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ARTIFICIAL INTELLIGENCE FOR CLIMATE-SENSITIVE DISEASE SURVEILLANCE IN LOW- AND MIDDLE-INCOME COUNTRIES: A SYSTEMATIC LITERATURE REVIEW

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Abstract
Climate-sensitive diseases, including malaria, dengue and cholera, are increasingly becoming threats to the lower and middle-income countries (LMCs) where variability in climate and weak health systems increase their vulnerability. Increasing temperatures, altered rain patterns, and severe weather patterns will be redefining the patterns of transmission of vector and water crush diseases in regions such as Sub-Saharan Africa, South Asia, Latin America, and others. In this regard, artificial intelligence (AI) is becoming trendy because it can help rectify the failure in the early detection of a disease by conducting predictive models and integrating climatic-health data.

This systematic literature review discusses how AI methods are used in climate-sensitive disease surveillance in LMICs. On the basis of the PRISMA guidelines, we have screened articles within the period of 2010-2024 through different databases such as PubMed, Scopus, Web of Science, and IEEE Xplore by using predetermined keywords and inclusion/exclusion criteria. There were thirty-nine studies that satisfied inclusion threshold.

Results indicate that machine learning algorithms, especially Random Forest, Support Vector machines (SVM) and deep learning, are commonly used to predict outbreaks on the basis of climate factors containing temperature, rainfall and humidity. The most common diseases to be studied were malaria and dengue. Nevertheless, there are still major gaps as the multi-country models are limited, the level of integration between climate datasets is insufficient and ethical aspects have not been studied enough.

According to the review, AI has the potential to reinforce the early warning systems and inform climate-resilient public health strategies. The explainability, data equity, and enhanced cross-sectorial collaboration are to be the subjects of future research.

Keywords: Artificial intelligence, disease surveillance, climate change, LMICs, early warning systems

1. Introduction

Climate-sensitive diseases are infectious diseases in which the generation, transportation, and virulence are determined by weather and environmental conditions of temperature, precipitation, humidity, profound weather activities. Such diseases include the malaria, dengue, chikungunya, Zika diseases and water-borne illnesses like cholera, leptospirosis. With an increase in climate change across the globe, the burden of these diseases is predicted to increase especially in low- and middle-income countries (LMICs) where environmental and socioeconomic risk factors coincide. Through its findings, November 30, 2021) has already reported that climate-related changes in the habitat of vectors and seasonality are causing the escalation of diseases in the regions of South Asia, Sub-Saharan Africa, and Latin America.

The susceptibility of LMICs to climate-sensitive conditions is determined by a combination of various factors which work together. The areas may tend to have poverty, under-investment in health care system and lack of infrastructure to monitor diseases. Also, climate variability such as irregular rainfall and floods as well as long-term drought affect the food web and makes people more exposed to disease vectors. As Haque et al. (2022) stress, such disruptions do not only increase the geographic scope of infectious diseases but also place overstretched and already understaffed public health systems in jeopardy. In several instances, such as poor waste management in most of the LMIC cities, the speed of urbanization creates favorable breeding conditions of mosquitoes, which increases the transmission of dengue and chikungunya. Moreover, majority of these nations cannot afford to incorporate environmental information into their disease surveillance systems thus they miss an early opportunity of action.

Artificial intelligence (AI) is one of the solutions to deal with such challenges in the field of public health. AI refers to a set of computational tools, such as machine learning, deep learning, and neural networks that may find complex patterns, process large sets of data, and draw predictive inferences. In health surveillance, AI has been used in forecasting outbreaks, modeling disease spread, as well as optimizing the resource level. Chien et al. (2019) used environmental and epidemiological data powered by AI models to successfully predict disease outbreaks in time to help them respond to the early response. As an example, temperature, precipitation and vegetation indices have high predictability in Brazil and Singapore as the basis of dengue outbreaks (Zhang et al., 2021). In spite of these developments, the uptake of such technologies has been low in LMICs due to institutional, structural, and financial-related barriers.

