

Impact of Weather and Climate Drivers on Waterborne Diseases: A Systematic Review of Mechanisms and Models

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Abstract

Global climate change significantly alters environmental and health dynamics, posing a major 21st-century public health threat. Diseases commonly transmitted through water and/or food (diarrhea, cholera, dysentery) are particularly sensitive to these changes. While numerous studies have investigated the climate impacts on waterborne diseases, a critical assessment of the applied methodologies and the consistencies of their outcomes is lacking. This systematic review synthesizes the impact of climate change on waterborne diseases, focusing on analytical methods and predictive models used to explain disease presence or abundance. We further evaluate the strengths and limitations of each approach, identifying key gaps for future research. We analyzed 78 indexed research articles published between 1996 and 2023. Our findings demonstrate that diverse climate-related extreme events, including precipitation, flooding, and drought, substantially impact waterborne disease incidence. Additionally, temperature, salinity, humidity, sunshine duration, wind patterns, and specific water quality parameters play significant roles, with regional variations observed. Sensitivity analysis methods and mathematical models are employed to assess sensitivities, quantify correlations, examine impacts, and predict risks. Based on these findings, we urge future research to prioritize elucidating mechanisms and developing models that leverage climate data to predict disease presence or abundance accurately and quantitatively.

Keywords: climate change; waterborne disease; modeling; impacts; forecast



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1. Introduction

Climate change is mainly driven by anthropogenic greenhouse gas emissions, impacting weather, socio-economic and health conditions [1,2]. While climate refers to long-term trends and multi-decadal shifts in variables such as temperature and precipitation, weather describes short-term atmospheric conditions experienced over days to weeks. Both forms of variability are reflected in changes to climate indicators such as temperature. The rapid and accelerating rise in the Earth's surface temperature represents an extremely serious threat to our planet. Frequent variations in abnormal weather phenomena in certain regions, such as flooding due to intense precipitation, erosion, drought, eutrophication and acidification of oceans and rivers, heat waves, storms and rising sea levels resulting from glacial melting, affect human life [1–3]. An analysis of temperature trends over the past five decades in subtropical and tropical Africa reveals critical increases attributed to global warming [4].

Global climate policy frameworks such as the 2015 Paris Agreement and the 27th Conference of the Parties (COP27) underline the need to restrict the increase in global mean temperature to well below 2 °C above pre-industrial levels, with an ambition to limit warming to 1.5 °C. Reaching this aim should make it possible to significantly reduce the negative effects associated with climate change [5]. Most of the effects induced by changing weather and climate variables are often harmful and affect not only the living environment but also human health [6]. It is therefore necessary to consider climate change as an important determinant of health, particularly for people living or working in vulnerable areas [7,8]. In 2012, the World Health Organization (WHO) reported that 12.6 million deaths worldwide were attributed to climate change or climate change-related driving forces, representing 23% of deaths worldwide [9]. The relationship between weather or climate variables and water greatly amplifies the increase in health risks worldwide, but particularly in low- and middle-income countries. Many water-related diseases are transmitted to humans due to changing weather patterns, which promotes their increase [3,10]. Climate change influences or modifies the weather cycle. Cold- and heat-related illnesses caused by extreme temperatures are direct human health consequences of climate change, whereas other illnesses are caused by changes in ecosystems, i.e., illnesses related to air quality or water-related illnesses. Water-related diseases such as cholera, diarrhea, dysentery, skin diseases and typhoid are closely linked to climatic and environmental conditions [11,12].

Numerous studies have shown that short-term weather variations such as daily temperature, rainfall, heat waves, floods or humidity play a decisive role in triggering and amplifying waterborne disease outbreaks. Short-term temperature increases promote an increase in bacterial load, as well as the multiplication of *Vibrio cholerae* and other enteric agents in aquatic environments [13,14]. Intense rainfall and extreme events, such as floods and tropical cyclones, are also major meteorological factors that contribute to the contamination of water sources by runoff [15–17]. Beyond short-term weather variations, long-term climatic conditions defined by seasonal, semi-annual, interannual or decadal averages influence the spatial and temporal distribution of waterborne diseases. Climate anomalies associated with large-scale events, such as the El Niño–Southern Oscillation (ENSO) and prolonged droughts, have been identified as important drivers of cholera and diarrhea dynamics in several regions of the world [18–21]. These climatic phenomena modify sea surface temperature (SST) regimes, sea level change (SSH), precipitation and primary productivity (chlorophyll-a), thus creating favorable conditions for the proliferation of enteric agents and their transport to coastal environments [22,23].

