American Journal of Advanced Multidisciplinary Innovation and Research (AJAMIR)

E-ISSN: XXXX-XXXX ● Website: www.ajamir.com ● Email: editor@ajamir.com

Climate-Sensitive Public-Health Surveillance for Emerging Community Risks

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Abstract

Climate variability is increasingly modifying the timing, geographical distribution, intensity, and population consequences of public-health hazards. Conventional surveillance systems that depend primarily on reported clinical cases can identify established health events but may provide insufficient lead time for risks influenced by temperature, rainfall, humidity, drought, flooding, air quality, vector ecology, and other environmental conditions. Climate-sensitive public-health surveillance offers a complementary approach by integrating meteorological, environmental, epidemiological, demographic, and community-level information to identify emerging risks before they develop into larger health emergencies. This study examines the conceptual foundations, operational architecture, and implementation requirements of climate-sensitive surveillance through a structured integrative review and evidence-mapping methodology.

Particular attention is given to extreme heat, vector-borne diseases, water- and food-related illness, respiratory hazards, and climate-related disruptions affecting vulnerable communities. World Health Organization guidance emphasizes that integrated surveillance linking disease and weather information can strengthen preparedness and support climate-informed early-warning systems. Recent forecasting research also demonstrates the potential value of combining epidemiological information with climatic variables. A 2025 Brazilian dengue study using weekly disease, temperature, and humidity data achieved sensitivity of 75% and specificity ranging from 75% to 100% for predicting high-incidence conditions. However, implementation remains a major limitation.

A recent assessment reported 37 validated climate-sensitive infectious-disease modeling tools, of which 30 focused on vector-borne diseases and only 20 had reached an accessible-product or implementation setting. The present study therefore proposes an integrated surveillance architecture that links environmental sensing, routine disease reporting, vulnerability indicators, predictive analytics, threshold-based alerts, community verification, and pre-defined response protocols. The analysis concludes that predictive accuracy alone is insufficient. Effective systems must also be locally calibrated, timely, interpretable, usable by decision-makers, connected to response resources, transparent regarding uncertainty, and inclusive of populations most exposed to climate-related health risks. Climate-sensitive surveillance should therefore be developed as an operational component of climate-resilient primary and public-health systems rather than as an isolated forecasting technology.

Keywords: climate-sensitive surveillance; public health; early warning systems; climate change; community health; environmental epidemiology; emerging health risks; dengue forecasting; heat-health surveillance; climate resilience

1. Introduction

Climate change is altering the environmental conditions within which human health risks emerge. Extreme heat, changing rainfall patterns, floods, droughts, wildfire smoke, altered vector habitats, water contamination, food insecurity, and disruption of essential health services can produce both immediate and delayed consequences for communities. The World Health Organization recognizes that climatic conditions influence the incidence and geographical distribution of several diseases and that heatwaves, droughts, and floods can alter disease ecology as well as population vulnerability. The 2025 Lancet Countdown further reported that 12 of 20 key indicators monitoring climate-related health threats had reached record levels, while average annual heat-related deaths were estimated at approximately 546,000, representing a 23% increase in the rate of heat-related mortality compared with the 1990s.

Traditional public-health surveillance generally depends on diagnostic notifications, health-facility records, mortality data, laboratory confirmation, syndromic reporting, or other indicators that become visible after illness has already occurred. These systems remain indispensable, but climate-sensitive hazards frequently develop through measurable environmental processes before their full health burden becomes apparent. Temperature, precipitation, humidity, air quality, water conditions, vector abundance, land-surface characteristics, and seasonal anomalies can therefore provide additional information for anticipating periods of elevated risk. WHO describes integrated climate-informed surveillance as the combination of disease and weather surveillance systems to improve detection, investigation, preparedness, and response.

