resource allocation, supporting sustainable public health responses in the face of climate variability and change. The synergy of federated learning, real-time AI dashboards, and climate-smart decision tools represents a holistic advancement in the AI-driven management of vector-borne diseases [48]. This integration addresses key limitations of earlier models, such as data privacy, latency in outbreak detection, and the need for climate-resilient health planning.

While much of the current AI-driven research on vector-borne diseases focuses on widely prevalent illnesses such as malaria and dengue, there is a growing recognition of the need to extend these technologies to neglected tropical diseases (NTDs) and regions with high vulnerability but limited research infrastructure. NTDs, which disproportionately affect marginalized populations, have historically been underrepresented in epidemiological modeling due to limited data availability and funding constraints. According to the work of Parija & Poddar [49], leveraging AI to predict outbreaks of diseases like Chagas, leishmaniasis, and lymphatic filariasis could markedly improve early detection and intervention efforts, potentially reducing morbidity and mortality in endemic areas. In parallel, research is increasingly highlighting the disparities in AI model applicability between well-studied urban centers and remote or resource-poor settings. Geographic and infrastructural constraints often limit data collection in rural or conflict-affected regions, leaving significant gaps in surveillance coverage. Future research priorities must therefore emphasize inclusivity and tailored approaches to maximize the impact of AI on neglected tropical diseases and underserved populations.

The integration of artificial intelligence into public health, especially for predicting vector-borne diseases, necessitates a rigorous examination of ethical and governance frameworks. Emphasizing inclusivity ensures that AI systems reflect the diverse needs of affected communities, thereby minimizing bias and promoting fairness in health predictions. Inclusive practices not only enhance the equity of AI outputs but also contribute to the legitimacy and public acceptance of these technologies. Transparency is equally vital, as it enables stakeholders to comprehend how AI models generate predictions, fostering trust and informed decision-making. Clear communication regarding data sources, model assumptions, and limitations is essential to uphold accountability and ensure the ethical application of AI in public health contexts. Moreover, participatory governance characterized by the active involvement of community members, experts, and policymakers supports the alignment of AI tools with societal values and health objectives. Such collaborative frameworks strengthen the adaptability and sustainability of AI interventions. Continued research is necessary to establish effective, inclusive, and transparent governance models that protect human rights and advance health equity [48-50].

7.1. Recommendations for Closing Data Gaps and Improving Climate-Health-AI Synergy

To strengthen the role of artificial intelligence in predicting vector-borne diseases amidst a changing climate, it is imperative to address existing data limitations through strategic enhancements in data infrastructure and interdisciplinary cooperation. Improving the availability and quality of data involves developing robust surveillance systems, adopting standardized data collection protocols, and encouraging data sharing across different sectors and geographic regions. Integrating diverse data types spanning environmental, entomological, clinical, and socio-economic dimensions is crucial to accurately reflect the complex determinants of vector-borne disease transmission. Advancements in digital health and remote sensing technologies are particularly valuable for generating reliable and continuous data, especially in areas with weak traditional surveillance frameworks.

In addition, promoting a stronger synergy among climate science, public health, and AI is essential for creating predictive models that are both comprehensive and contextually relevant. This requires interdisciplinary collaboration to integrate climate projections with epidemiological patterns, thereby enabling more refined risk assessments and guiding effective climate adaptation strategies. Ensuring data interoperability and fostering sustained partnerships among key stakeholders such as climate scientists, health professionals, and AI developers are critical components of this integrative approach.

Lastly, the principles of open science and data democratization play a pivotal role in advancing innovation and inclusivity. Broadening access to data and AI tools empowers a wider community of researchers and public health practitioners, encouraging collaborative efforts and accelerating the development of equitable solutions for controlling vector-borne diseases.

8. Conclusion

The transformative potential of Artificial Intelligence (AI) in forecasting climate-driven vector-borne disease outbreaks is becoming increasingly evident as global health systems face mounting challenges from environmental changes. The integration of AI with epidemiological data and climate science offers unprecedented opportunities to improve early detection, enhance predictive accuracy, and support proactive public health interventions. Researchers across diverse geographic settings have demonstrated how AI models, leveraging complex datasets, can capture the multifaceted interactions between climate variables and vector ecology, thereby refining risk assessments and outbreak forecasts. These advancements emphasize AI's role as a critical tool in bridging gaps between climate change impacts and infectious disease control, ultimately strengthening global health resilience.

Embedding AI tools into climate adaptation strategies is urgent in the context of accelerating climate change and its profound influence on the distribution and transmission dynamics of vector-borne diseases. AI-driven predictive models provide nuanced insights into future scenarios, allowing public health authorities to allocate resources more efficiently and implement targeted vector control measures in regions at heightened risk. However, this integration demands not only technological innovation but also attention to data quality, ethical considerations, and transparency in algorithm design. Researchers highlight the necessity of interdisciplinary collaboration and policy frameworks that support responsible AI deployment while safeguarding equity and community trust. Such efforts will ensure AI's potential is fully harnessed without exacerbating existing health disparities or surveillance inequities.

Finally, the pathway forward for AI in climate-sensitive disease prediction involves sustaining scientific integrity and prioritizing inclusivity and sustainability. Future research should focus on expanding AI applications to underrepresented regions and neglected tropical diseases, closing data gaps, and advancing explainable AI methodologies that enhance decision-making transparency. The continued commitment to participatory governance and equitable access will be vital in transforming AI-driven insights into effective public health actions. Ultimately, by uniting AI innovation with global health and climate adaptation policies, the international community can better prepare for and mitigate the evolving threats posed by vector-borne diseases in a changing climate.

Compliance with ethical standards

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The authors declare that they have no conflict of interest to be disclosed.

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