Associations between Climate Change and Infectious Diseases: A Systematic Review

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Abstract

Climate change is increasingly recognized as a major driver of infectious disease dynamics, influencing disease distribution, seasonality and outbreak intensity. This systematic review synthesizes evidence on how climate variability affects infectious diseases and evaluates predictive modeling approaches. Following PRISMA guidelines, we searched Web of Science, PubMed, Embase and Scopus for studies published between 2010 and 2025. From 106 initial records, 48 studies met inclusion criteria after screening and quality assessment. Results show that temperature variability, altered precipitation and extreme weather events consistently increase transmission of vector-borne, water-borne and zoonotic diseases, particularly in vulnerable populations. Machine-learning and statistical models including LASSO regression and neural networks showed potential for outbreak forecasting but limited ability to predict outbreak magnitude. Publications increased 150% after 2018, reflecting growing attention to climate-health linkages. Integrating predictive models with surveillance systems, adaptive health policies and interdisciplinary collaboration will be crucial to reduce climate-related disease risks.

Introduction

Climate change is one of the most pressing environmental challenges of our time, with far-reaching impacts on human health, ecosystems, and global economies. Among its many consequences is the impact on the distribution and incidence of infectious diseases [1, 2]. A growing body of evidence links climate change to a range of negative health outcomes, including the emergence and spread of infectious diseases. The Intergovernmental Panel on Climate Change has reported that climate change is likely to increase the incidence and spread of diseases such as malaria and dengue fever (vector-borne), cholera (waterborne), and salmonellosis (foodborne) [3]. As global temperatures rise and weather patterns become more unpredictable, the risk of disease transmission is increasing, raising serious public health concerns worldwide [4, 5].

Several studies have shown a significant correlation between climate change and infectious diseases. Changes in temperature and precipitation can create ideal breeding conditions for vectors such as mosquitoes and ticks, increasing the risk of vector-borne diseases including dengue fever, malaria, and Lyme disease [6–8]. Waterborne illnesses such as cholera and cryptosporidiosis, and foodborne illnesses like salmonellosis and campylobacteriosis, have also been linked to climatic changes [9–12]. Climate change can further exacerbate health disparities, particularly in vulnerable populations such as those in low-income communities and developing countries [13]. Given the potential public health implications, there is a growing need to understand the relationship between climate change and infectious diseases. One promising area of research involves developing predictive models that can forecast disease outbreaks based on climate data [14]. These models may support public health officials in making timely decisions to mitigate disease spread [9]. However, developing such models requires a comprehensive understanding of the complex relationship between climate variables and disease transmission. There is growing interest in the use of predictive models to forecast the risk of infectious disease outbreaks, based on climate data. Such models may enable public health officials to take preventive measures before an outbreak occurs and to allocate resources more efficiently in response to an outbreak. Several studies have investigated the relationship between climate variables and infectious disease incidence, with some finding significant correlations [15]. However, the development of accurate and reliable predictive models remains a complex and challenging task due to the complex interplay of environmental, social, and biological factors that contribute to disease transmission [16]. Preventing and controlling climate-related disease outbreaks requires a multi-disciplinary approach that integrates public health, environmental science, and climate policy [17]. Strategies include early warning systems, vector control measures, improvements in water and sanitation infrastructure, and the promotion of sustainable agricultural practices [15, 18]. However, the effectiveness of such measures is likely to vary depending on local socio-economic and environmental conditions, highlighting the need for context-specific solutions [19].

To conduct this systematic review, we searched electronic databases including PubMed, Embase, and Web of Science using a predefined strategy. Search terms focused on climate change, infectious diseases, and prediction models, targeting studies that explore how climate factors influence disease outbreaks and how technology can help predict these patterns. We also manually screened reference lists of identified articles. Two independent reviewers screened titles and abstracts, with discrepancies resolved through discussion or by a third reviewer. Studies were included if they examined: (1) the correlation between climate change and infectious diseases, (2) the potential for building predictive models, and (3) the effectiveness of interventions. Full texts were reviewed and data extracted using a standardized form, with synthesis conducted through narrative review.

This review is guided by three research questions (RQs):

- **RQ1:** What is the correlation between climate change and infectious diseases?
- **RQ2:** Is it possible to build a prediction model that forecasts infectious disease outbreaks based on climate change data?
- **RQ3:** How can we prevent and control climate-related disease outbreaks?

The rest of this paper is structured as follows. Section 2 explains the research identification and selection processes. Section 3 discusses the correlation between climate change and infectious disease outbreaks (RQ1). Section 4 reviews machine learning approaches used in predictive modeling (RQ2). Section 5 addresses prevention and control strategies (RQ3). Finally, Section 6 concludes the study and summarizes the key findings.

Method

Protocol

This study followed a systematic review protocol developed based on a PRISMA statement [**?**] to ensure methodological transparency and reproducibility.

Systematic Review Framework

Systematic reviews aim to answer specific research questions by identifying existing gaps, comparing theories, or broadening understanding within a field of expertise [5, 20, 21]. This approach provides researchers with organized evidence to guide future studies that address knowledge gaps. In this study, we investigated the correlation between climate change and infectious diseases and examined strategies to minimize epidemic impacts. Following guidelines by Gough et al. and Petticrew & Roberts [20, 22], the systematic review was conducted through six key steps: (a) creating a conceptual background and research questions; (b) conducting a search and inclusion screening using appropriate criteria; (c) selecting studies that fit the conceptual framework; (d) applying quality assessment standards; (e) summarizing the studies using the theoretical structure or study codes; and (f) interpreting and communicating the results. The steps of the systematic review are shown in Fig 1.

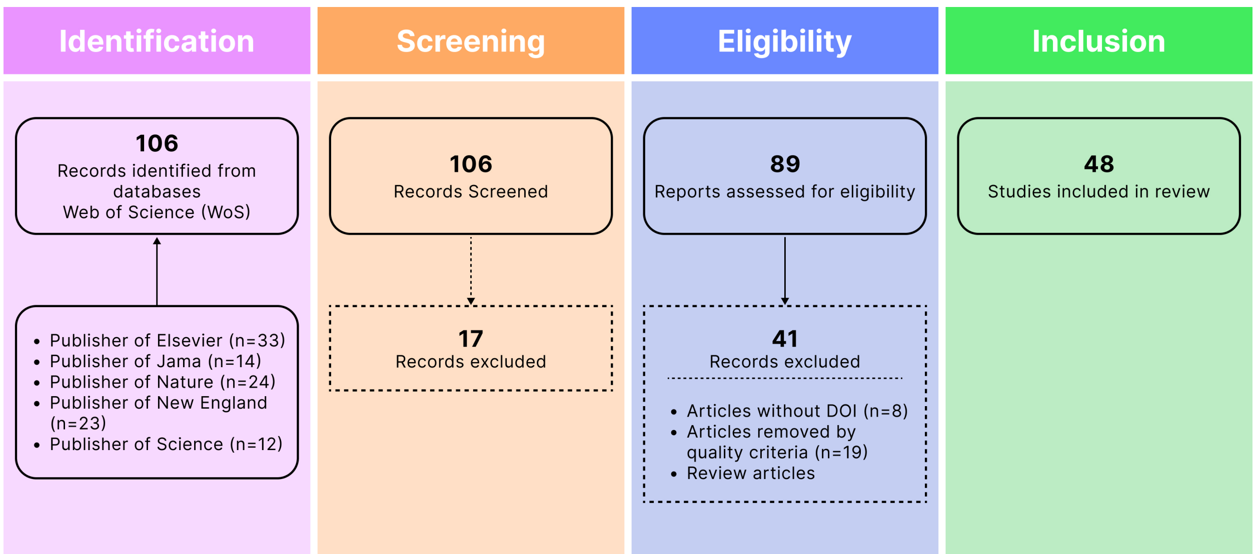

Fig 1. PRISMA guidelines for our study legend.