Many existing studies use a wide range of statistical and modeling methods to study the relationships between weather, climate and waterborne diseases. Analytical approaches include classical statistical tests (Pearson, Spearman or Kendall correlations), linear and multiple regression models, as well as generalized models (GLMs, GLMMs) that have

shown a significant association between the different air or water variables and the incidence of cholera or infectious diarrhea on a daily, weekly or monthly scale [24–27]. To better capture nonlinear relationships and delayed effects, several studies have adopted generalized additive models (GAMs, GAMMs) and nonlinear distributed delay models (DLNMs), which are particularly suitable for analyzing effects with delays ranging from a few days to several months [28–31]. Other studies have relied on autoregressive time series models, such as the ARIMA, ARIMAX, SARIMA or SARIMAX models, to describe the seasonality and time dependence of waterborne disease cases [32–34]. Beyond these models, compartmental dynamic models (SIR and derivatives) have been used to represent the transmission mechanisms of waterborne diseases explicitly and to integrate environmental forcing into the epidemic dynamics [30,35]. More recently, algorithmic and machine learning approaches, such as classification and regression trees (CARTs), random forests, and clustering analyses, have been applied in studies to improve risk prediction and identify complex combinations of environmental variables associated with waterborne disease outbreaks [36–38].

Despite the abundance of work, synthetic and in-depth studies of this field are still limited. Therefore, this systematic review aimed to examine how variations in weather and climate factors influence water-related and climate-sensitive diseases (diarrhea, cholera and dysentery diseases), with a particular focus on the mathematical models and analytical methods used to study these associations. It also aimed to facilitate the identification and selection of robust and appropriate models for studying the relationships between climate and waterborne diseases in future research.

2. Materials and Methods

This systematic review was conducted in accordance with the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [39]. The study protocol is available in the PROSPERO database (ID: CRD420251073641), ensuring transparency and reproducibility of the process. In addition, the completed PRISMA checklist (Table S4) is provided as Supplementary Material.

2.1. Search Strategy

The studies included were selected based on the relevance of the subject, the type of publication (articles published in peer-reviewed journals), the language (English only) and the publication period (January 1996 to December 2023). The search was carried out using scientific search engines such as ‘Web of Science’, ‘PubMed’ and ‘Google scholar’. We conducted the searches between 19 and 22 February 2024. The combination of the different terms and keywords as presented in Figure 1 was searched in Web of Science. The complete search strategy was structured around three main areas of research (Figure 1):

- Axis 1: Analysis methods and models

This area aimed to identify studies using quantitative analysis approaches or modeling tools.

TS = (“model*” OR “correlation*” OR “regression*” OR “association” OR “time series*” OR “forecast*” OR “impact” OR “lag*” OR “mathematical model*” OR “statistical model*” OR “predictive model*” OR “simulation”)

- Axis 2: Waterborne disease

Human diseases or conditions transmitted by water or related to water contamination were addressed in this axis.

TS = (“waterborne disease*” OR “cholera*” OR “bloody diarrhea” OR “diarrhea” OR “dysentery”)

- Axis 3: Climate change variables and extreme weather events

Environmental and climate factors associated with variations in water quality or extreme events were taken into account in this axis.

TS = (“climate change” OR “weather” OR “temperature” OR “sea surface temperature” OR “salinity” OR “precipitation” OR “Rain*” OR “humidity*” OR “water level” OR “water quality” OR “atmospheric pressure” OR “wind” OR “vapor pressure” OR “sunshine” OR “drought” OR “flood*” OR “cyclone*” OR “heat wave” OR “El Nino” OR “chlorophyll” OR “river flow”)

The final search was a simultaneous combination of the three axes, i.e., #1 AND #2 AND #3. The records returned from the searches, therefore, included at least one term from all three sets (Figure 1). From these different combinations, we revised the search strategy to obtain additional publications and search more databases.