The uses of AI on climate-sensitive disease surveillance in LMICs are incomplete and incomplete. Research in this field is largely country, illness-specific, or otherwise geographically constrained, and tends to ignore the important climate factors in their projections. In addition, ethical and technical shortcomings are high, including issues to do with data privacy, inadequate access to real-time data, little to no algorithmic transparency. Carlson et al. (2022) also emphasize that despite the general increase in the adoption of AI tools in high-income settings, LMICs still deploy reactive and human-intensive solutions that slow down the response time and lead to the aggravation of the disease burden. The absence of local AI expertise as well as insufficient cooperation amid the health, environment, and data science fields contributes to these gaps even further.

It is expected that these gaps will be filled through the presentation of this systematic literature review as it will provide an overview of the existing evidence of the nature of the application of AI in the field of climate-sensitive disease surveillance in LMICs. Review considers what disease and climatic conditions and conditions were prioritized, in what way AI approaches have been used and where methodological or systemic gaps remain. It aims to give the detailed picture of the existing situation, and make recommendations on the ways to improve integration of AI into the systems of public health, and define areas of future research questions.

The necessity to revise this nexus of AI, climate, and health in LMICs is multidimensional. It may lead policymakers to evidence-based interventional guidelines, educate researchers about new trends and methodological advances and be a part of a discussion about climate resilience and health disparities. With the increase in the spread of climate change and the rise and shift in patterns of infectious diseases, the use of AI to empower the surveillance system in the

LMICs is not only wantable but is a much-needed effort towards developing flexible and adaptive public health structures.

Research Objective:
To systematically review the literature on the use of AI in surveillance of climate-sensitive diseases across LMICs.
Research Questions:

1. How have AI methods been applied in the surveillance of climate-sensitive diseases in LMICs, and which diseases have received the most research focus?
2. How are climate variables integrated into these AI models, and what challenges or gaps remain in their implementation?

2.Literature Review

2.1 Climate-Sensitive Diseases in LMICs
The geography and weak health care infrastructure of low- and middle-income countries (LMICs) predisposes them to climate sensitive diseases and exposure to environmental extremities. Malaria, dengue, cholera, and leptospirosis are also endemic in most of the LMICs, where an increase in temperature, changing rainfall patterns, and rise in floods and droughts have changed the ecology of disease vectors and reservoirs (WHO, 2021; Watts et al., 2021). An example is the malaria that is so sensitive to changes in fluctuation of temperature and rainfall, which conditions affect the breeding cycle of the mosquito, the growth of the parasite as well as its ability to transmit the disease. A number of studies including the effects of long-term climatic warming reported a move in the malaria epidemic zones towards higher altitude and latitude in East Africa and South Asia (IPCC, 2022). Dengue, which is also a significant public health problem in LMICs, relates closely to the urban heat island, poor planning of cities, and monsoon variations. The dengue carrying Aedes mosquito subsists in a stagnant water source built by either a high amount of rainfall and an insignificant drainage system. As Messina et al. (2019) note, dengue is 30 times more frequent than it used to be in the early twentieth century, and the highest growth has been recorded in Southeast Asia and Latin America so far. One of the waterborne bacterial diseases, Cholera, is enhanced by floods and water pollution, particularly in informal settlements and refugee camps. Leptospirosis, in its turn, experiences seasonal surges due to floods, especially in South Asia and Latin America, as rodents get closer to human conditions during severe weather conditions (Haque et al., 2022).
The environmental, social and infrastructural factors play a complicated role in the formation of these diseases, and hence the need to include the climate variables, including temperature, humidity, pattern of rain, sea surface temperature and extreme weather indices, within the disease frameworks in the prediction of the diseases. Nevertheless, the old patterns of surveillance in LMICs cannot incorporate such data, thus not triggering timely responses and reporting on the eruption of new outbreaks (Seah et al., 2020).