Searching criteria

. To address the given objectives, the search was limited to the period from 2010 to 2025. This period coincides with the occurrence of climate change, which is associated with the increase of infectious illnesses in recent times, including OSHW and OSS. The search string underwent systematic refinements to maximize the inclusion of pertinent papers within the systematic literature review. As an illustration, the first search query included the phrases ”Climate and diseases”, ”Correlations between climate and diseases”, and ”Prevent and control climate-related disease”. This resulted in a small number of papers obtained from the Web of Science (WoS). Subsequently, a secondary search query was constructed using the key terms often used in academic research, as identified in the systematic reviews. The search technique includes many specialized journal records from publishers Elsevier, Jama, Nature, New England, and Science, all of which were found inside the specified source, the WoS database. 106 records were obtained from the specified sources and imported into the Mendeley software in research information system (RIS) format. These records were then examined for duplicates, and any missing information, such as authors, DOI, abstract, keywords, or publisher, was added.

Screening eligibility, and appraisal criteria

The screening procedure for the n = 106 records started by reviewing the title and abstract of the papers. The studies that fell beyond the scope of the systematic literature review and did not match the inclusion criteria specified in Table 1 were excluded.

Table 1. Description of search criteria for the systematic literature review (SLR).

Aspect	Description
Timeframe	2010–2025
Databases, Journals, Webpages	Web of Science (WoS); Elsevier; JAMA; Nature; New England Journal of Medicine; Science
Searching String	(”infectious disease” OR ”global warming” OR ”extreme weather”) AND (”infectious disease” OR ”vector-borne” OR ”water-borne” OR ”food-borne” OR ”zoonotic” OR ”respiratory”) AND (”prediction” OR ”forecast” OR ”risk assessment” OR ”prevention” OR ”control”)
Inclusion Criteria	- Peer-reviewed primary research studies - Examines climate–disease relationships - Includes quantitative or qualitative findings - Published between 2010–2025
Exclusion Criteria	- Not focused on climate–disease links - Review or commentary articles - No empirical data or methods - Duplicate or inaccessible papers - Non-infectious health outcome focus
Total Records Obtained	Total: 106 from the following sources— Web of Science (WoS); Elsevier (32); JAMA (14); Nature (24); New England (23); Science (12)

Table notes: Search conducted from 2010–2025 across major databases and journals using a predefined string. Inclusion/exclusion applied during screening.

Following this procedure, 17 entries were eliminated from the database, resulting in a remaining count of 89 articles. The publications underwent an eligibility assessment, excluding those without DOIs or facing accessibility issues (n = 8), as well as those that were not main research, such as literature reviews and surveys (n = 14). Subsequently, each of the remaining articles underwent a thorough assessment based on a quality criterion (QC) using a Likert scale survey. The survey consisted of a set of questions outlined in Table 2, with responses ranging from 1 to 4.

Table 2. Quality survey to assess the articles in the SLR.

Survey Questions	Range (1–4)
Q1. Does the study describe clear criteria for the identification of a correlation between climate change and infectious disease outbreaks?	(1: strongly disagree to 4: strongly agree)
Q2. Does the study show a method and experiments that allow the building of a prediction model that can predict the outbreak of infectious diseases?	(1: strongly disagree to 4: strongly agree)
Q3. Does the study indicate the scope of how to prevent and control climate-related disease outbreaks?	(1: strongly disagree to 4: strongly agree)
Q4. Has the study been cited by other authors?	(1: No, 4: Yes)

Table notes: Each article was scored on a 1–4 scale per question to evaluate quality and relevance within the systematic literature review.

The construction of these questions considered the characteristics of the research questions (RQs) and the significance of the studies within the scope of the systematic literature review (SLR). Each question in the poll carried equal weight, meaning that the total score of an article was determined by calculating the average of the scores for these questions. Out of the 19 reviews included in the quality survey (as shown in Table 3), all 19 reviews answered questions Q1 to Q4. Omissions of citations were made due to the item's greater suitability for research publications. The papers with an overall score below 2.8 were chosen to be eliminated from the systematic literature review (SLR), resulting in a total of 19 articles (n = 19). All the remaining publications, totaling n = 48, were included in the review, as seen in Fig 1.

Data extraction and analysis of the study

The data extraction and analysis were conducted on 106 publications, under the research questions (RQs) outlined in the systematic literature review (SLR). In order to address Research Question 1, certain software tools and programs designed for bibliometric analysis, such as VOS Viewer [23], and Leximancer [24] , were utilized. VOS Viewer is a software application designed for bibliometric analysis using network data. It primarily focuses on analyzing items and clusters, and it serves two main purposes: generating maps and visualizing them [25]. Leximancer is a text analytics program capable of analyzing the contents of document collections and visually representing their patterns using idea maps [26]. The primary ideas and clusters that unite the research in the systematic literature review (SLR) were examined using these two techniques to determine the patterns observed in the gathered studies. During this study, some terms were combined or eliminated to ensure the significance of the clusters and ideas in the analysis. The VOS Viewer program analyzed the keywords in each article, requiring a minimum occurrence of three terms. In contrast, Leximancer concentrated on the abstracts of the article description to enhance the findings in this specific section of the systematic literature review (SLR).

Reporting the results

The review was written following the guidelines suggested by Webster and Watson [27]. These guidelines encompassed various aspects, including the identification of pertinent literature, adopting a concept-centric approach for the review, presenting information through tables and figures, and ensuring an appropriate tone and structure for the synthesis. The findings are organized and presented in alignment with the specified research questions (RQ). Comprehensive details of each of the 48 articles, which summarize the synthesis of the results, are provided. Following the screening and quality assessment, we examined the bibliometric characteristics of the included studies to contextualize research trends in this field.

Bibliometric Characteristics of Included Studies

After reviewing the publications of our study, we can make some observations and analysis on different bibliometric parameters such as publication year, publisher, and publisher country.

Until 2017, very few publications were made in this category, ranging from one to three annually. However, in 2018, the number increased to five. In the next two years, four and six articles were published, respectively. A sharp rise was observed in 2021 with sixteen publications, accounting for 37.21% of all the studies considered in this review. A possible cause of this surge could be the global virus outbreak during that period. In 2022, seven publications appeared, which is also a notable number.

The graph shows that most of the publications appeared in Elsevier journals, accounting for 40.4% of the total. The second most frequent source was Science, representing 27.7% (n=13) of the publications. Furthermore, 12.8% (n=6) and 10.6% (n=5) of the articles were published in JAMA and The New England Journal of Medicine, respectively. Fig. 2 illustrates the distribution of publications by country.

Country-wise, the United States is leading in terms of publication, followed by the United Kingdom (n=7). The next major country was France, publishing three articles. After that, Germany has two publications in this category, which is the same as India, Iran, and Sweden. The rest of the countries, such as Finland, Indonesia, Israel, Japan, South Korea, Singapore, and Taiwan, each have one publication.