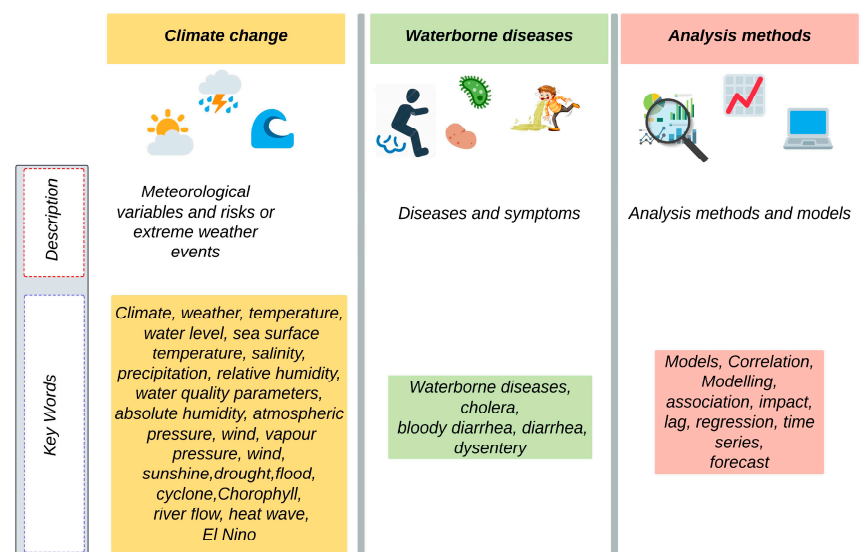


Figure 1. The list of keywords that was used to select the literature.

2.2. Data Extraction

Data extraction was performed using search terms and selection criteria, stored in a Microsoft Excel file for sorting. Subsequent processing was performed using the “Biblioshiny” tool from the “bibliometrix” package in R software. The data extracted from the included studies are as follows:

- General data: title, authors, affiliations, year of publication, total number of citations, journal, country of the main author, keywords and location of the study.
- Description of the disease and climate factors: type of diseases, context and climate variables or factors.
- Model methodology: model (compartmental, agent-based, etc.), model type (population/individual, deterministic/stochastic, dynamic/static), data integration (parameters, calibration) and validation.
- Model description: objective, main results, strengths, limitations and conclusions.
- Additional results: sensitivity analyses and uncertainty analyses.
- Metadata: software used, funding and potential conflicts of interest.

3. Results and Discussion

3.1. Distribution of Included Studies

Of 48,532 articles, 48,345 were excluded based on title, themes, and abstract screening, with 109 more excluded during full-text screening. Ultimately, 78 studies were included

in the review. A summary of the exclusion process is presented in Figure 2. Publications were identified for review during the screening process. We removed publications that were duplicates in the database. A filter was then used to select articles dealing with the analytical and modeling aspects of the impacts of climate change on water-related diseases. In the same process of filtering and excluding publications from the database, eligibility assessment was limited to titles and abstracts. Next came the full texts, which were carefully examined for a more in-depth assessment of the subject (Figure 2).

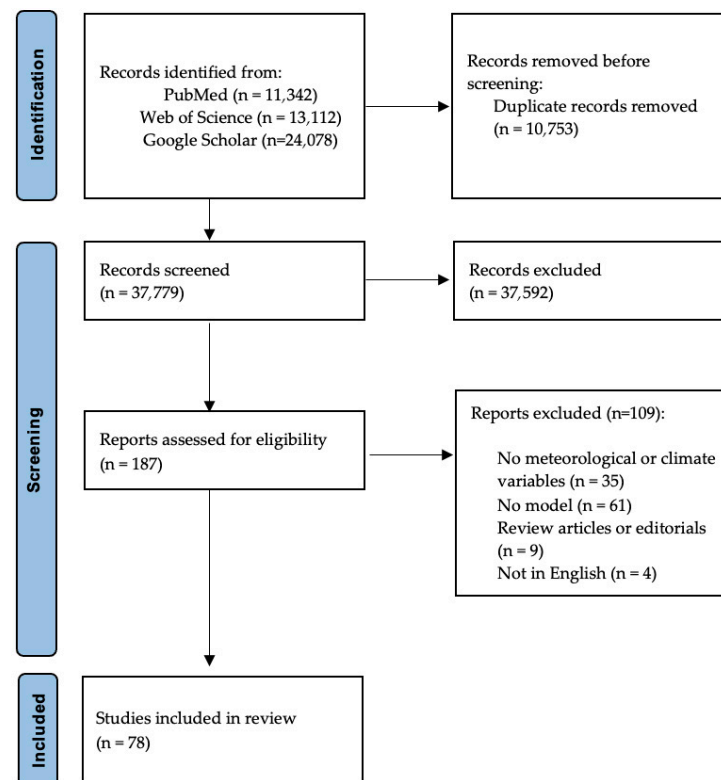


Figure 2. PRISMA (Preferred Reporting Items for Systematic Review and Meta-Analysis) diagram illustrating the systematic process of article selection.

Table 1 provides descriptive information on the 78 articles that met the inclusion criteria. The articles were published in 43 journals indexed by Web of Science, PubMed and Google Scholars, with an average number of citations per document of 46.56. The papers were written by 448 authors, of whom only 3 were sole authors of the papers, while the remaining 445 authors produced collaborative papers (Table 1).

Table 1. Main data information of the articles included in the review.

