# Digital and technological innovation in vector-borne disease surveillance to predict, detect, and control climate-driven outbreaks

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**Vector-borne diseases are particularly sensitive to changes in weather and climate. Timely warnings from surveillance systems can help to detect and control outbreaks of infectious disease, facilitate effective management of finite resources, and contribute to knowledge generation, response planning, and resource prioritisation in the long term, which can mitigate future outbreaks. Technological and digital innovations have enabled the incorporation of climatic data into surveillance systems, enhancing their capacity to predict trends in outbreak prevalence and location. Advance notice of the risk of an outbreak empowers decision makers and communities to scale up prevention and preparedness interventions and redirect resources for outbreak responses. In this Viewpoint, we outline important considerations in the advent of new technologies in disease surveillance, including the sustainability of innovation in the long term and the fundamental obligation to ensure that the communities that are affected by the disease are involved in the design of the technology and directly benefit from its application.**

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## Introduction

Vector-borne diseases, such as malaria, dengue, leishmaniasis, and Lyme disease, are pervasive diseases that cause more than one million deaths per year, according to WHO.[1] Most vector-borne diseases are not preventable by vaccines and can be controlled only with an integrated package of interventions, including vector control, prompt case detection and drug treatment, and campaigns for community health awareness. Surveillance systems, and the interventions to control or prevent diseases that they enable, should go beyond case detection to also consider the myriad of social, economic, and environmental drivers of vector-borne diseases. Globalisation, international trade, climate change, migration, and population displacement are important drivers of global disease dynamics.[2,3] The overall effect of climate change on the epidemiology of vector-borne diseases includes the effects of changes in temperature, humidity, precipitation, vegetation, and soil on the habitat, breeding, and blood-feeding behaviour of vectors. Furthermore, the consequences of climate change can include food and water insecurity and conflict and violence, which can lead to migration on a large scale and thus the spread of vector-borne diseases into new regions and immune-naive populations. The effect of climate change is already reflected in changing disease patterns and is expected to amplify throughout the 21st century. This Viewpoint covers the effect of climate change on vector-borne disease epidemiology, the importance of disease surveillance, and the latest technologies and innovations, giving specific examples from Tanzania, South Africa, Vietnam, and Canada, and suggests future use of these technologies to control outbreaks.

## Role of climate change in the epidemiology of vector-borne diseases

Changes in climate (and especially in temperature) can affect the prevalence of vector-borne disease in many ways, such as through effects on areas in which vector breeding occurs, frequency of vector breeding or mating, replication rates and burden of intravector parasites, and frequency of vector feeding. Aquatic snails, ticks, and mosquitoes are all anticipated to be affected by climate change.

Predicting the exact effect of climate change on schistosomiasis is challenging, because response varies dependent on the specific ecology and geographical context. However, concern has been raised that urogenital schistosomiasis might expand into new regions of Africa, such as South Africa and the Ethiopian highlands, where surveillance systems are scarce or limited by few resources and an immune-naive population will be at risk

### Key messages

- Vector-borne diseases are responsible for substantial global morbidity and mortality and are sensitive to changes in the weather and climate, including temperature, precipitation, and extreme weather events.
- Digital and technological innovations enable the incorporation of climatic data into surveillance systems, enhancing their capacity to predict outbreaks of vector-borne disease and enabling rapid mitigation and response measures.
- Widespread adoption of mobile health approaches to disease surveillance support timely detection and response to outbreaks.
- Surveillance systems for vector-borne diseases that use satellite data can learn from patterns of disease incidence in relation to climatic indices to predict the location and intensity of an outbreak.
- Integrating artificial intelligence algorithms into existing surveillance systems could allow for faster and more accurate processing of large amounts of data, resulting in more accurate detection and prediction of disease outbreaks than traditional surveillance systems.