The articles reveal a common focus on the impact of climate change on infectious diseases, exploring various dimensions including the direct and indirect effects of climate change on the emergence or re-emergence of infectious diseases, the role of vectors and host-pathogen interactions, and the geographical and seasonal variations in disease patterns. The keywords ”climate change” and ”infectious diseases” are central to these discussions, highlighting a critical area of concern within public health, environmental studies, and epidemiology. The articles emphasize the need for predictive frameworks, integrated research approaches, and global public health strategies to address the challenges posed by climate change to infectious disease management and prevention. They also point to the importance of considering the

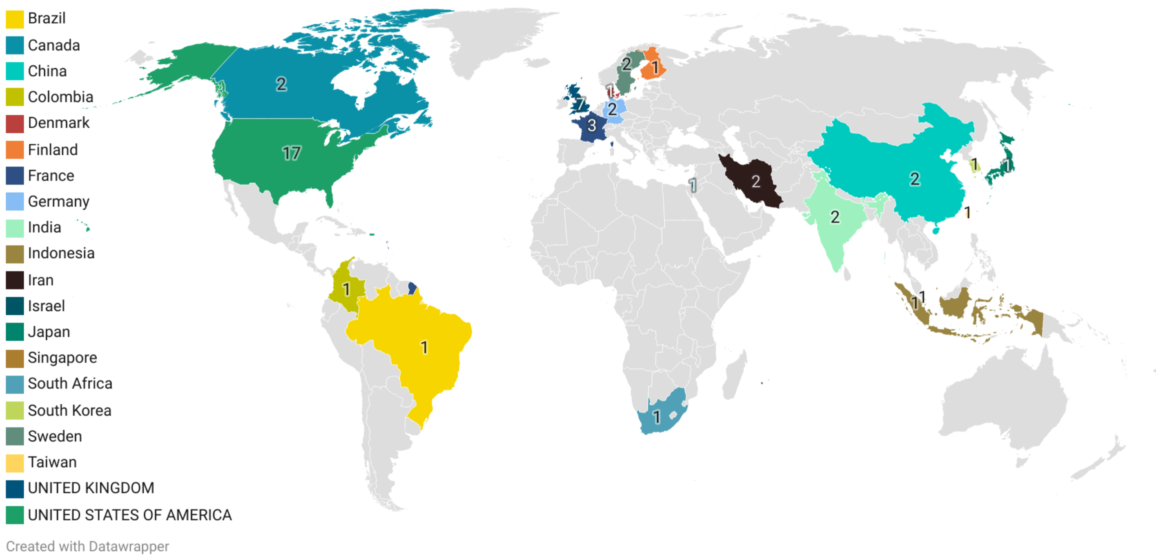

Fig 2. Represents the articles published by each country.

spatial and temporal dynamics of infectious diseases in the context of a changing climate, underscoring the complex interplay between environmental factors, human behavior, and disease transmission mechanisms.

Correlation between climate change and infectious diseases (RQ1)

As indicated previously, climate change factors such as temperature, humidity, precipitation, wildfire, drought, heat waves, floods, sea level, and storms have a considerable correlation with transmittable ailment outcomes (vector-borne diseases, water-borne disease, food-borne disease, zoonoses, etc.) where the disease is transmitted through biological (vector, pathogen, host), socioeconomic (human behavior, population mobility, and urban water supply), and ecological (vegetation cover, animal habit, and virus spillover) pathways. Fig 3 illustrates the overall correlation between climate change and infectious diseases. Each interconnection among climate change factors, pathways, and disease risks will be described elaborately in the next These studies describe the relationship between climate and disease, which were classified as articles based on different publishers. It is also worth mentioning that 48 studies on climate disease transmission (n=18) are interdependent with disease transmission and health risk. Each type of climate change and disease transmission way and outcome will be described in the next subsections.

To examine the relationship between climate change and infectious diseases, we reviewed relevant studies from different geographic regions and disease categories across various publications. Table 3 summarizes key research findings that demonstrate how climatic factors such as temperature, humidity, precipitation, and extreme weather events influence the transmission of vector-borne diseases (malaria, dengue, Zika), respiratory infections (COVID-19, influenza, RSV), and emerging zoonotic pathogens. The studies span multiple scales from local to global contexts and employ diverse methodological approaches including epidemiological analysis, predictive modeling, and economic assessments. While the research consistently shows significant correlations between climate variables and disease outcomes, the magnitude and nature of these relationships vary considerably depending on the pathogen type, geographic location, and presence of public health interventions, supporting the multi-pathway framework presented in Figure 3.

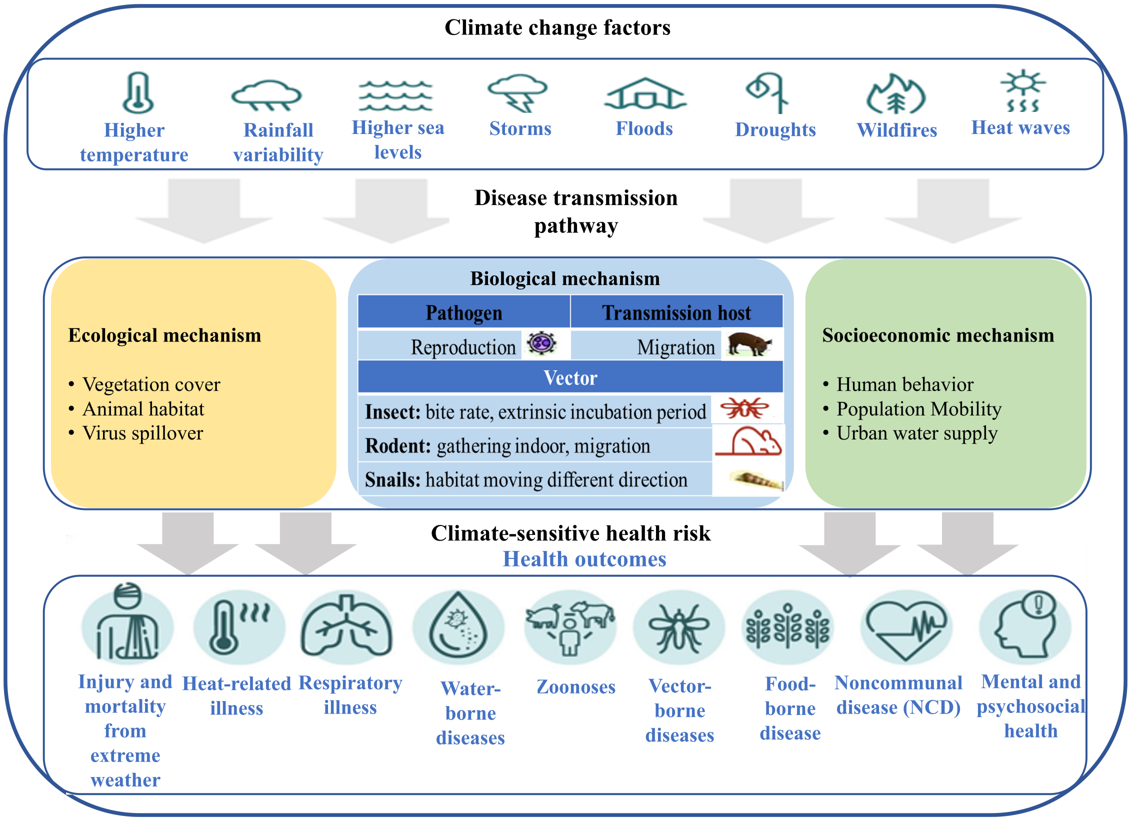

Fig 3. Schematic diagram of the transmission pathway of climate-sensitive health risk.