Description	Results
Times	1996:2023
Sources (journals, books, etc.)	43
Articles	78
Average # of citations per articles	46.56
# of references	2243
# of authors	448

Table 1. Cont.

Description	Results
# of authors of single-authored articles	3
# of single-authored articles	3
Average # of co-authors per article	6.99

Furthermore, in our study, cholera was the most common condition ($n = 41$, 50.6%), followed by diarrhea ($n = 26$, 32.1%) and finally dysentery ($n = 14$, 17.3) (Table S1). The majority of countries where the waterborne disease studies were conducted were in Asia (China, Bangladesh and India) and America (United States of America), followed by Africa (Tanzania, Zimbabwe, Uganda), Australia and Europe (Figure 3).

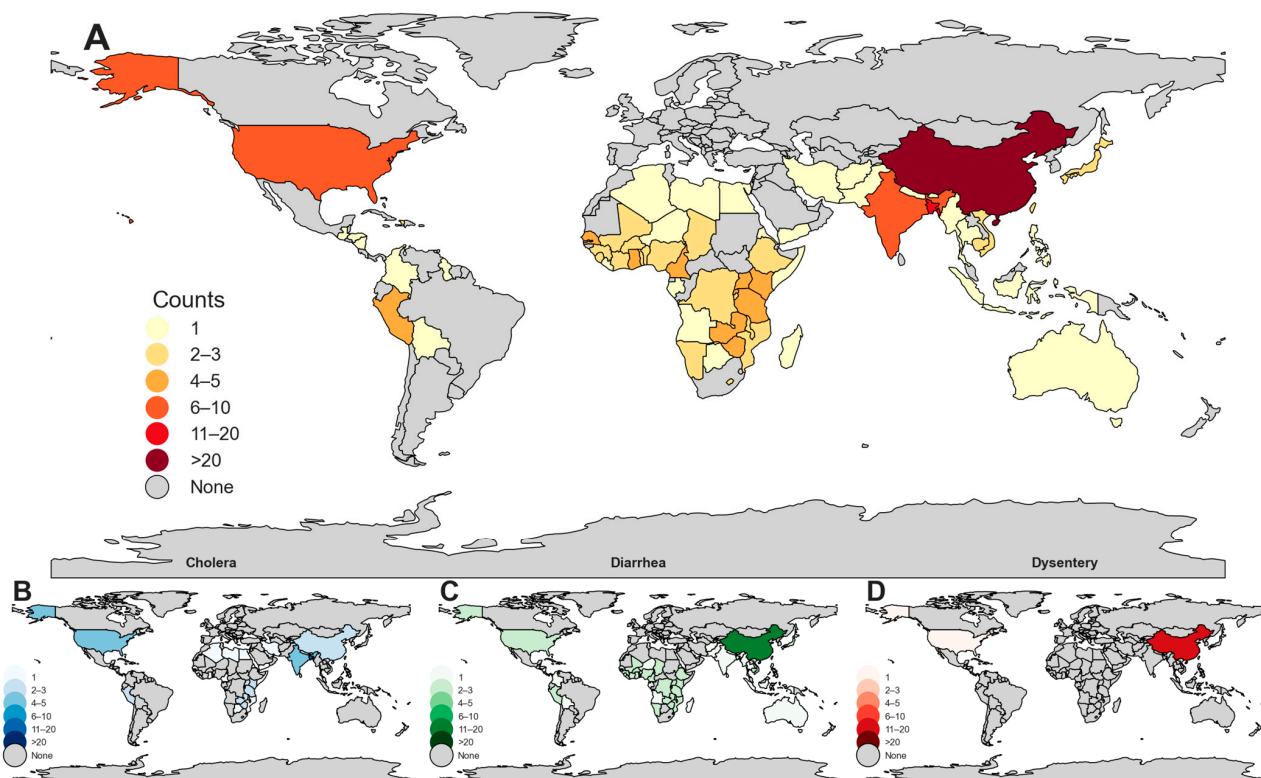


Figure 3. Geographic distribution of included studies by country (A), cholera (B), diarrhea (C) and dysentery (D).

3.2. Climate Variables

Several authors have dealt with many climate parameters or variables and extreme weather events. Thus, the climate variables that have been considered in the works reviewed are divided into three subgroups: meteorological and climate variables or parameters, hydrodynamic variables (linked to rivers or estuaries) and finally oceanic variables. All these variables are associated with climate-sensitive and waterborne diseases (cholera, dysentery and diarrhea in Figure 4).