The preventive value of this integration is particularly evident in climate-sensitive infectious diseases. Temperature can influence vector survival, feeding behavior, pathogen development, and transmission seasons, while rainfall can affect breeding environments in disease-specific and location-specific ways. However, climate should not be treated as a single causal explanation for infectious-disease emergence. Disease transmission is also influenced by immunity, population movement, sanitation, land use, health-system capacity, socioeconomic conditions, vector control, reporting practices, and human behavior. Charnley and Kelman consequently caution that inaccurate attribution of disease patterns to climatic variables may generate inefficient allocation of prevention resources.

Recent analytical developments demonstrate that climate-informed surveillance can provide operationally meaningful prediction. Villela's 2025 analysis of weekly dengue cases, temperature, and humidity across Brazilian municipalities used data covering 2014–2024 and reported sensitivity of 75%, with specificity between 75% and 100%, for detecting high-incidence risk. In Singapore, Finch and colleagues integrated more than 20 years of dengue surveillance with climate and serotype information. Their combined model improved predictive performance by 60% compared with a seasonal baseline, achieved an area under the curve of 98% for outbreak detection in the principal analysis, and retained useful predictive capacity at an eight-week forecasting horizon. These studies demonstrate that environmental data can become considerably more informative when integrated with epidemiological and biological information.

The central challenge has consequently shifted from proving that climate and health are connected toward designing surveillance systems that convert climate intelligence into timely public-health action.

Effective surveillance must move through a complete operational chain:
Observation → integration → prediction → interpretation → warning → community response → evaluation. The present study examines this chain with particular emphasis on emerging community risks. It proposes climate-sensitive surveillance architecture intended to support local health departments, primary-care systems, environmental agencies, meteorological institutions, emergency planners, and community organizations while preserving realistic limits on predictive certainty.

2. Objectives of the Study

2.1 To Identify Climate-Sensitive Community Health Signals

The first objective is to determine which environmental and health indicators can contribute to earlier detection of emerging community risks. These include temperature extremes, humidity, precipitation, drought conditions, flooding, air-quality deterioration, vector abundance, water-quality indicators, syndromic health data, confirmed disease cases, hospital utilization, and population-vulnerability information. The purpose is not to replace established epidemiological surveillance but to improve its anticipatory capacity by incorporating environmental precursors.

2.2 To Develop an Integrated Early-Warning Surveillance Architecture

The second objective is to develop a structured framework linking meteorological information with epidemiological, environmental, demographic, and community-level data. The framework emphasizes interoperable data streams, locally validated thresholds, predictive analytics, uncertainty assessment, geographic targeting, alert generation, community verification, and predefined response actions.

2.3 To Examine Operational and Equity Requirements

The third objective is to identify the conditions under which climate-sensitive surveillance can move from research modeling into routine public-health practice. These conditions include sufficient forecast lead time, accuracy, usability, stakeholder participation, trained personnel, sustainable financing, ethical data governance, communication capacity, and deliberate prioritization of vulnerable communities.

3. Review of Literature

3.1 Climate, Environmental Exposure, and Emerging Health Risk

Climate-sensitive health outcomes include both communicable and noncommunicable conditions. WHO identifies temperature and precipitation as important determinants of vector-borne disease risk and recognizes extreme heat as a major environmental and occupational health hazard capable of aggravating cardiovascular disease, diabetes, asthma, mental-health conditions, and other illnesses. Climate-related public-health surveillance must therefore extend beyond infectious-disease notification.

Alcayna and colleagues' examination of climate-sensitive disease outbreaks following extreme climatic events highlighted the importance of recognizing connections among environmental disruption, infectious-disease emergence, population exposure, and health-system vulnerability. Their work supports a multi-hazard approach rather than independent surveillance programs for every climatic exposure. Phung and colleagues similarly describe vector-, food-, water-, and respiratory diseases as categories in which climatic information can contribute to anticipatory surveillance.

Heat represents another important surveillance domain because its impact is often distributed across different diagnostic categories rather than captured only through records explicitly coded as heat illness. The 2025 Lancet Countdown estimated approximately 546,000 average annual heat-related deaths and reported substantial increases in population exposure to dangerous heat. Climate-sensitive surveillance therefore requires integration of environmental exposure with mortality, emergency attendance, occupational health, chronic-disease vulnerability, and community-level indicators.