Table 3. Summary of Studies on Climate Factors and Infectious Diseases

Ref.	Title	Journal	Geographic Focus	Climatic Factors	Associated Diseases	Key Findings
[28]	A cross-sectional analysis of meteorological factors and SARS-CoV-2 transmission in 409 cities across 26 countries	Nature Communications	Global (409 cities, 26 countries)	Temperature, humidity, solar radiation, precipitation, wind speed	COVID-19	Temperature and humidity modestly influenced transmission; interventions mattered far more.
[29]	Seasonality of Respiratory Viruses at Northern Latitudes	JAMA	Subnational (Alberta, Canada)	Seasonal variation	Respiratory viruses (RSV, hMPV, coronaviruses)	Respiratory viruses in northern climates follow a biennial seasonal pattern.
[30]	Climate change and infectious disease in Europe: Impact, projection, and adaptation	The Lancet Regional Health – Europe	Regional (Europe)	Temperature, precipitation	Vector-borne, food-borne, water-borne diseases	Warming and extreme weather expand vector, food, and waterborne disease risks.
[31]	Temperature, Humidity, and Latitude Analysis to Estimate Potential Spread and Seasonality of Coronavirus Disease 2019 (COVID-19)	JAMA	Global (30°–50°N latitude corridor)	Latitude, temperature, humidity	COVID-19	COVID-19 outbreaks clustered in cool, low-humidity midlatitude regions.
[32]	Climate Change — A Health Emergency	New England Journal of Medicine	Global	Temperature, extreme weather, air pollution	Vector-borne, heat-related, respiratory diseases	Climate disruption intensifies heat, pollution, and vector-borne disease risks.

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Ref.	Title	Journal	Geographic Focus	Climatic Factors	Associated Diseases	Key Findings
[15]	Climate Change and Infectious Diseases: From Evidence to a Predictive Framework	Science	Global	Temperature, precipitation, humidity	Vector-borne, water-borne, zoonotic diseases	Climate warming alters disease ranges, timing, and host–pathogen dynamics.
[33]	Climate Change and Vectorborne Diseases	New England Journal of Medicine	Global	Temperature, precipitation, extreme weather conditions, humidity	Vector-borne diseases	Climate change expands disease vector habitats, requiring enhanced surveillance and public health preparedness systems.
[34]	Correlation between air pollution and prevalence of conjunctivitis in South Korea using analysis of public big data	Scientific Reports	National (South Korea)	Temperature, humidity, precipitation, wind speed, air pollution	Conjunctivitis	Air pollution and climate variability significantly influence conjunctivitis prevalence.
[35]	Associations Between Simulated Future Changes in Climate, Air Quality, and Human Health	JAMA	National (United States)	Temperature, humidity, precipitation, wind speed, air quality	Cardiovascular, respiratory diseases	Climate-driven warming increases PM2.5 and O mortality, mitigated by emission cuts.
[36]	Toward the use of neural networks for influenza prediction at multiple spatial resolutions	Science Advances	National (United States)	Seasonal variation	Influenza	Neural networks improve influenza forecasts despite seasonal reporting delays.
[37]	A Gaussian process-based big data processing framework in a clustering computing environment	Cluster Computing	Regional (Tamil Nadu, India)	Temperature, precipitation, wind speed, solar radiation, humidity	Dengue fever	Seasonal climate variability strongly predicts dengue outbreaks in Tamil Nadu.
[38]	Climate change: an enduring challenge for vector-borne disease prevention and control	Nature Immunology	Global (tropical, subtropical, temperate regions)	Temperature, precipitation, humidity	Malaria, dengue, Zika	Climate warming expands vector ranges and lengthens transmission seasons.
[39]	Human infectious diseases and the changing climate in the Arctic	Environment International	Arctic (Russia, Canada, Finland, Sweden, Norway, Alaska)	Temperature, humidity, precipitation, extreme weather events, seasonality	Vector-borne, zoonotic, waterborne diseases	Warming expands vector ranges and precipitation/heat raise water- and foodborne risks.
[40]	Environmental Racism and Climate Change — Missed Diagnoses	New England Journal of Medicine	National (United States)	Temperature, humidity, air pollution	Asthma, cardiovascular disease	Environmental racism increases exposure to pollution and heat and intensifies risks, especially for vulnerable communities.
[41]	The One Health aspect of climate events with impact on foodborne pathogens transmission	One Health	Europe (cold and temperate regions)	Precipitation, extreme weather events, temperature, humidity	Food-borne diseases	One Health perspective links climate extremes to pathogen persistence, antimicrobial resistance, and transmission across food systems.

Vector-borne disease and zoonoses

In the last 25 years, the rising appearance of zoonotic and vector-borne diseases has increased significantly. This is due to climatic change being a key modifying factor in disease transmission dynamics [?]. The climatic variables indirectly influence zoonotic and vector-borne illnesses through changes in environmental conditions, host populations, and vector habitats. For example, rising temperatures extend the life of a pathogen, expand vector ranges, and influence host susceptibility, thus promoting disease transmission.

Northward shifting of boreal forests and displacement of tundra enable the animal and insect vectors to move into new ranges, increasing disease transmission risks. Regions with marked temperature variability frequently experience vector-borne disease outbreaks [15]. Figure 4 further illustrates this pattern, showing that temperature and precipitation display the strongest correlations with the spread of vector-borne and zoonotic diseases. For example, studies reveal that temperature and humidity significantly impact the transmission dynamics of SARS-CoV-2. Sera et al. [28] found a modest non-linear correlation between the virus's reproduction number (Re) and mean temperature, with Re decreasing slightly (0.087%) for every 10°C temperature increase. Extreme weather conditions such as hurricanes, droughts, floods, and wildfires, which are becoming increasingly frequent due toria, thrive in warmer temperatures and wet environments and tend to cause more cases of malaria during the rainy season. On the other hand, droughts promote diseases such as the West Nile virus, since vectors and hosts climate change, further exacerbate the spread of infectious diseases. Tropical mosquitoes, especially the Anopheles spp. that cause mala congregate around the few available water points. In both ways, climatic changes facilitate disease spread by changing the vector populations and related ecological interactions.

The European and Arctic regions vividly illustrate the complex relationships between climate change and disease emergence. Certain VBDs in Europe, such as borreliosis and tick-borne encephalitis, are strongly linked to climatic shifts, as warmer conditions allow insects to thrive and transmit diseases more effectively [30]. Initiatives like the European Green Deal aim to build resilience against future outbreaks. In Arctic and Northern territories, several infections are closely tied to temperature and precipitation, with Spearman's coefficients up to $\rho = 0.85$—for instance, Puumala virus infection and cryptosporidiosis. The COVID-19 pandemic further underscored the connection between climatic conditions and infectious disease dynamics, as major outbreaks occurred in cities with specific climate patterns [31]. As global temperatures rise from greenhouse gas emissions, infectious diseases will likely spread more widely, making adaptive health policies and mitigation strategies crucial.

Severe weather events, flooding, storm surges, and droughts are all consequences of a disrupted hydrological cycle. Unlike gradual climate changes, rapid and unexpected shifts pose greater challenges for public health. Rising global ambient temperature raises sea surface temperature, enhancing the proliferation of harmful Vibrio bacteria in marine waters. Human-induced climate change has increased Vibrio infections in the Baltic Sea, causing illness and death among recreational water users. A major precipitation event may dislodge animal pathogens from pastures and flood deteriorating water treatment and distribution systems, leading to a waterborne epidemic [30]. Similar to vector-borne illnesses, aquatic infectious diseases are also strongly influenced by climate. During droughts, water scarcity causes poor sanitation, exposing populations to polluted water. Currently, northern Kenya faces a cholera outbreak following severe drought. Excessive rainfall and floods can likewise trigger waterborne outbreaks by overflowing sewage or contaminating water with livestock waste. One example is the 1993 Milwaukee Cryptosporidium outbreak after heavy spring rains, while another is the seasonal pattern of bacterial and protozoal diarrheal diseases [32]. The prevalence of waterborne infections in the Arctic is also shaped by overcrowded housing and inadequate sanitation. Disease transmission risk rises in confined dwellings, and cold weather keeps people indoors. In Arctic regions, many homes lack centralized water and sewage systems; for instance, 22% of rural Alaskan households lack indoor plumbing. Residents often haul water manually, increasing hygiene-related infection risk. Severe water scarcity may lead to reusing water for multiple washings, heightening bacterial skin disease risk [39].