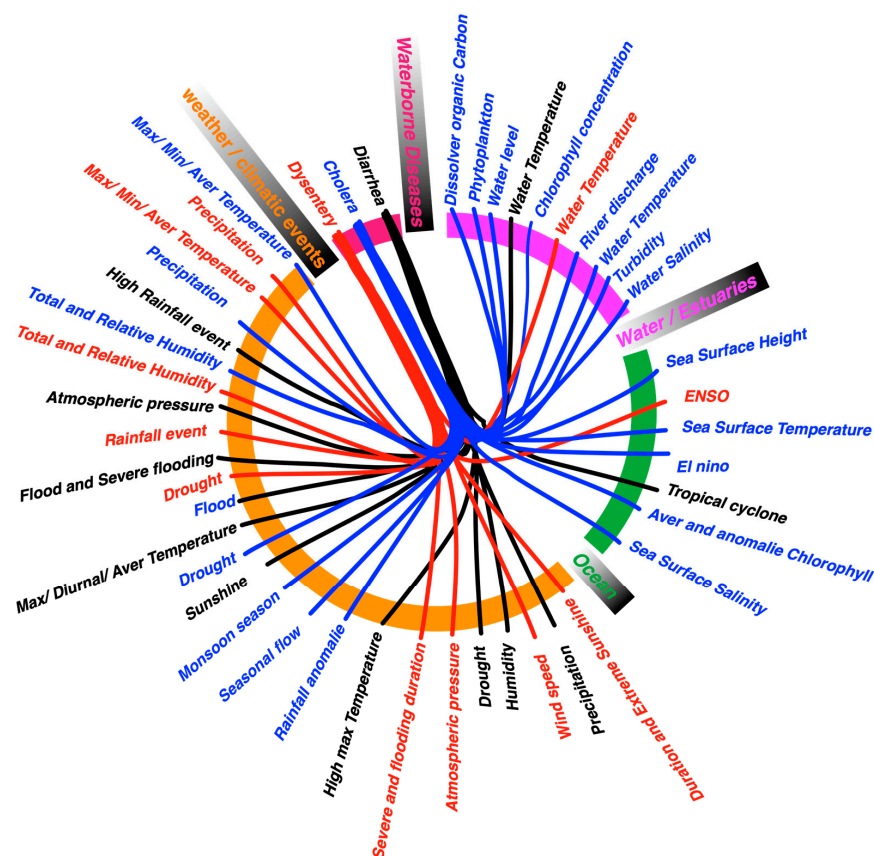


Figure 4. Maps of the semantic network of thematic attributes for diarrhea, cholera and dysentery. The literature was published between 1996 and 2023 on climate change for waterborne diseases. Note: The map should be read counter clockwise; the thematic aspects are arranged concentrically and color-coded (waterborne disease = red; weather/climatic events = orange; ocean variable = green; water/estuary variables = purple). Diseases at the top left of the circle are colored and establish links with other terms, represented by barbs that refer to terms of the same color.

3.2.1. Meteorological Variables and Climate Factors

Several weather and climate variables were used by the authors to assess the impact of climate on waterborne diseases.

Air temperature is an important climate factor and is widely studied as a variable, including minimum, maximum, diurnal and mean temperatures over annual, seasonal, monthly, weekly and daily periods. Half of the articles ($n = 39$, 50%) examined the relationship between the incidence of waterborne diseases and this air temperature, with 23.1% referring to cholera, 16.7% to diarrhea and just 10.2% to dysentery (Figure 5, Table S2). The results of two studies on cholera show that positive variability in cholera incidence is associated with increasing temperature [33,40]. Three different studies have shown that increasing the temperature, minimum temperature and maximum temperature by 1 °C respectively in Zanzibar in East Africa [34], Matlab [32] and Dhaka [33] in Bangladesh increases cases of cholera. The presence or abundance of cases of bacillary dysentery is strongly influenced by average temperature [41]. A temperature of 29 °C could influence cholera cases depending on the season in the province of Kolkata in India [42]. Studies carried out on diarrhea in Brisbane showed a statistically significant relationship between daytime temperature and childhood diarrhea [43], while in Tongcheng Province in China, an increase in daytime temperature during the warmer seasons had an impact on the number of daily cases of diarrhea, which was not the case in the colder seasons. This air temperature is highly correlated with the incidence of the disease in this region. A study

carried out in Chaoyang during the period from 1991 to 1997 showed a good correlation between temperature and dysentery [44]. Diarrhea and cholera were significantly well correlated with temperature, as demonstrated by studies conducted in Jiangsu [31], Peru [45] and Kolkata [42], confirming the predictive capacity of the model used. Two additional studies showed that temperatures are significantly correlated with increases in cholera cases in Bengal and Vellore, as well as in Bangladesh and Vietnam [46].