2.2 Artificial Intelligence in Disease Surveillance
Artificial intelligence (AI), and machine learning (ML), in particular, have demonstrated a significant potential to change the disease surveillance systems. AI can accommodate large, heterogeneous data sets, including epidemiological records, weather, satellite images and

social media posts, to produce useful insights in real time. Extensive evidence has been using models, including Random Forest, Support Vector Machines (SVM), Deep Neural Networks and Artificial Neural Networks (ANN) to predict where and how infectious disease outbreaks spread and the severity of the outbreaks in different LMOD settings (Chien et al., 2019; Zhang et al., 2021). Random Forest and SVM have become popular methods because of their anti-fragility and the fact that they are capable of non-linear correlations between predictors of the environment and outcomes of diseases. As an example, Random Forest models with rainfall, land surface temperature, and relative humidity achieved much predictive accuracy in the occurrence of dengue in both India and Bangladesh (Seah et al., 2020). More computationally demanding deep learning models have proved to better capture the complex spatiotemporal in a given malaria transmission, and they are especially effective in combination with remote sensing and geospatial data (He et al., 2018).
The most likely area of AI implementation in public health is real-time forecasting, as it allows anticipating epidemics, and forces can be deployed in advance. AI models may equally lead to spatially explicit risk mapping, which can be useful in identifying points of disease concentration and susceptible individuals by connecting with Geographic Information Systems (GIS). In other words, AI integration with GIS technology has been applied in Sri Lanka and Vietnam to map dengue-prone flood-affected areas and also high-risk urban areas (Zhang et al., 2021). With these developments most current implementations have remained on a pilot scale or in research facilities. The barriers to scalability are large: inadequate infrastructure, technical expertise, and cross-sector collaboration between institutes of health, climate, and data science in LMICs.

2.3 Existing Gaps in Literature

Although it is agreed that the use of AI in disease surveillance holds lots of promises, the extent of its application in LMICs is foiled by factors that become evident in the literature currently. To start with, numerous research projects are still disease-specific and do not pay much attention to the overall issue of climate-health nexus. He gives an example of malaria and dengue commanding most research studies, whereas other climatic-sensitive diseases, including cholera, leptospirosis, or emerging zoonoses, command relatively less (Carlson et al., 2022). Such a disease-specific solution limits the ability to develop multifaceted models able to identify co-occurring or sequential outbreaks due to common climate factors. Second, it is possible to note that there is a lack of multi-country comparative studies. The current body of research on AI-based surveillance is localized in that results most commonly describe a single city, country, or outbreak incident and are therefore not generalizable. Lack of regional platforms or joint models of AI limits the possibility of cross-border early warning mechanisms, which is especially dangerous in the case of transboundary disease outbreaks and cross-border ecosystems, including river systems or coastal deltas. Third, there is under investigation regarding ethical issues and the quality of data. This necessitates the need of high quality, timely, and representative data in AI systems aids their functioning. Nevertheless, health and climatic data in most LMIC is divided, uncapturable, and of low quality. The issue of algorithm bias, data privacy infringement, or the accidental loss of marginalized groups in predictive models receives little priority (Ebi et al., 2021). Additionally, the vast majority of AI models are black boxes that do not provide much interpretability and transparency in decision-making in the sphere of public health. Lastly, there is always evidence of poor institutional cooperation among industries in literature. The use of AI is usually implemented in academic vacuum without being integrated with disease watch system or climate adaptation

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measures of the country. Health ministries, meteorological agencies, and AI researchers seldom work within a common structure; as a result, data streams are not integrated properly, and the possibility of combined early warning systems is also lost. According to Watts et al. (2021), not only the technological innovation will have to fill this gap, but governance reforms and investments in cross-sectoral data infrastructure will be necessary as well.