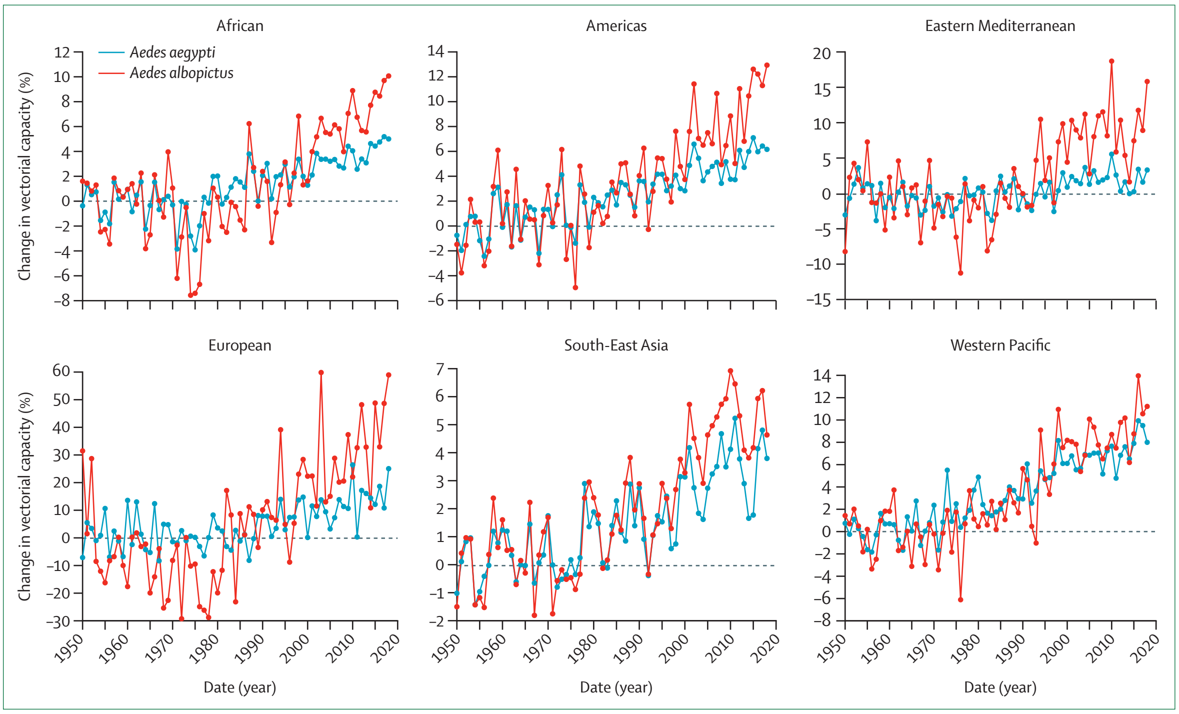


***Figure:* Climate suitability for transmission of dengue**

Change in the vectorial capacity for the transmission of dengue virus from a 1950–59 baseline, by vector. Climate suitability for the transmission of dengue has increased since 1950 in all WHO regions (reproduced from the 2020 *Lancet* Countdown on Health and Climate[15,16]). Vectorial capacity for the transmission of dengue virus is derived from a temperature-driven, process-based mathematical model, with positive change in vectorial capacity associated with more suitable temperatures for the transmission of dengue virus.

of infection.[4] Vector-borne diseases that are transmitted by arthropod vectors are particularly sensitive to changes in weather and climate. Variations in temperature, humidity, precipitation, and the frequency and severity of extreme weather events all have the potential to influence the prevalence, distribution, reproduction, and behaviour of such vectors.[5] As arthropod vectors are ectothermic, their internal temperature is influenced by ambient temperature conditions.[6] The speed of replication of pathogens that are transmitted by arthropod vectors tends to increase with rising temperatures, as does the biting rate of arthropods, until an upper limit is reached.[5] Increased rainfall can also influence vector survival and reproduction through the creation of breeding sites.[7] Urbanisation has created environmental conditions that are suitable for some mosquito species, with decreased numbers of predators and a high density of human hosts.[8] Open surface drains and water collections near human habitations present opportunities for *Aedes aegypti* and *Aedes albopictus* reproduction and development.[9] High population density and open storage of water is associated with increased risk of dengue epidemics in urban areas, however, rural villages with low population densities can also have high rates of dengue.[10] Many of the mosquitoes that transmit malaria thrive in rural environments that contain natural or manmade water sources.[11]