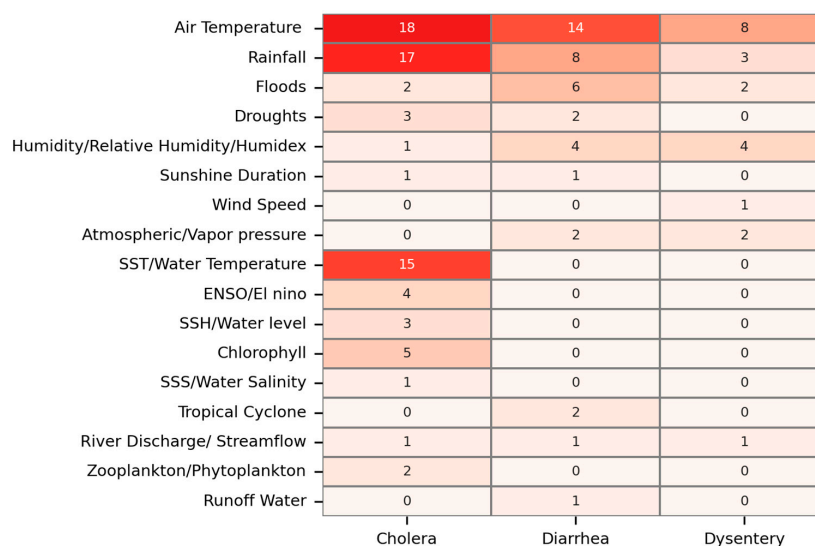


Figure 5. Heatmap of climatic variables and factors used in the literature.

Rainfall is also a major determinant and indicator of climate-sensitive diseases [47–50]. Thus, more than a third of the articles ($n = 28$, 35.9%) showed an association between rainfall and these diseases, revealing the usefulness of this variable (Figure 5). The daily recording of diarrhea cases in children under the age of five in Rwanda showed that diarrhea was strongly linked to heavy rainfall [49]. Regarding cholera, there is a strong correlation between rainfall patterns and this disease. This association has been shown in West Africa, Tanzania [34], Kolkata, India [22], Bangladesh [47] and Cameroun [51]. A correlation of 0.43 was found between rainfall and the incidence of cholera in Dhaka between 2000 and 2013 [33]. In fact, two studies in 2013 showed an increased risk of cholera caused by heavy rainfall in Peru [52] and Haiti [30]. In India, on the other hand, the incidence of cholera was negatively correlated with rainfall over a long study period [53]. A study carried out in Iran [54] also showed that cholera cases were significantly linked to lower rainfall from July to December. Studies carried out in Beijing and Wuhan in China showed that increases or extreme variations in rainfall are conducive to a high incidence of bacillary dysentery [41,55]. An intermittent average rainfall of 10 cm can influence cholera cases depending on the season in Kolkata Province in India [42]. In some cases, rainfall has been influenced by El Niño Southern Oscillation (ENSO) events that impact disease occurrence. Rainfall is also due to tropical cyclones, which is also a risk factor for these diseases. Deng et al. [48] showed in their study that when rainfall reaches or exceeds 25 mm and 50 mm, respectively, there is an increased risk of diarrhea-related disease.

Humidity is another determining climate factor that has an impact on climate-sensitive diseases [38,41,55]. Humidity, relative humidity and humidex all influence these diseases, as nine articles in our study reveal their intrinsic relationship with these diseases, especially diarrhea ($n = 4$, 5.12%) and dysentery ($n = 4$, 5.12%) (Figure 5). A study on bacillary dysentery in Kon Tum Province [56] showed that a 1% increase in humidity was associated with a 1% increase in this disease. Higher relative humidity (>80%) can influence cholera cases seasonally in Kolkata Province, India [42]. In addition, humidity synchronized

with other climate factors (temperature, sunshine and rainfall) can affect the spatial and temporal distribution of these diseases [29,57]. In Nigeria, temperature and rainfall played an important role in explaining the spatial and temporal dynamics of cholera, but so does relative humidity [58].