Fig 4 summarizes studies linking climate variables with vector-borne and zoonotic diseases. The figure reflects our synthesis approach: pooled effect estimates where comparable, and otherwise a vote-count of significant associations by climate variable and disease class.

Foodborne diseases

Foodborne illnesses can be influenced by rising temperatures and excessive rainfall. An elevated temperature promotes the proliferation of pathogens and enhances their ability to survive, while excessive rainfall can lead to floods, causing disruption and contamination of water and waste treatment systems. Figure 5 highlights this relationship, showing that temperature and precipitation emerge as the most consistent climatic drivers linked with foodborne illness across studies. The escalating temperature in the Arctic and forecasts of heightened precipitation indicate that foodborne illnesses will be substantially

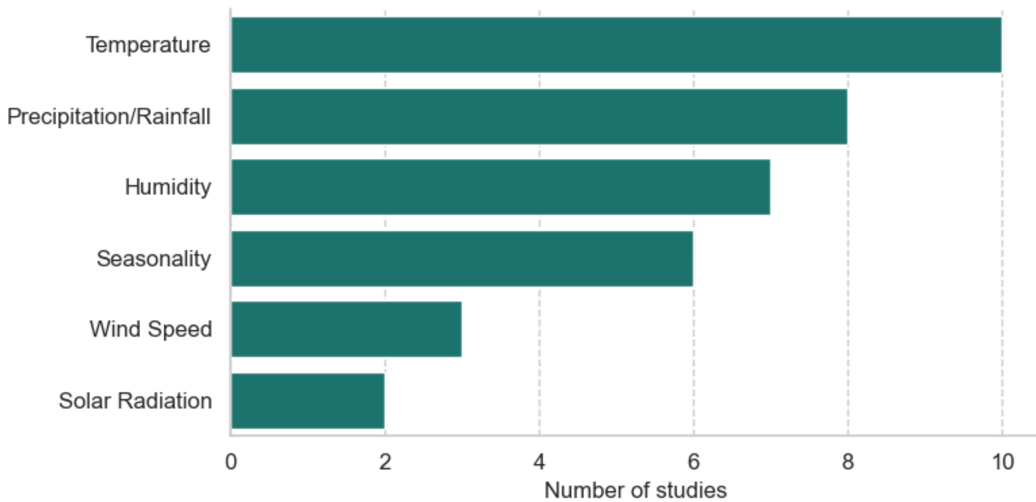

Fig 4. Climate variables linked to vector-borne and zoonotic diseases.

affected in a direct manner [39]. The transmission route of food-borne viruses from farm to fork is intricate. A significant number of the microorganisms responsible for food-borne illnesses can survive in the surroundings, endure high temperatures, and cause infection even in small quantities. For instance, Campylobacter is the predominant bacterial source of diarrhea in industrialized nations, accounting for about 220,000 cases annually and a reporting rate of 60 cases per 100,000 individuals (about the seating capacity of the Los Angeles Memorial Coliseum). There is a clear connection between seasonality and climatic variability, particularly with rising temperatures, which can lead to higher levels of bacterial contamination at different stages of the agricultural production process [32]. The elements like air pollution, ground-level ozone, and pollen need to be considered when a patient is treated as well as in internal body treatment. For instance, fine particulate matter (PM), a diameter of 2.5 micrometers causes cardiovascular ailment and consequence increases the rate of death. The resulting rise in air pollution has been caused by fossil fuels. The vulnerability of ambiance issues has been determined by considering susceptibility, exposure, and ability to adapt [40].

Figure 5 reflects our synthesis of reported associations between climate drivers and foodborne illness, showing that temperature and precipitation were the most frequently cited risk factors across studies.

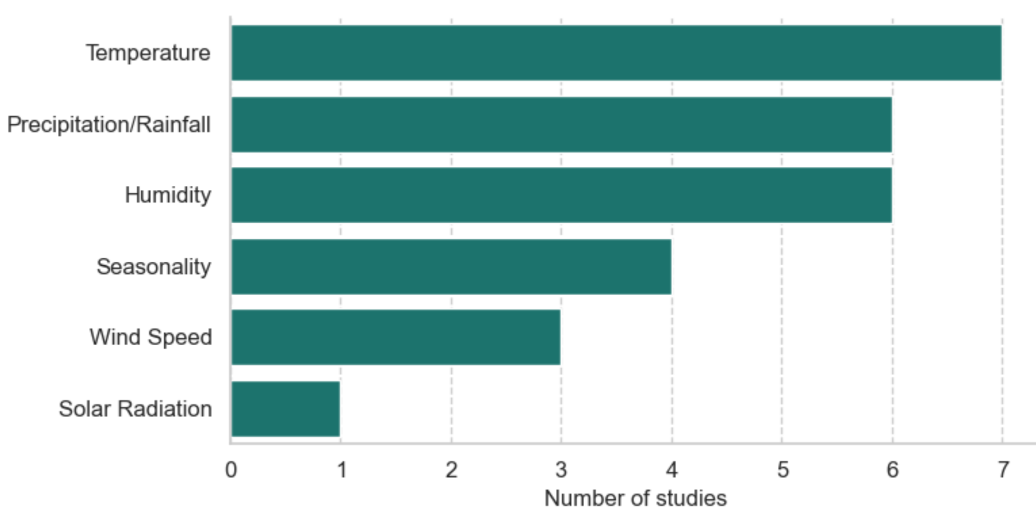

Fig 5. Climate variables linked to food-borne diseases.

Possibility of building prediction model that can presence the outbreak of infectious diseases (RQ2)

Building a prediction model to foresee disease outbreaks using data related to climate change is not only possible but also becoming increasingly important in our ever-changing environment. As the correlation between climatic patterns and the incidence of specific diseases is well-established, utilizing this connection to make predictions seems reasonable. The first stage is collecting data with great care, combining historical climatic data with historical disease outbreak information, and capturing the temporal and spatial variations. Following data pre-processing, missing values and outliers are dealt with, guaranteeing the dataset's integrity. Following that, modelling can be done using machine learning techniques to identify intricate relationships in the combined data. Simply, the combination of data analytics and climate science offers a potential path toward the creation of predictive models that can greatly aid in the early identification and containment of disease outbreaks.

Dengue outbreak prediction

Yirong Chen et al. [42] developed a machine-learning model, with the LASSO regression technique, for the forecast of infectious disease outbreaks with a focus on dengue among three other diseases in Japan, Taiwan, Thailand, and Singapore. This model is able to make predictions up to four weeks ahead while its short-term forecasts have considerably higher accuracy. Although this model was very effective in predicting the timing of the outbreaks, it had difficulties with the exact estimation of outbreak size. They suggested that the health agencies should give early warnings in priority manners for timely interventions. Manogaran and Lopez [37] identified the dengue hotspot zones using Moran's autocorrelation and a Gaussian process regression model, which showed high efficiency in outbreak predictions. These techniques can keep health workers prepared to act accordingly when an outbreak is predicted. Other predictive models, such as the host-vector mathematical model in Nuraini et al. [43] , used the ARDL method to study infection rates according to various climatic variables; their findings indicated that rainfall and humidity have a positive influence on outbreaks, with the optimal temperature of infection being between 24.3-30.5 °C. Likewise, Caldwell et al. [44] developed the SEI-SEIR epidemiological model, taking into consideration mosquito physiology and climate parameters to project outbreak duration, time, and intensity. The model demonstrated a variable accuracy of 28–85% for vector prediction and 44–88% for incidence. Martheswaran et al. discussed a dengue fever EWS implemented using Bayesian Markov Chain Monte Carlo techniques, using climate data and showing variances of 98.5% and 75.3%, respectively, for seasonal and climate-based models [45]. Lastly, Johansson et al. made a comparison among different models in relation to dengue outbreaks in Mexico [46]. The conclusion reached was that seasonal autocorrelation models gave the best short- and long-term predictions. These complementary studies build a deeper appreciation for the use of climate-driven modelling and statistical techniques to better predict infectious disease outbreaks which is displayed in Fig 6.