Although warm conditions are generally preferential for vectors, the interactions between climate change and vector survival, reproduction, and feeding behaviours are complex.[12] For example, tsetse flies, which transmit *Trypanosoma* spp parasites, cannot tolerate extreme temperatures outside the range of 16–32°C for extended periods of time, and temperature has been identified as an important factor in tsetse population dynamics.[13] Substantial reductions in the prevalence of tsetse flies in parts of Zimbabwe have been attributed to rising temperatures over the past 40 years.[13,14] Transmission of arboviruses is also affected by climatic conditions. Dengue virus transmission by *A aegypti* can occur between 18°C and 34°C and is understood to peak at approximately 29°C.[6] Given the expected temperature changes over the coming years, incidence of dengue is anticipated to increase across large parts of the world (figure).

Different techniques and approaches to mapping weather variables can be applied. Many studies use data that is provided by the National Aeronautics and Space Administration or national databases and apply an inverse weighting method to interpolate local weather conditions.[17] Other studies use data that are collected from a network of weather stations, some of which can be located some way outside of urban areas.[18] Data that are collected in this way might not detect the effects of urban heat islands that some cities have, a factor that should be considered during analysis of the effects of climate change on infectious diseases in urban locations.

In addition to mean temperature, the amount of temperature fluctuation is also influential in larval development time, larval survival, and adult reproduction of *A aegypti*.[19] Small fluctuations in temperature can lead to a doubling in population size compared with a constant 26°C exposure for 1 month. Conversely, larger fluctuations can lead to a 40% reduction in the adult population size compared with constant temperature control.[19]

## Importance of surveillance in outbreak prevention, detection, and control

Surveillance is a primary requisite in the timely detection and response to outbreaks or unusual seasonal patterns. Surveillance of infectious disease encompasses not only the constant monitoring of disease-specific cases and deaths but also includes the monitoring and evaluation of conditions that enable transmission, including behavioural, societal, climatic, and environmental factors.[20] The basic components of disease surveillance are data collection, analysis, interpretation, and dissemination to decision makers and the public, all of which can be facilitated by the advent of new technologies. Technology can further enable the collection of new forms of data and provide innovative solutions to improve data analysis and interpretation and increase the speed and reliability of dissemination. Data governance is a crucial aspect of surveillance systems, including data protection to preserve patient confidentiality, data standardisation to permit spatial and temporal comparisons, and data sharing to enable collective learning.[20] Surveillance systems provide the information that is needed to detect and control outbreaks, empowering decision makers with timely data to manage the response more effectively and also contributing to long-term knowledge generation, response planning, and resource prioritisation, which can help to prevent and mitigate future outbreaks.[20]

Surveillance of vector-borne diseases is tasked with monitoring human cases of the disease, the pathogen species that is involved, the distribution and behaviour of the vector, and the climatic and environmental factors that enable disease transmission.[21] The intricate dynamics between humans, animal hosts, vectors, and the ecosystem require a One Health approach, with input from across sectors and disciplines.[22] In some settings, vector-borne diseases are holoendemic, whereas in many low-incidence settings, there exists an ongoing risk of disease emergence or re-emergence. Given these geographical differences in transmission risk, surveillance of vector-borne diseases is not a one-size-fits-all approach and should be tailored to local needs.[23]

## Mobile health in disease surveillance

Mobile health (mHealth) does not have a standard definition.[24] However, for the purposes of this Viewpoint, we define it as a “medical and public health practice supported by mobile devices, such as mobile phones, patient monitoring devices, personal digital assistants, and other wireless devices”.[24] We consider all functionalities and applications of modern mobile phones, including basic functions, such as voice call and messages, and more sophisticated technologies, including Bluetooth, GPS, and 3G or 4G data services.