Floods are one of the natural disasters increasingly faced worldwide today. Flooding is also one of the environmental phenomena most closely linked to diseases ($n = 10$, 12.8%) according to our studies, with a significant effect on diarrhea ($n = 6$, 7.7%) (Figure 5). The floods that occurred in 1998 in Jiangxi Province, China, increased the dysentery morbidity rate in that region in 1999 by 74.85% compared to the rates in the previous year [28]. The increase in cholera cases in Bangladesh during the period of 1979–1995 [59] and a significantly increased risk of bacillary dysentery in Dalian [60] are also associated with flooding. The impact of floods on disease depends on the duration and extent, volume and space occupied by the flood. The volume of flooding and the extent of the areas affected during the different seasons of the year in the Bengal Delta region are responsible for the cholera epidemics observed between 1980 and 2000 in this region [61]. Use of a Poisson regression model by Saulnier et al. [62] showed a three-month lag between flooding and the high risk of skin infections and diarrheal disease in Cambodia. In addition, concerning the magnitude of flooding, moderate and severe flooding can significantly increase the risk of diarrhea in one week depending on the region [27] and the incidence of bacillary dysentery. Liu showed in one of his 2017 studies that the relative risks associated with moderate and severe flooding on the incidence of dysentery in Guangxi Province in China were 1.40 and 1.78, respectively, over the period 2004 to 2012.

Drought is one of the environmental factors influencing waterborne and climate-related diseases. However, the effect of drought varies according to the type of disease, with 7.9% of articles showing these effects, which should not be overlooked (Figure 5). During drought, a reduction in humidity is often observed. An increased risk of diarrhea due to drought caused by climate change in the South-Saharan region was shown by Wang and his group in their study in 2022 [63]. However, drought can affect disease incidence by compromising water quality. Poor water quality at springs can increase the prevalence of disease in humans, particularly in children under five [64]. In relation to dysentery, one study indicated that a significant increase in drought in Shandong Province was associated with the risk of dysentery with a lag of 3 months [65]. Studies carried out in the provinces of China have revealed that atmospheric pressure is a climate factor that affects the incidence of diarrhea in the provinces of Fujian [66] and Jiangsu [38], but it also influences bacillary dysentery [67]. Vapor and atmospheric pressure were revealed in four articles as important variables in the study of these diseases. They were used to explain cases of bacillary dysentery in Beijing between 1970 and 2016 [68]. Yan and his group focused on wind speed associated with other factors to explain the number of cases of bacillary dysentery in Jiangsu in China [55]. Area fluxes were also used in a study carried out in Chaoyang Province in China, to quantify the risks associated with the incidence of bacillary dysentery over a 30-year period (1981–2010).

The sunshine duration of solar activity also influences diseases such as diarrhea and cholera. In Bangladesh, solar activity between 1980 and 1998 was negatively correlated with the incidence of cholera [69], while the study by [36], conducted between 1989 and 2005, showed that, in the same country, the monthly incidence of cholera was positively associated with sunshine duration. In most cases, sunshine is associated with temperature [44,50].

3.2.2. Hydrodynamic Variables

Certain hydrodynamic or water-related variables, such as rivers and estuaries, are used to quantify the impact of climate on diseases. In this study, the association between cholera incidence and water temperature ($n = 3$, 3.8%), water salinity ($n = 1$, 1.3%), river discharge or streamflow ($n = 3$, 3.8%) and zooplankton or phytoplankton ($n = 2$, 2.5%) was assessed (Figure 5).

There is a correlation between water temperature and the presence or abundance of diseases. This correlation was shown in the study of the incidence of cholera in Haiti [35]. A significant association is highlighted between the risk of cholera transmission and climate factors such as water temperature [70]. On the other hand, a study conducted in Vietnam between 1983 and 2003 revealed that the rise in river levels associated with river discharges was significant and had positive effects on the distribution of cholera in Nha Trang, a city in Vietnam [46]. In Bangladesh, two scenarios were observed during cholera epidemics between 1890 and 2000; a first phase in autumn when cholera epidemics were positively correlated with flow and a second in spring where they were negatively correlated with flow [61]. A study carried out in Peru showed a strong correlation between river flow and the incidence of cholera [52]. In Bangladesh, however, this relationship was negative [46,61]. Vertical mixing, tidal effect, tide and nutrient loading can modify the microbial community by affecting water quality, which is also a factor influencing climate-sensitive and waterborne diseases [51]. Nutrients and phytoplankton are also variables that have impacts on diseases [71]. Hsieh in his study on the Neuse River estuary emphasizes the strong relationship between salinity and temperature with the additional influences of chlorophyll-a and dissolved organic carbon while using analytical methods to see their impact on disease [14].