Infectious diseases prediction

An infectious disease is a pathogen-induced illness or its noxious by-product that spreads from an infected person, animal, or contaminated object to a susceptible host. One typical example is the coronavirus, a main cause of COVID-19. I-Hsi Kao et al. [47] proposed a deep learning-based approach to predict the severity of COVID-19 in the USA for two models: one a convolutional auto encoder and the other a hybrid architecture that leveraged CAE combined with long short-term memory. These models used the data from the WHO and CDC by ingesting case distributions from 14 days prior to predict case distributions 7 days ahead. The result showed that the AL-CNN model outperformed existing methods with the mean squared error of 1.664 and a signal-to-noise ratio of 55.699, which is very reliable in outbreak prediction. Chen et al. proposed the model of infectious disease outbreak prediction based on a machine-learning model using the LASSO regression technique for chickenpox in Japan, Taiwan, Thailand, and Singapore [42]. The model was able to forecast outbreaks quite accurately with approximately four weeks of lead time but was limited with respect to predicting outbreak size. Results show that the short-term forecast had higher accuracy, which is useful in early warnings and timely interventions. The work of Juhyeon Kim et al., also did

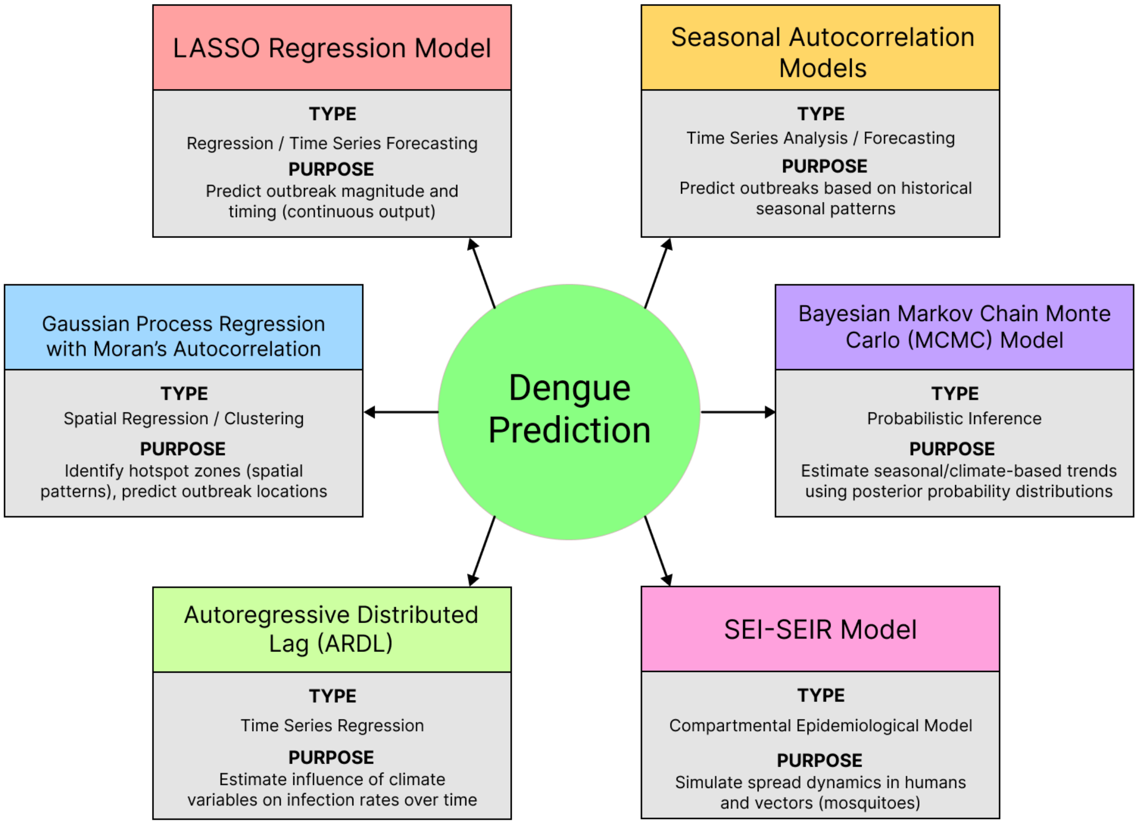

Fig 6. represents the state-of-the-art dengue prediction models.

outbreak predictions from media articles using SSL, SVM, and DNN. SSL gave the best performance with a mean accuracy of 0.838 and F1 score of 0.832 [48]. Other works, like that of Emily L. Aiken et al., developed real-time forecasting systems and showed that neural network models such as GRU are superior in modelling for USA influenza [36]. Finally, Yoonhee Kim et al. presented a weather-based malaria prediction model for South Africa, reaching high short-term accuracy with r > 0.8, while effective forecasting up to 16 weeks was possible but with reduced accuracy over time [49].These studies really illustrate the critical function machine learning and climate data serve in enhancing infectious disease predictions and prevention which is shown table 4.

Table 4. Summary of machine learning and statistical models applied for infectious disease prediction in the reviewed studies

Ref.	Title	Journal	Inputs	Predicted Diseases	Models	Results
[34]	Correlation between air pollution and prevalence of conjunctivitis in South Korea using analysis of public big data	Scientific Reports	Climate: Temperature, Humidity, Precipitation, Wind speed, Air Quality	Conjunctivitis (prevalence)	Multiple regression, XGBoost, Random Forest, Decision Tree	XGBoost achieved best performance (RMSE=1.180), followed by regression (1.195), RF (1.206), DT (1.544).