3.2 Evolution of Climate-Informed Early-Warning Systems

One of the earliest operational concepts in climate–health research was to use weather information as a precursor for disease risk. Lowe and colleagues demonstrated this approach in Brazil through a probabilistic dengue early-warning system that integrated seasonal climate forecasting with epidemiological information. Their work illustrated the importance of probabilistic rather than deterministic alerts because forecasting inherently contains uncertainty.

Subsequent systems have incorporated increasingly diverse data streams. Muñoz and colleagues developed AeDES as a monitoring and forecasting system for environmental suitability of Aedes-borne transmission, emphasizing that historical, current, and forecast climate information can support health planning and targeted resource allocation. Martheswaran and colleagues later incorporated climatic variation within stochastic epidemic models for Singapore and Honduras, demonstrating that both climatic and seasonal components could explain substantial variation in dengue outbreaks, although performance differed between outbreak contexts.

Recent work has further strengthened predictive specificity. Villela's 2025 Brazilian study incorporated weekly epidemiological observations with temperature and humidity, while Finch and colleagues' Singapore analysis showed that combining climate information with dengue serotype competition improved prediction beyond climate information alone. These results are methodologically important because they demonstrate that climate variables should generally be integrated with disease-specific epidemiological information rather than used as independent predictors.

3.3 The Research-to-Implementation Gap

Despite rapid development of forecasting methodologies, relatively few models become sustained operational tools. Phung and colleagues identified this translation problem as one of the major barriers in climate-sensitive infectious-disease prevention. They proposed the 3-U framework—useful, usable, and used—arguing that prediction tools require adequate accuracy and lead time, alignment with user needs, and evidence of practical effectiveness and cost-effectiveness before routine adoption.

The same study summarized a landscape analysis identifying 37 transparently described and validated climate-sensitive infectious-disease modeling tools. Thirty focused on vector-borne diseases, but only 20 had been presented as accessible products or used in implementation settings. Only about one-quarter had interfaces considered legible to decision-makers. This indicates that technically sophisticated modeling is not synonymous with operational surveillance.

WMO has similarly emphasized that scientific climate information is not yet sufficiently accessible or utilized within health systems. Its *State of Climate Services for Health* highlights applications ranging from extreme-heat warnings and pollen monitoring to satellite surveillance for climate-sensitive diseases. The research gap is therefore not merely the production of more prediction algorithms, but the development of governance, data integration, and communication, implementation, and response systems capable of using forecasts effectively.

4. Research Methodology

4.1 Research Design

The study employed a structured integrative review, evidence-mapping, and conceptual framework-development design. It did not involve recruitment of human participants, collection of identifiable health information, or generation of a new disease dataset. Consequently, no simulated incidence or mortality outcomes are presented as empirical findings.

Evidence published or available up to August 10, 2026 was examined. Priority was given to WHO and WMO guidance, major climate–health monitoring reports, peer-reviewed forecasting research, studies evaluating early-warning systems, and publications concerned with translation of predictive models into public-health practice. Searches focused on combinations of climate-sensitive surveillance, climate-health early warning, public-health surveillance, dengue prediction, heat-health surveillance, climate-sensitive infectious disease, weather and disease forecasting, and community health risk.

4.2 Surveillance Domains and Data Architecture

Climate-sensitive surveillance was conceptualized as multi-source information architecture in which risk assessment depends on both hazard and vulnerability.