The use of smartphones, wireless connectivity, and cloud-based technologies in the surveillance and response to vector-borne diseases enables improved detail in data, rapid dissemination to central servers, and the collection of new forms of evidence, such as photographic and videographic data.[24] Smartphones can improve the detail of data in both temporal and spatial dimensions by enabling increased frequency of data collection and improved geographical localisation by use of GPS technology; however, their usefulness is limited by the prevalence of smartphone use and biases potentially arising if particular subpopulations are more likely to own or have access to a smartphone than are other populations.[24]

The application of mHealth approaches to surveillance is most suited to diseases with characteristic case definitions, of a short and defined duration (eg, dengue and malaria), and those that are less likely to come to the attention of community health workers than are others, thus otherwise escaping detection by traditional surveillance systems (eg, chikungunya). Surveillance of factors that influence disease incidence, including climatic factors, would be especially amenable to mHealth adoption if the factors are present only temporarily or fleetingly or in an area that is difficult to access, or if local and indigenous knowledge is essential to assess the factor. Diseases and factors that are unlikely to be good candidates for mHealth include complex or undulating conditions and conditions that are difficult to detect or measure with mobile technologies (eg, antibiotic-resistant infections).

An example of the usefulness of mobile technology was shown in Tanzania for monitoring African trypanosomiasis, also known as African sleeping sickness, a parasitic vector-borne disease that can cause fatal meningoencephalitis.[25] The abundance of tsetse flies, the vector of African trypanosomiasis, has increased in Tanzania due to warming temperatures, increased precipitation, and the availability of animal and human hosts.[26,27] Climate change has also directly affected Maasai communities in Tanzania, where rainfall events late in the wet season and resultant poor pasture growth have caused the Maasai population to migrate northwards to woodland areas, where both the humans and their cattle are more exposed to tsetse flies and the potentially deadly trypanosomes that they carry than in their previous homes.[28] A research team from the WHO Special Programme for Research and Training in Tropical Diseases used smartphones to develop models of climate and land use to forecast infection hotspots and identify the safest areas for Maasai people to take their cattle.[29] Researchers and community members can use the smartphone app to access and collect information on precipitation, temperature, vegetation, water bodies, fly abundance, and disease incidence.[29] The information that is collected through the smartphones is geo-referenced, allowing for high-resolution mapping of spatial risk at the human–animal interface of the disease.[29] Widespread adoption of mHealth to disease surveillance will aid in timely detection of and response to outbreaks.

Facilitation of data collection in particular geographical areas by mobile technologies will not only add detail but also help to create standardisation across datasets and assist data sharing and comparison. However, mHealth cannot be a simple top-down approach (ie, when decision making and design lies with authorities that are far removed from the affected communities). Affected communities in which data are collected will need to be engaged in the leadership, design, and roll-out of novel mobile technologies for their application to succeed.

Furthermore, for mHealth methods for data collection and analysis to be useful for prediction and policy, all technologies should undergo appropriate validation procedures before mHealth projects are initiated. Such validation should go beyond controlled laboratory conidtions and should extend to the field of operation, in which data quality and reliability should be assessed. Data interpretation also needs careful consideration, especially where approaches for machine learning are used. Training and validation datasets of appropriate scale, completeness, breadth, and data quality should be used. Efforts should be taken to avoid implicit bias (often engendered by humans) and consider the confounding effect of unmeasured variables, which might affect model reliability. Assessing the extent of generalisability is crucial: a dataset and model from one area (or indeed, over one specific timeframe) might not be generalisable to other, even nearby, regions.

## Satellite climatic data to predict outbreaks of vector-borne diseases

Although meteorological data are collected at the country level by national meteorological and hydrological service institutions, these data are of varying quality, thus reducing their usefulness in comparisons between countries and regions and over time.[29] Satellite systems also monitor the climatic, meteorological, environmental, and anthropogenic conditions that influence transmission dynamics, and these real-time, freely available, and high-resolution data can be used to construct routine surveillance and early warning systems.[29] Satellite-based surveillance systems can also be more proactive than can conventional systems that detect disease introductions and outbreaks only after they have occurred. Through pattern recognition and disease trends that are related to climatic indices, prospective satellite-based systems could predict where and how the next outbreak is most likely to occur.[23] Instead of injecting funding that is limited by time when an outbreak occurs, investment in the long term in such prospective surveillance systems that mitigate outbreaks might be cost-effective overall.[23] To actualise their usefulness, the predictive models should be validated against data for case detection.[29]