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Ref.	Title	Journal	Input Parameters	Predicted Diseases	Models	Results
[37]	A Gaussian process based big data processing framework in cluster computing environment	Cluster Computing	Climate: Temperature, Precipitation, Wind speed, Humidity, Solar radiation	Dengue	Gaussian Process Regression (GPR)	GPR outperformed MR, SVM, RF with lowest RMSE (0.281), MSE (0.078), MAE (0.156), MAPE (2.0%), and R^2 0.30.
[42]	The utility of LASSO-based models for real time forecasts of endemic infectious diseases: A cross country comparison	Journal of Biomedical Informatics	Climate: Temperature, Humidity, Precipitation	Chickenpox, Dengue, Malaria, HFMD	LASSO-based regression	LASSO models achieved good short-term accuracy (MAPE <20% for 1–4 week forecasts), but performance declined for longer horizons.
[45]	Prediction of dengue fever outbreaks using climate variability and MCMC techniques in a stochastic SIR model	Scientific Reports	Climate: Temperature, Humidity, Precipitation, Wind speed, Sea level pressure	Dengue	Stochastic SIR model with Bayesian MCMC	Seasonal model explained up to 98.5% variance (Singapore 2020) and 92.8% (Honduras 2019).
[46]	Evaluating the performance of infectious disease forecasts: A comparison of climate-driven and seasonal dengue forecasts for Mexico	Scientific Reports	Climate: Temperature, Precipitation, Humidity	Dengue	Seasonal autoregressive models (SARIMA)	SARIMA models achieved R^2 0.85–0.9 for 1–3 month forecasts.
[47]	Early prediction of coronavirus disease epidemic severity in the contiguous United States based on deep learning	Results in Physics	Epidemiological: Confirmed COVID-19 cases	COVID-19	Autoencoder–LSTM hybrid (AL-CNN)	AL-CNN achieved MSE=1.664, PSNR=55.7, SSIM=0.99.
[50]	Predicting Foodborne Disease Outbreaks with Food Safety Certifications: Econometric and Machine Learning Analyses	Journal of Food Protection	Food safety certification data, GDP, Farm income, Food manufacturing, Agricultural labor	Foodborne diseases	OLS regression, Decision Tree, Random Forest, Multinomial classifier	Random Forest achieved highest testing accuracy (76%) for illness prediction and 81% for death classification; certifications showed strong negative correlation with outbreaks.
[48]	Infectious disease outbreak prediction using media articles with machine learning models	Scientific Reports	Media: article counts from Medisys (115 diseases)	Infectious diseases	ML classifiers (SSL, SVM, DNN)	Semi-supervised learning achieved the best performance, with average accuracy 0.84, ROC 0.80, and F1 score 0.83 across prediction tasks.
[49]	Malaria predictions based on seasonal climate forecasts in south africa: A time series distributed lag nonlinear model.	Scientific Reports	Epidemiological: Weekly malaria cases, Climate: Temperature, Precipitation	Malaria	Generalized linear model (GLM) with distributed lag nonlinear model (DLNM)	Model achieved strong short-term prediction accuracy (correlation $r > 0.8$ for 1–2 weeks ahead; retained good performance with $r > 0.7$ up to 16 weeks).
[51]	Time series forecasting of new cases and new deaths rate for COVID-19 using deep learning methods	Results in Physics	Epidemiological: case and death counts	COVID-19	Deep RNNs (LSTM, GRU, Conv-LSTM variants)	Bi-GRU achieved best accuracy (MAPE 2.6% for 1-day forecasts; errors rose to 17% at 7 days).
[52]	Impact of climate change on dengue fever epidemics in South and Southeast Asian settings: A modelling study	Infectious Disease Modelling	Climate: Temperature, Precipitation	Dengue	SEI–SEIR compartmental transmission model	Under SSP585, dengue incidence projected to rise up to 2.25× in Colombo and >10× in Chiang Mai by 2090s.

Continued on next page

Ref.	Title	Journal	Input Parameters	Predicted Diseases	Models	Results
[53]	Predicting climate-sensitive water-related disease trends based on health, seasonality and weather data in Fiji	Journal of Climate Change and Health	Climate: Temperature, Rainfall, Seasonality	Water-borne diseases	Poisson Generalized Linear Models (GLMs)	Explained variance 0.4–43% across conditions; rainfall lags (2–11 weeks) important for dengue/jaundice.

Table notes: This table summarizes machine-learning and statistical models used to predict infectious disease outbreaks, listing climate inputs, target diseases, modeling approaches, and reported outcomes.

Airborne, waterborne, and Foodborne diseases

Airborne, waterborne, and foodborne diseases are illnesses caused by the contamination or consumption of air, water, or food that contains harmful microorganisms or toxic substances. The authors of [34] showed the correlation between conjunctivitis eye disease and air pollution in South Korea. Here, extreme gradient boosting (XGBoost), random forest, and decision tree machine learning methods predict meteorological factors producing eye conjunctivitis. Based on the RMSE (root mean square error) value, the XGBoost shows the best performance among the three models. Another study tried to build a prediction model for water-related diseases such as typhoid and for forecasting their outbreaks in Fiji [53]. They fit the Early Warning Alert and Response System (EWARS) with Poisson's generalized linear model to predict the outbreaks based on temperature, rainfall, and seasonality data. Bloody diarrhea, acute jaundice, and acute fever with the rash syndrome did not show seasonality, while dengue, prolonged fever, and watery diarrhea showed seasonal trends. Here, the relationship between rainfall and EWARS depicts that it is possible to predict the outbreaks of water-related diseases. Similarly, Zheng et al. (2023) [50] used food safety certification and economic data to predict foodborne disease outbreaks in the United States and Europe. Using econometric and machine learning models, they found that higher certification adoption was associated with fewer outbreaks. The random forest model achieved the best predictive performance, highlighting the value of regulatory indicators in foodborne disease forecasting. A review study tried to find out the relationship between climate change and infectious disease transmission. Due to hazardous weather conditions, people suffer from numerous vector-borne, food-borne, air-borne, and water-borne diseases nowadays. It showed how temperature, humidity, and precipitation could increase or decrease disease transmission. By observing climate change and associated with infectious data, it can be possible to predict the upcoming disease outbreak. Neal L. Fann et al. tried to build two climate models associated with two air pollution scenarios for the prediction of the changes in climate, air quality, and human health based on air pollution data in 2021 [35]. CM3 (Coupled Model version 3) and CESM (Community Earth System Model) simulate the meteorological disorder in the US from 1995 to 2005. The actual output of this research was to simulate the number of deaths associated with the change in ozone (O3), and Particulate Matter sized less than 2.5 μm (PM2.5). In the CESM model, the projected increase in the highest daily temperatures was 7.6 °C and 11.8 °C from the CM3 model. Lastly, this study suggests that decreasing air pollutants can also decrease climate-related death.

Prevention and control of climate-related disease outbreaks (RQ3)

While the studies are about climate change and outbreaks of infectious disease. In Fig 7, state some preventing and controlling pathways of climate-related disease outbreaks.

The direct relationship between climate change and infectious disease demands comprehensive prevention and control strategies that address multiple transmission pathways. Understanding zoonotic disease emergence is fundamental, as Edward C. Holmes (2022) emphasized, particularly for RNA viruses like influenza, paramyxoviruses, and coronaviruses that drive most outbreaks. Bernstein et al. [54] quantified the economic urgency of this challenge, demonstrating that pathogen surveillance systems, responsible wildlife trade management, and reduced deforestation could cut global outbreak costs by up to one-twentieth annually. Complementing surveillance efforts, Semenza and Ko (2023) [55] highlighted how climate variability disrupts water and sanitation systems, increasing transmission of waterborne pathogens