Table 1: Proposed Climate-Sensitive Public-Health Surveillance Architecture

Surveillance Domain	Example Variables	Public-Health Function
Meteorological surveillance	Temperature, rainfall, humidity, heat index, drought	Detect changing exposure conditions
Environmental surveillance	Air quality, surface water, vegetation, flooding, wildfire smoke	Identify environmental pathways
Vector surveillance	Mosquito abundance, breeding indices, vector distribution	Anticipate vector-borne disease risk
Epidemiological surveillance	Confirmed cases, syndromic reports, test positivity	Detect health-event trends
Health-service surveillance	Emergency visits, admissions, ambulance demand	Identify health-system pressure
Population vulnerability	Age, comorbidity, housing conditions, occupation	Locate high-risk groups
Spatial intelligence	GIS layers, satellite observations, neighborhood indicators	Detect geographic clusters
Predictive	Statistical, Bayesian, ML, time-	Estimate future risk

analytics	series models	
Community intelligence	Local reports, citizen observations, outreach feedback	Verify emerging conditions
Response monitoring	Vector control, cooling access, WASH interventions	Evaluate intervention delivery

The architecture deliberately avoids relying on a single indicator. For example, an increase in rainfall may not independently indicate a dengue outbreak. Its significance depends on temperature, vector abundance, population immunity, circulating serotypes, baseline disease activity, local sanitation, mobility, and intervention coverage. Finch and colleagues' Singapore results illustrate this principle: climate information improved forecasting, but combining climate with serotype dynamics produced stronger predictive performance.

4.3 Analytical and Warning Procedure

A climate-sensitive surveillance cycle can be structured into seven operational stages:

Environmental and Health Data Acquisition
↓
Data Quality Assessment and Harmonization
↓
Spatial–Temporal Risk Modeling
↓
Threshold and Probability Estimation
↓
Public-Health Interpretation
↓
Targeted Community Warning and Intervention
↓
Outcome Evaluation and Model Recalibration

A warning should not be triggered solely because one environmental threshold has been exceeded. The analytical system should evaluate combinations of exposure, baseline incidence, vulnerability, model uncertainty, and the potential consequences of false-negative and false-positive alerts. WHO emphasizes that early-warning systems should anticipate risks in sufficient time to trigger responses that prevent outbreaks or reduce harmful impacts.

Forecast performance should therefore be evaluated through sensitivity, specificity, positive predictive value, false-alarm rate, calibration, discrimination, lead time, timeliness, geographical resolution, interpretability, and operational usefulness. Model accuracy that becomes available after the useful intervention window has passed has limited surveillance value.

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E-ISSN: XXXX-XXXX ● Website: www.ajamir.com ● Email: editor@ajamir.com

5. Analysis

5.1 Evidence for Predictive Climate–Health Integration

Published studies demonstrate that climatic information can improve risk detection when it is integrated appropriately with epidemiological information.

Table 2: Selected Evidence Supporting Climate-Sensitive Surveillance

Study/System	Data Integrated	Principal Finding	Surveillance Significance
Lowe et al.	Climate forecasts + dengue incidence	Demonstrated probabilistic dengue forecasting in Brazil	Established early-warning feasibility
Muñoz et al.	Climate + environmental suitability	Developed AeDES monitoring/forecast platform	Supports prospective vector-risk monitoring
Martheswaran et al.	Dengue cases + multiple climatic variables	Climate model explained substantial outbreak variation	Shows value of climatic covariates
Villela, 2025	Weekly dengue + temperature + humidity	75% sensitivity; 75–100% specificity	Demonstrates municipal high-incidence prediction
Finch et al., 2025	Climate + cases + dengue serotypes	60% improvement over seasonal baseline	Demonstrates benefit of biological integration
WHO EWARS-csd	Historical health + climatic/environmental indicators	Supports prediction of several climate-sensitive diseases	Provides operational public-health framework
Phung et al., 2025	Digital prediction-tool landscape	Major gap between modeling and implementation	Highlights translation requirement