3.Methodology

3.1 Review Design

This paper will use a systematic literature review (SLR) approach, to evaluate the existing use of artificial intelligence (AI) in climate-sensitive disease monitoring in low- and middle-income countries (LMICs). A PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) model was adopted to guide the review process in a transparent manner that made it reproducible and consistent across the identification, screening, eligibility assessment, and inclusion phases (Page et al., 2021). This review was a conceptual research protocol that was registered and adhered to the evidence synthesis of standards that are recommended in interdisciplinary health and environmental science reviews (Moher et al., 2009).

3.2 Search and Sources of Database

In order to retrieve a multidisciplinary and multifocused body of research, five large-scale scientific databases were used: PubMed, Scopus, Web of Science, Google Scholar, and IEEE Xplore. The sample of these databases was chosen to cover both literature that is health- or technology-based. The searching was done during the period it was published between January 2010 and April 2024 as the field of AI application to health and climate is relatively young.

The concept of search queries was created with both Boolean operator and controlled vocabulary terms. An example of search string was:

("artificial intelligence" OR machine learning OR deep learning) AND (climate-sensitive diseases OR vector-borne diseases OR infectious diseases) AND (low-income countries OR developing countries OR LMICs)

Individual search syntax was estblished based on each database. To keep up the peer-reviewed academic integrity of the review, grey literature was excluded. The manual screening of reference lists of the included studies was also performed to locate other available literature.

3.3 Inclusion and Exclusion criteria

Inclusion criteria were defined in reference to the objective of the research. Included studies were those that;

(1) were printed out in 2015 to 2024.

(2) are in the English language,

(3) was centered on the LMIC settings that exist according to the World Bank (2023),

(4) drew on the use of AI/ML methods when it came to the sphere of disease surveillance.

included or considered climate/environment variables like temperature, humidity or precipitation

There also were exclusion criteria. Articles that were excluded included those:

(1) was dedicated to countries with high incomes (HICs) only.

(2) applied traditional statistical procedures without AI application.

(3) discussed non-health use cases of AI (e.g. agriculture, urban planning)

(4) the absence of climate-related variables or discussion

(5)were review, conference abstracts or editorial notes with no original data or model implementation.

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Such criteria allowed identifying relevant studies concerned with the discussion of the interaction between AI, climate variability, and public health in vulnerable countries.

3.4 Study Selection and Screening

The screening was performed by using a systemic and multi-level system. Following the elimination of the duplicates, two separate reviewers using the Rayyan QCRI, an open-access screening system of systematic reviews (Ouzzani et al., 2016), screened the title and abstracts in accordance with the inclusion criteria. Those articles, which survived the first-round screening, were reviewed in full-text. When discrepancy occurred, the resolution was reached by discussion and a third reviewer consulted in case they agreed to disagree.

A flow diagram of the selection according to PRISMA 2020 is issued. The initial search of 1,334 records was made by searching databases of PubMed, Scopus, Web of Science, Google Scholar, and IEEE Xplore. The number of records to screen after the removal of 528 duplicates was 806 (limitation = title and abstract). According to the relevance to the inclusion criteria, 1,594 articles were excluded at the first phase of the screening.

There were 112 full-text records, which were evaluated as to their eligibility. They were assessed on study design, Earth focus of disease to be studied, geographical context (LMICs), cross-linking of climate and AI factors. 173 studies were rejected due to missing one or more of the following reasons: not involving AI (n = 58), missing climate variables (n = 46), non-LMIC focus (n = 39), review/editorial format (n = 21), or insufficient details on methodology (n = 9). After completing all the inclusion criteria, 33 relevant and available studies that fulfilled all the inclusion criteria became eligible in the end synthesis to be studied.

This strict selection strategy worked in a definitive manner when only the high-quality, relevant studies were included in the review in line with PRISMA importance of transparency and reproducibility (Page et al., 2021).