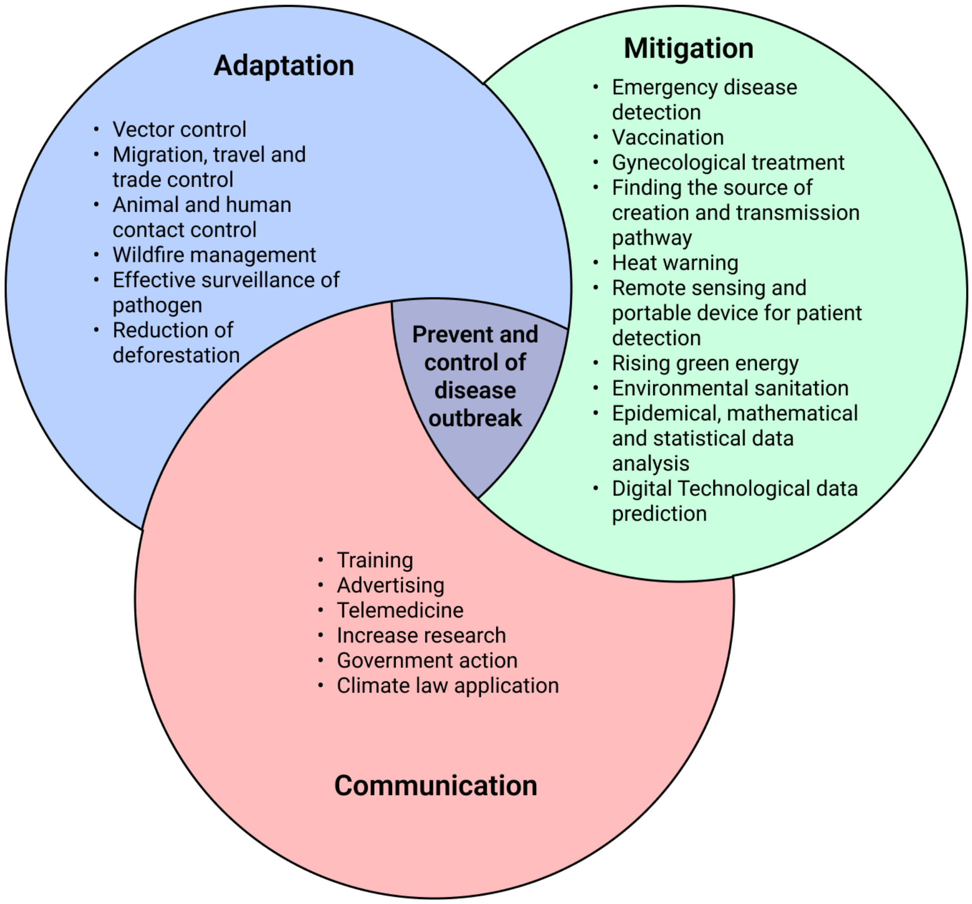

Fig 7. Framework for preventing and controlling climate-related disease outbreaks.

such as Vibrio cholerae, Cryptosporidium, and Leptospira through extreme rainfall, flooding, and drought. They advocate for climate-resilient WASH infrastructure, wastewater monitoring, and integrated early-warning mechanisms as essential defenses for vulnerable communities. Chen et al. (2025) [56] reinforced these priorities through a nationwide study showing that extreme temperature fluctuations significantly elevate infection risks across respiratory, gastrointestinal, and vector-borne diseases in children and adolescents, underscoring the need for improved sanitation, climate-resilient infrastructure, and early warning systems.

Innovative control strategies are expanding the prevention toolkit across multiple disease categories. Biological vector control shows remarkable promise, as demonstrated by a large-scale Singapore field study where releasing Wolbachia-infected male Aedes aegypti mosquitoes reduced dengue incidence by over 60%. Lin et al. [57] advanced arboviral disease prevention through CRISPR gene-editing in mosquitoes, achieving 16.5% success rates, and developed enveloped virus-like particles (eVLPs) as promising vaccine candidates. Digital innovations further strengthen disease surveillance, with Seo et al. [58] demonstrating how satellites and predictive mathematical models can forecast disease dynamics and improve mitigation strategies, while telemedicine enhances health management during climate-related crises. Policy frameworks provide essential structure through the UNFCCC and agreements like the Kyoto Protocol and Paris Agreement, which address vaccine distribution and technology transfer obligations. Rother [59] emphasized that green energy initiatives and reduced greenhouse gas emissions in sub-Saharan Africa can combat climate-sensitive non-communicable diseases alongside improved governance and climate-health planning. Yoobi et al. [51] highlighted operational improvements such as enhanced hospital triage systems, waste management, and emergency care protocols during pandemics like COVID-19. These findings collectively demonstrate that combining surveillance, technological innovation, policy frameworks, and early government intervention is essential for mitigating the dual threats of climate change and infectious diseases.

Table 5. Summary of Studies on Climate-Related Diseases, Main Drivers, and Prevention/Control Strategies

Ref.	Title	Journal	Focus	Main Drivers	Control Strategy	Key Insights
[54]	The Costs and Benefits of Primary Prevention of Zoonotic Pandemics	Science Advances	Zoonotic diseases	Deforestation, Agricultural intensification and wildlife trade	Pathogen surveillance, regulate wildlife trade and reduce deforestation	Primary prevention costs less than 5% of pandemic damages.
[49]	Malaria predictions based on seasonal climate forecasts in South Africa: A time series distributed lag nonlinear model	Scientific Reports	Malaria	Transmission peaks under warm, wet conditions; strong seasonality shapes malaria outbreaks.	Weather-based early warning system, automated malaria forecasting	Accurate malaria prediction achieved using temperature (23–24 °C) and moderate rainfall as key predictors.
[51]	Time Series Forecasting of New Cases and Deaths for COVID-19 Using Deep Learning Methods	Results in Physics	COVID-19	High infectivity, overwhelmed hospital systems during outbreaks	Enhanced triage systems, waste management, digital health tools	Machine learning supports hospital preparedness.
[55]	Waterborne Diseases That Are Sensitive to Climate Variability and Climate Change	The New England Journal of Medicine	Water-borne diseases	Rising temperature, flooding, drought, sea-level rise, and disrupted WASH infrastructure	Climate-resilient WASH systems, wastewater monitoring, early-warning systems, emission reduction	Extreme weather events amplify waterborne disease burden; integrated climate–health adaptation is essential.
[56]	Impact of climate change and extreme temperature on the incidence of infectious disease among children and adolescents in China	Journal of Infection	Respiratory, Food-borne, Water-borne, and Vector-borne diseases	Extreme temperature fluctuations, global warming, rapid urbanization	Climate-based early warning, surveillance, improved sanitation and infrastructure	Non-linear temperature–disease relationships; public health systems must adapt to temperature extremes.
[57]	Efficacy of Wolbachia-mediated sterility to reduce the incidence of dengue: a synthetic control study in Singapore	The Lancet Microbe	Dengue	High rainfall, humidity, and temperature extending mosquito lifespan	Release of Wolbachia-infected male mosquitoes causing non-viable eggs	Wolbachia coverage reduced dengue incidence by up to 77% in 2022 at 68% area coverage.
[58]	Beyond the Paris Agreement: Climate Change Policy Negotiations and Future Directions	Regional Science Policy and Practice	Climate–health governance and policy	Weak international coordination and funding mechanisms	Legal frameworks, vaccine distribution, technology transfer	Strong climate law enables equitable disease control.
[59]	Controlling and Preventing Climate-Sensitive Noncommunicable Diseases in Urban Sub-Saharan Africa	Science of the Total Environment	Climate-sensitive non-communicable diseases	Poor governance, emissions, lack of adaptation plans	Green energy, emission reduction, climate-health planning	Integrating mitigation and adaptation reduces health burdens.
[60]	A systematic review and meta-analysis of ambient temperature and precipitation with infections from five food-borne bacterial pathogens	Epidemiology and Infection	Food-borne bacterial infections	Ambient temperature rise, heavy rainfall, floods	Cold-chain integrity, WASH resilience, and climate-integrated surveillance are the key prevention strategies.	Climate extremes like heat and floods increase food-borne illnesses including gastroenteritis and bacteraemia.

These studies illustrate the diverse strategies and pathways used to prevent and control climate-related disease outbreaks, as summarized in Table 5.

Conclusion

In this systematic review, a detailed outline of the complex relationship between climate change and infectious diseases has been given. Evidence outlines those changes in environmental factors, temperature, extreme weather conditions, and changing precipitation conditions are the main factors influencing disease transmission dynamics. These changes facilitate the spread of vector-borne, waterborne, and zoonotic diseases, hence posing increased risks among vulnerable populations. Hence, it underscores the need for strong public health strategies in ways that embed climate variability into the frameworks of disease prevention and mitigation. Advanced models of prediction, leveraging machine learning and climate data, emerge as promising tools to forecast outbreaks and enable timely interventions. Moreover, such findings do point to the paramount relevance of multi-disciplinary approaches toward addressing health crises driven by climate. This includes early warning systems, improved international networks of surveillance, and novel technologies in vector control, like CRISPR. The collaborative policy will be required on greenhouse gas emission cuts and lowering the roots of climate change, such as adherence to the Paris Climate Agreement and the Green Deal. Ultimately, this synthesis will be very important for researchers, policymakers, and healthcare professionals in that it underlines the base for proactive strategies in protecting global health in view of an evolving climate landscape

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