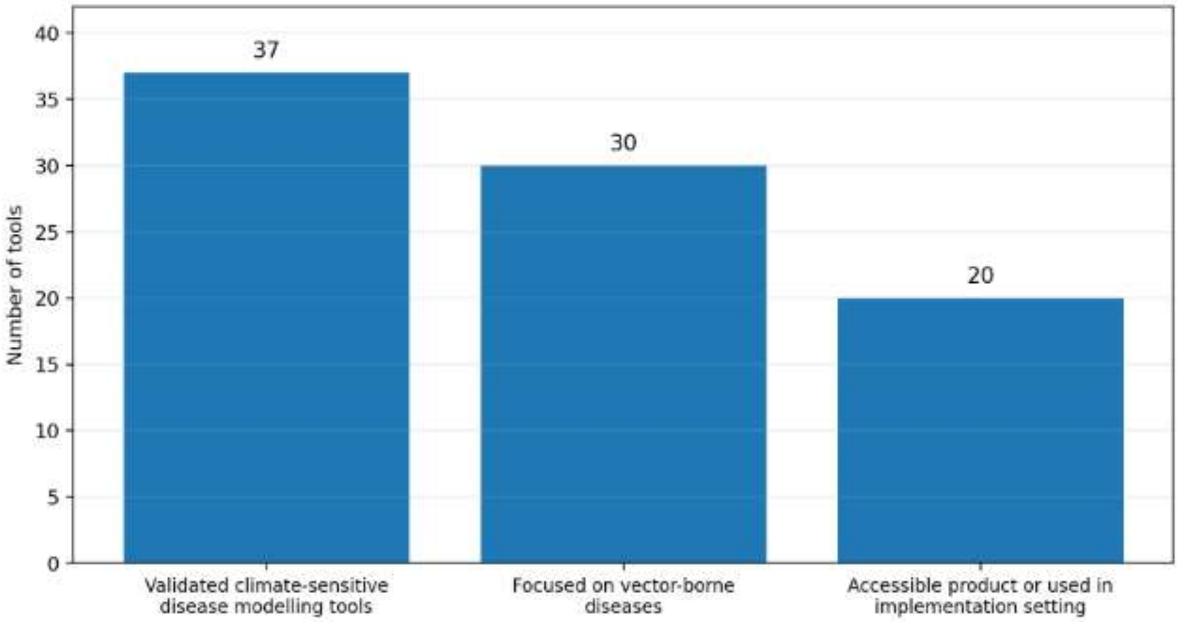
The findings show that there is no universally superior climate variable or forecasting method. Performance depends on the disease, location, surveillance quality, temporal horizon, environmental context, model specification, and availability of complementary epidemiological variables.

For example, Martheswaran and colleagues found differences between climate-based and seasonal dengue models across Singapore and Honduras, demonstrating that a method performing well in one epidemic context may not generalize automatically to another. This reinforces the importance of local model calibration.

5.2 Translation of Predictive Models into Surveillance Practice

The most important analytical finding is the contrast between model availability and operational adoption

Figure 1. Translation Profile of Climate-Sensitive Disease Prediction Tools



Interpretation: The graph demonstrates that the principal limitation is no longer the absence of predictive models. The more substantial challenge is translating scientific models into systems that health departments can access, understand, trust, maintain, and use during real decision-making.

The evidence also reveals a disease-domain imbalance. Approximately four-fifths of the identified tools focused on vector-borne disease. Climate-sensitive surveillance development should consequently expand toward heat-related illness, waterborne disease, respiratory hazards, food insecurity, wildfire-related health impacts, and climate-sensitive chronic-disease exacerbation.

5.3 Proposed Community Climate–Health Alert Matrix

A practical surveillance system should transform analytical risk into graduated action.

Table: 3 Alert Levels, Surveillance Patterns, and Recommended Public-Health Responses

Alert Level	Surveillance Pattern	Recommended Public-Health Response
Level 0 — Baseline	Expected seasonal conditions	Routine monitoring and preparedness
Level 1 — Watch	Environmental indicators becoming favorable for increased risk	Intensified surveillance and communication preparation
Level 2 — Early Warning	Multiple indicators exceed locally validated thresholds	Targeted prevention and community outreach
Level 3 —	Environmental signal	Expanded field

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High Risk	plus epidemiological escalation	response and resource deployment
Level 4 — Public-Health Emergency	Sustained high transmission/exposure and health-system pressure	Emergency coordination and intensive intervention

6. Discussion

6.1 From Reactive Surveillance to Anticipatory Public Health

The fundamental contribution of climate-sensitive surveillance is temporal. Conventional case surveillance frequently asks, "What health event has occurred?" Climate-informed surveillance adds the question, "What conditions are developing that may increase health risk next?"