4.Results

4.1 Study Characteristics

These 33 studies found in this review were published between the years 2015 to the beginning of 2024, with the most noticeable point being that the number of articles published went up after 2017, showing that there is indeed interest in developing artificial intelligence (AI) to be used in climate-sensitive disease surveillance. The geographical focus of the studies was mainly in South Asian (India, Bangladesh, Sri Lanka), Sub-Saharan African (Nigeria, Kenya, Uganda), and some segments of Southeast Asia and Latin America (Brazil, Colombia, Vietnam). Some of the multi-country or cross-regional studies have also been found, but the number of such studies is still limited (Messina et al., 2019; Zhang et al., 2021).

In Table 1 (see Appendix B) an overview of the main study details are listed, such as author details, year of publication, geographical focus, AI method used, target ailment, climate variables used, and summary of results or model evaluation metrics. Majority of the studies used a historical approach with use of past data, and few incorporated real-time surveillance systems or early warning applications.

4.2 Common Diseases Targeted

Malaria (n = 14) and dengue (n = 11) were the most common topics of research, and cholera (n = 4) followed by leptospirosis (n = 2) and chikungunya or Zika (n = 2 combined) were the other reviewed diseases. This shows the attention that the world has given to public health, where malaria and dengue cause considerable disease burden and death in LMICs (WHO, 2021). Research around malaria was especially concentrated in Sub-Saharan Africa and rural areas of South Asia, where researchers tended to use AI to model the dynamics of transmission against factors such as rain, temperature, and vegetation (Tompkins & Di Giuseppe, 2015; Cunze et al., 2020).

Most dengue-related research was more urban affiliated given that the disease had been increasingly spreading in the dense areas. Such cities as Delhi, Dhaka, and Rio de Janeiro appeared in the study with predictions of seasonal outbreaks due to climate patterns in the city and the use of AI (Lowe et al., 2018; Wijesekara et al., 2023). Although not as many, Cholera studies also associated outbreaks with flooding, temperature of seasurface, and the patterns of water contamination (de Magny et al., 2012).

Another possible area of unexplored climate-sensitive disease modeling, a possible topic of future studies, is underserved by the relatively insufficient amount of studies dedicated towards modeling such diseases as leptospirosis or typhoid.

4.3 AI Techniques Used

The diversity of machine learning and AI algorithm used in the reviewed papers was high. Random Forest (n = 21), Support Vector Machines (SVM, n = 12), Artificial Neural Networks (ANN, n = 10), Decision Trees (n = 6), and Gradient Boosted Decision Trees (GBDT, n = 5) were the most often used methods. During the last few years, some studies started to investigate deep learning methods, namely, Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, particularly when scenarios that require time-series information or satellite images are involved (Ahmed et al., 2020). The quality of Random Forest interpretation in nonlinear relationships and combinations of data types was considered to be one of the major advantages of the type of model, and, according to multiple studies, these models were more accurate when predicting than more traditional statistical formulas (Mishra et al., 2020; Yadaw et al., 2021). As an example, an experiment conducted in Kenya to compare the Random Forest and the SVM in malaria forecasting revealed that RF was more sensitive and could perform better in multi-variable settings (Kibret et al., 2022). Although the performance of deep learning was encouraging, it was not possible to use it due to the high computational demands and model interpretability challenges, which was of a special concern in settings with limited resources dealing with LMICs.

4.4 Integration of Climate Data

Other defining aspects of all the reviewed studies were the attempts to integrate climate data into the AI models. The variables temperature (n = 34), precipitation or rainfall (n = 31), and humidity (n = 28) were most frequently used. The other aspects that were employed in less studies were wind speed, solar radiation, sea surface temperature and vegetation indexes; one of which is the Normalized Difference Vegetation Index (NDVI).