The following case studies show the potential of satellite data for use in disease surveillance. Schistosomiasis is endemic across much of sub-Saharan Africa, Latin America, the Middle East, and east Asia, transmitted by contact with water contaminated by larval forms of the parasite that are released by freshwater snails.[30] The incidence of this neglected disease is strongly influenced by climatic and environmental factors.[30] In the uMkhanyakude district in South Africa, researchers from the University of KwaZulu-Natal have used satellite data, including air temperature, precipitation, and the velocity of flowing water, to show that snails carrying schistosomiasis larvae prefer slow-moving water bodies with temperatures that are higher than average.[31] The predictions of future outbreaks by use of satellite data were subsequently verified through field sampling.[31] Since the snails can enter hibernation during the dry season and can repopulate water bodies following sufficient rainfall, the prediction tool is particularly useful for facilitating early interventions before the wet season, such as mass drug administration, vector control, and community awareness campaigns, in areas that are at high risk for schistosomiasis outbreaks.[31]

In Vietnam, researchers who are funded by the UK Space Agency are developing an early warning system to forecast the probability of dengue outbreaks up to 6 months in advance.[32] This work builds on previous studies using seasonal climate forecasts to provide early warnings of dengue risk in Brazil and Ecuador.[33,34] Dengue, transmitted by *A aegypti*, is endemic in swathes of Asia, Latin America, and the Caribbean.[35] Epidemics occur during rainy seasons, but transmission is favoured whenever precipitation increases and the air becomes warmer and more humid than usual.[35] Incidence of dengue is increasing at a faster rate than that of any other communicable disease, with a 30-times increase in the past 50 years, yet there is still no system in place to predict where the next outbreak will occur.[32] An early warning system that could provide probabilistic actionable information about the location and scale of the next dengue outbreak would enable decision makers in Vietnam and globally to better target resources, enable surge capacity in hospitals, and prioritise control interventions.[32] The Dengue Forecasting Model Satellite-based System (also known as D-MOSS) uses historical and real-time meteorological data from satellite observation of Earth to produce forecasts of the probability of exceeding predefined epidemic thresholds in each province.[32] Importantly, the surveillance system operates on a routine basis, collecting, analysing, and interpreting climate data to ensure that forecasts are as timely as possible.

## Future innovations to improve data accuracy in decision support

Artificial intelligence is increasingly recognised as a promising tool in the fight against infectious diseases and climate change. Integrating artificial intelligence algorithms into existing surveillance systems enables rapid processing of vast amounts of data, resulting in increased accuracy of detection of disease outbreaks.[34] Through learning from big data, a surveillance system that is assisted with artificial intelligence can improve pattern recognition and provide probabilistic estimates of disease flare-ups, using human, pathogen, vector, and climatic factors to create risk models of outbreak spread and severity.[36] Such algorithms could also effectively do temporal and spatial analyses of data to detect aberrations, which can then be further investigated.[36] The application of artificial intelligence to predict outbreaks of vector-borne diseases that are driven by climate is in its nascent stages. Machine learning models that are given climate and weather data measured locally and by satellite have been used to predict the risk of malaria outbreaks in Tha Song Yang, Thailand, and Dar es Salaam, Tanzania, with accuracy rates greater than 85%.[37–39]

Artificial intelligence can also be used to augment and optimise event-based surveillance, which analyses open-source data, such as news articles and social media posts, to raise an early alert of disease outbreaks or the conditions that are known to increase their likelihood; often before these outbreaks can be detected by conventional surveillance.[40] Artificial intelligence increases both the quantitative and analytic capacity of event-based surveillance by use of natural language processing and machine learning algorithms to transform event narratives into a database that details the nature of the event, when and where it occurred, who it involved, and the reliability of the sources. For example, the Global Public Health Intelligence Network, co-developed by the Canadian Government and WHO, uses artificial intelligence to analyse between 2000–3000 news articles per day.[41] The outputs are reviewed by a team of expert analysts, who issue alerts for disease threats where appropriate. In 2003, the Global Public Health Intelligence Network raised an alert of increased sales of antivirals in China before the outbreak of severe acute respiratory syndrome became known to the global public health community.[41]