This shift can create additional lead time for vector control, cooling-center activation, targeted risk communication, water-quality interventions, medical-supply planning, staffing adjustments, outreach to vulnerable populations, and community preparedness. WHO's EWARS-csd system is designed around this principle and incorporates historical disease information together with climatic and environmental alarm indicators for dengue, chikungunya, Zika, malaria, and cholera.

Forecasting must nevertheless remain decision-oriented. A technically accurate risk score is of limited value when the health department does not know what action should follow the alert. Each surveillance threshold should therefore correspond to a predefined operational protocol specifying responsible institutions, target populations, intervention activities, communication channels, and escalation criteria.

6.2 Community Vulnerability Must Remain Central

Climate hazards do not generate equal health consequences across populations. Exposure is modified by housing quality, age, occupation, chronic illness, and access to clean water, sanitation, cooling, income, transportation, health services, social support, and the capacity to act on warnings. WHO identifies disadvantaged communities and health systems with limited adaptive capacity as particularly vulnerable to climate-related health impacts?

Consequently, climate-sensitive surveillance should not only generate hazard maps; it should produce health-risk maps. A temperature anomaly may have substantially different consequences in a neighborhood with adequate housing, tree cover, reliable electricity, and accessible health care than in an informal settlement characterized by occupational heat exposure, limited water access, and inadequate cooling.

6.3 Predictive Accuracy Is Necessary but Not Sufficient

The reviewed literature demonstrates considerable advances in forecasting performance. Villela reported high specificity in municipal dengue prediction, while Finch and colleagues achieved strong outbreak discrimination after integrating climate and serotype information. These findings support predictive surveillance, but they should not be interpreted as evidence that a single model can be transferred unchanged to every population.

Data quality remains a major constraint. Case notifications can be affected by underdiagnosis, delayed reporting, changes in testing practices, health-care access, and surveillance policy. Climate variables themselves may contain measurement gaps or spatial-resolution limitations. Charnley and Kelman emphasize the difficulty of separating climatic influences from economic, behavioral, health-system, and ecological factors.

Phung and colleagues therefore argue that sustainable predictive tools must be useful, usable, and used. In practical terms, this means a system must deliver acceptable predictive accuracy with enough lead time to intervene; present information in forms understandable to public-health personnel; fit existing surveillance workflows; have clearly defined responsibility for responding to alerts; and demonstrate sufficient public-health value to justify continuing operational and financial support.

7. Conclusion

Climate-sensitive public-health surveillance provides an important mechanism for transforming environmental intelligence into preventive community-health action. Climate change is altering the epidemiological context of extreme heat, vector-borne disease, water- and food-related health threats, respiratory exposures, and other hazards, while the 2025 Lancet Countdown demonstrates that several major climate-related health indicators have already reached unprecedented levels.

The evidence reviewed in this study indicates that surveillance becomes more informative when meteorological and environmental data are combined with epidemiological observations, biological information, health-system indicators, spatial data, and measures of community vulnerability. Contemporary dengue forecasting illustrates this potential particularly clearly: models integrating climate with epidemiological or serotype information can provide meaningful advance warning and strong predictive discrimination.

The principal challenge, however, is implementation. The existence of dozens of validated prediction models contrasts with the substantially smaller number translated into accessible operational tools. Future development should therefore prioritize interoperable data systems, locally calibrated models, decision-relevant lead times, transparent uncertainty, community participation, workforce training, sustained financing, ethical governance, and predefined response protocols.

Climate-sensitive surveillance should ultimately be judged not by the sophistication of its algorithm but by whether it enables communities and health systems to recognize emerging danger earlier, direct resources more intelligently, protect high-risk populations, and reduce preventable illness and death.

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