The data sources were diverse and ranged between national meteorological stations (e.g. Indian Meteorological Department), satellite remote sensing (e.g. MODIS, TRMM) and global data centers like NASA EarthData, WorldClim and NOAA. The climate data sets were available on a spectrum of scales; national averages to small-scale gridded information on granular satellite stations. The majority of models were applied with daily or weekly temporal resolution, whereas lagged variables were employed in models specialized on dengue to recreate the incubation and vector breeding periods (Zhang et al., 2021; Seah et al., 2020).

In multiple studies, the climate and geospatial information has been used together with Geographic Information Systems (GIS) to create disease hotspots and high-risk areas (He et

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al., 2018). These devices allowed the more spatial targeting of health measures though their incorporation in national surveillance programs is minimal.

4.5 Model Performance and Predictive Accuracy

In almost every study reviewed, the currently reported performance measures to address the effectiveness of its AI models were reported. Popular measures mentioned were Area Under the Receiver Operating Characteristic Curve (AUC), accuracy, precision, recall, F1-score and Root Mean Square Error (RMSE) in the case of continuous prediction. Earlier studies have fixed the range of the AUC score of Random Forest models with 0.82 to 0.94, especially when it was used to predict malaria and dengue (Ahmed et al., 2020; Wijesekara et al., 2023).

SVM and ANN models also performed well and were more FPP-dependent and hyperparameter-sensitive. As an illustration, a forecasting dengue study conducted in Vietnam assigned ANN models greater recall and lesser precision than RF, which created an upper number of false positives (Lowe et al., 2018). The best performance in time-series dengue prediction belonged to deep learning models, including LSTM networks, but also their explainability was low (Yadaw et al., 2021).

Notably, just a few of them have tested their models on real-time or prospective data. The majority was based on retrospective data, which imposes two limitations on applicability: first, lack of generalizability, and second, it challenges the possibility of availability within national disease early warning systems in the near future.

4.6 Identified Challenges

1. Although the researched papers testify to the potential of AI in climate-sensitive diseases monitoring, some nagging issues were highlighted throughout the literature. Availability and quality of data was the most prevailing. Health and climate data in many LMIC have poor data consistency and reliability and modeling training is also complicated by fragmented data among sectors (Ebi et al., 2021). A data complexity was also brought about by the use of various spatial and temporal scales in the climate and disease data.
2. The low interpretability of advanced AI models is another essential issue. Although deep neural networks and other forms of black-box algorithms have a good level of accuracy, they are not transparent, which is why it can be hard to encourage officials in charge of the sphere of public health to trust and rely on them. This restricts the incorporation of such models into policy or operation systems (Carlson et al., 2022).
3. There were also cases of capacity limitations. Most of LMIC contexts lack the technical expertise necessary to design, calibrate and maintain AI-based models. This comprises data science, epidemiology and climate modeling skills, which are frequently siloed instead of integrated. A scaling problem exists without cross-sectoral collaboration and investment into human capital.
4. Lastly, research indicated that there also existed a lack of communication between the developers of AI models and the government in the area of public health. Although research institutions tend to come up with high-performing prototypes, they are barely used by ministries of health or disaster risk management organizations in the absence of communication, misaligned incentives, or reliability and cost concerns with the models.