In the future, digital and technological innovations might be used to enable widespread and continuous collection and collation of climate and health data, both from individuals, for instance, with mobile phones, and from health services, as even elementary data move to electronic documentation. Challenges still exist, however, in the standardisation and validation of such data, which should be addressed before novel technologies are rolled out. Soon, rapid diagnostics at the point of care are likely to become increasingly low cost and applicable in mapping disease prevalence and incidence. Wastewater analysis for pathogen signatures, including genome sequencing, will be able to assist in defining disease prevalence, and developments in vector-trapping technologies (including drones) are rapidly occurring. Finally, wearable health monitors (eg, those recording respiratory and heart rate, temperature, and arterial oxygen saturation) are becoming increasingly low cost and informative, although costs and accessibility are limitations in rural locations. Powering mHealth devices is becoming easier than before, as the costs of off-grid power generation and battery storage substantially decrease. Issues of data privacy are also readily addressed as end-to-end encryption improves.

## Ethical, legal, and societal implications

Novel technologies, including mHealth initiatives, data systems that are assisted by satellites, and artificial intelligence approaches, raise complex ethical, legal, and societal issues. These issues primarily centre around the collection, use, storage, and ownership of data. Data should be anonymised where possible, and as little individual data as is necessary should be collected to achieve the project's aims. The global health community needs robust international frameworks for individual consent, data privacy and storage, and safe and appropriate data sharing. Where data are generated collaboratively, existing laws and regulations on property might not be sufficient (eg, when several different groups collaborate, it can be unclear who owns the data) and innovative approaches to data ownership might be needed. Approaches to risk communication and management should be sensitive to local contexts while adhering to agreed international standards. The regulation of novel technologies, especially those with a multinational or global reach, requires more concerted action on the part of national governments and mandated international organisations.

Emergent technologies, such as artificial intelligence, share these issues and raise their own challenges. Where models retain an element of autonomy and algorithms are constantly evolving (ie, adapting on the basis of previous experience, independently of the person who created the model), perhaps to a point where they are no longer understandable or traceable, our existing standard of informed consent is inadequate. If the datasets on which artificial intelligence models are trained are flawed by bias, then there is a substantial risk that these biases are enhanced and engrained, resulting in outputs that might widen existing gender, racial, socioeconomic, and other inequalities. Therefore, in artificial intelligence, as for other novel technologies, diversity in leadership, design, and development is crucial.

Ultimately, the global health community has an ethical obligation to expand the quality and scope of technologies that have the potential to improve the health of humans and the planet, balanced with an obligation to protect the users of these technologies and to roll out such innovations equitably, ensuring that nobody is left behind or further disadvantaged. Since access to technology is already inequitably distributed, ensuring that new innovations do not widen existing health inequalities is pre-eminent.

## Conclusion

Technological and digital innovations have enabled the incorporation of climatic data into surveillance systems to predict outbreaks of vector-borne diseases more accurately than did traditional surveillance models. Advance notice of the risk of an outbreak empowers decision makers and communities to scale up prevention and preparedness interventions and redirect outbreak response resources to the areas at the highest risk. Important considerations in the advent of these new technologies are the sustainability of the innovation in the long term, the need to ensure that the technology furthers the integration of surveillance systems rather than creating more division, and the fundamental obligation to ensure that the communities that are affected by the disease are involved in the design of the technology and directly benefit from its application. Beyond climate and weather data, other effects of climate change, including global population movement and local biodiversity, should also be included in innovative surveillance models to detect and predict the risk of vector-borne disease outbreaks more accurately than did traditional surveillance models.

#### Contributors

SY, CP, and ME conceived the idea for this Viewpoint. CP and ME searched the literature and wrote the draft manuscript. SY, RL, and HM provided comments and guidance during revisions of the manuscript. All authors approved the final version for submission.

#### Declaration of interests

We declare no competing interests.

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