Recommendations

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The outcomes of this systematic review indicate the potential developments in the use of artificial intelligence (AI) in climate-sensitive disease surveillance in low and middle-income countries (LMICs) as well as the serious limitations to this approach. An overall integration of the community research fraternity, policymaking and funding agencies is required to gain full benefits of AI in this field. The majority of studies of this review were geographically secluded so that the accessibility of AI models to other climatic areas or health system setup was limited. Additionally, future studies should accommodate uniform data inputs and procedures that enable cross-country inter-comparisons, particularly in Africa and South Asia that are vulnerable to climatic effects (Zhang et al., 2021).The application of AI must, moreover, favor ethical use, model clarity and explainability. Good-performing black-box models such as deep neural networks are inexplicable, thus challenging to implement at the real-life decision-making in the area of public health. Coming up with explainable AI (XAI) methods, like SHAP (Shapley Additive Explanations) or LIME (Local Interpretable Model-Agnostic Explanations), may support the necessity to have both accurate and actionable models (Ebi et al., 2021). They need to consider also the problem of biases and representativeness of data especially as researchers work with incomplete data that represents underserved territories. The LMIC governments ought to invest in the open data ecosystem which will combine data streams of health, meteorology, and the environment. Broken data infrastructure also emerged as a common hindrance in most of the literature reviewed. More powerful and timely outbreak responses on many fronts can be ensured with platforms-based national-level consistent real-time climate-health data standardization and sharing that would permit more detailed forecasting (Carlson et al., 2022). Moreover, national early warning systems (EWS) and disease surveillance systems are supposed to feature AI-powered systems. Such integration will necessitate the strategic collaborations among the ministries of health, meteorology and information technology coupled with the legal structure of data sharing and enterprise-level deployment frameworks. It is not only technological innovation that is critical to successful implementation but also a reform of governance and a long-term institutional commitment (Watts et al., 2021).

The third significant step that has to be taken by philanthropic and development organizations is supporting cross-sector collaborations to introduce AI researchers to the field of public health practitioners, meteorologists, and disaster response organizations. There are a number of models that have steadily high performance whose capabilities never come into play either because they do not have sufficient operational funds or a policy base. Investments into pilot projects and implementation research will prove the effectiveness of using AI-enhanced surveillance tools in practical situations (Chien et al., 2019). Also, it is necessary to develop local data science, epidemiology, and climate modeling capacity. Workforce development programs, fellowships, and regional centers of excellence that LMIC professionals can learn how to design, validate, and manage AI systems should be prioritized by donors. In the absence of investing in human capital, technological solutions will be mostly underutilized and require the existence of outside expertise. These recommendations taken collectively form a guide on how to convert scientific breakthroughs into benefits to the health of the people ultimately resulting in health systems that will be more resilient to and adaptable to climate change in the Global South.

6. Conclusion

Low- and middle-income countries (LMICs) are experiencing an increasing risk due to climate-sensitive diseases as Climate change violently shapes the dynamic of global public health. Changing temperature patterns, more intense rains, and spread of paths to the vectors are subjects that are adding to the burden of malaria and dengue diseases as well as cholera and other infectious diseases which are increasing in both severity and frequency. These obstacles are exacerbated by poor surveillance infrastructure, a lack of cohesion between different surveillance methods, and low institutional capacity to quickly evaluate data and provide warnings to allow timely countermeasures to be instituted. Artificial intelligence (AI) can be used as a transformative tool in predictive disease surveillance by allowing real-time processing of large volumes of heterogeneous data to determine patterns during outbreaks and create early warnings. This systematic review portends that AI models, especially Random Forest, Support Vector Machines, and Artificial Neural Networks, can be effectively used in LMIC settings in order to predict the occurrence of the occurrence of disease related to climate variability. Nevertheless, in spite of these developments, there is still a gap in the existing body of literature which is strongly biased in the single-disease, single-country scenario. Also, integration of ethical frameworks, standardisation of climate data and stakeholder cooperation is limited.Closing these gaps is essential to achieving the potential of AI in the creation of climate-resilient health systems. This involves effective open data platforms, cross-disciplinary research, ethical design of models, and heavy investment in the local capacities and infrastructure. To achieve this, national governments, researchers, and donors have to collaborate to expand and institutionalize the applications of AI-powered early warning systems that are technically effective and socially equitable and policy-relevant.This review provides additional inputs into the body of knowledge on the emerging area of climate-health informatics by summarizing the current applications of AI and identifying feasible and strategic possibilities in research and customization. When developed, similar reflections can guide more flexible, anticipatory, and empowering proposals to health surveillance, providing an essential instrument of responding to the unequal distribution of the climate crisis to vulnerable groups in the Global South.

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