3.2.3. Ocean Variables

Sea surface temperature (SST) is an ocean variable that often influences the presence, abundance or transmission of diseases in coastal areas [22,32,59,72,73]. It should be noted that 12 studies (15.4%), which focus solely on cholera cases, show this influence (Figure 5). Studies have shown a good correlation between SST and cholera incidence in coastal areas of Peru [52] and Bangladesh [59,69,72]. The increase in cholera cases in Bangladesh between 1979 and 1995 was found to be associated with an increase in SST [72]. Sea surface temperature anomalies are parameters that have an impact on disease incidents. Between 1975 and 1995 in Ghana, it was observed that the incidence of cholera cases was strongly associated with land and sea surface temperature anomalies [16]. In his 2009 study, Paz found that a 1 °C increase in SST in certain South-East African countries could lead to a 1.31-fold increase in the cholera rate [25]. Seasonal SST also influences the variability of cholera cases, such as found in Bangladesh [46].

Sea Surface Height (SSH) is often associated with SST to explain or assess the effects induced by climate change in coastal areas. Only 3.8% ($n = 3$) of the articles address these effects and all focus on cholera cases. In the coastal area of Nha Trang, Vietnam, there was a significant correlation between SSH and the incidence of cholera, while in the Hue region, the increase in SST had a greater influence on epidemics [46]. SSH during the pre-monsoon period was negatively correlated with cholera incidence in Bangladesh. Furthermore, in Tanzania, SSH was not found to correlate with cholera disease [34]. Xu et al., in their study carried out in China, also showed that the incidence of cholera was strongly influenced by both SST and SSH [73].

Chlorophyll concentration is one of the variables used to assess cholera incidents ($n = 5$, 6.4%). The various studies conducted on chlorophyll concentration and the incidence of disease were well correlated. The prevalence of cholera cases showed a significant

relationship with chlorophyll concentration in coastal Bangladesh [72]. In addition, the incidence of cholera in both Bangladesh and India showed significant relationships with the variability of chlorophyll concentration in the ocean [22]. In addition, chlorophyll concentration during the pre-monsoon period was positively correlated with cholera incidence in Bangladesh [46]. Chlorophyll concentration in China's coastal ocean is not significantly associated with cholera incidence but shows a one-month lag effect with disease cases [73].

The El Niño Southern Oscillation (ENSO) is a phenomenon that causes oceanic changes and extreme meteorological events. A rate of 5.1% ($n = 5$) of articles highlights their relationship with waterborne diseases. In the analysis carried out in Bangladesh by Pascual et al., over the period from 1980 to 1998, the impact of variations in the atmospheric circulation of South Asia on regional SST anomalies was demonstrated, and this phenomenon was subsequently shown to influence the incidence of cholera in the coastal region [18]. Rodo et al., in their study, confirmed the strong association between cholera incidence and ENSO between 1980 and 2001 [19]. The increase in the number of cholera cases in Bangladesh following the rise in sea surface temperatures corresponds to the ENSO event [59]. In Peru, the rise in air and sea surface temperatures, as well as the increase in rainfall and the decrease in maximum temperature observed during El Niño events, led to an increase in cholera cases [74].

Tropical cyclones or typhoon hurricanes also have an impact on disease. These events are not common, with only 2 out of 78 articles (2.6%) demonstrating their link to disease. Deng et al. showed that rainfall from tropical cyclones is also a risk factor for diarrhea when it reaches or exceeds 25 mm and 50 mm, respectively [48]. The proliferation of tropical cyclones may increase the risk of infectious diarrhea [75].

3.3. Analysis Methods and Modeling Approaches

The studies included in this systematic review employed a wide range of analytical methods and models to investigate associations between climatic and meteorological variables and waterborne diseases. These approaches can be broadly classified into exploratory association analyses, variable selection and sensitivity assessment methods, and statistical or mathematical models for inference and prediction. Together, these methods serve three main purposes: (i) identifying potential climate–disease relationships, (ii) prioritizing influential climatic drivers while accounting for multicollinearity and lag effects, and (iii) quantifying risks and predicting disease incidence under varying climatic conditions (Figure 6; Table S3).

3.3.1. Exploratory Association and Sensitivity Analyses

Correlation-Based Association Methods

Correlation analyses were widely used as initial exploratory tools to assess the strength and direction of associations between climatic variables and waterborne disease incidence. Pearson, Spearman, and Kendall correlation coefficients were the most frequently applied methods, together accounting for more than 19% of the analytical approaches identified in the reviewed studies.

Pearson correlation analysis was commonly used to evaluate linear relationships between continuous climatic variables and disease incidence. Several studies reported significant positive correlations between temperature or humidity and diseases such as cholera and dysentery, often incorporating lag structures to reflect delayed effects. For example, temperature and humidity were shown to be positively correlated with dysentery incidence with a one-month lag, while sunshine duration exhibited a negative association in some

settings [51]. Similar approaches were applied in studies conducted in Bangladesh to assess associations between temperature, rainfall and cholera incidence among children [47].

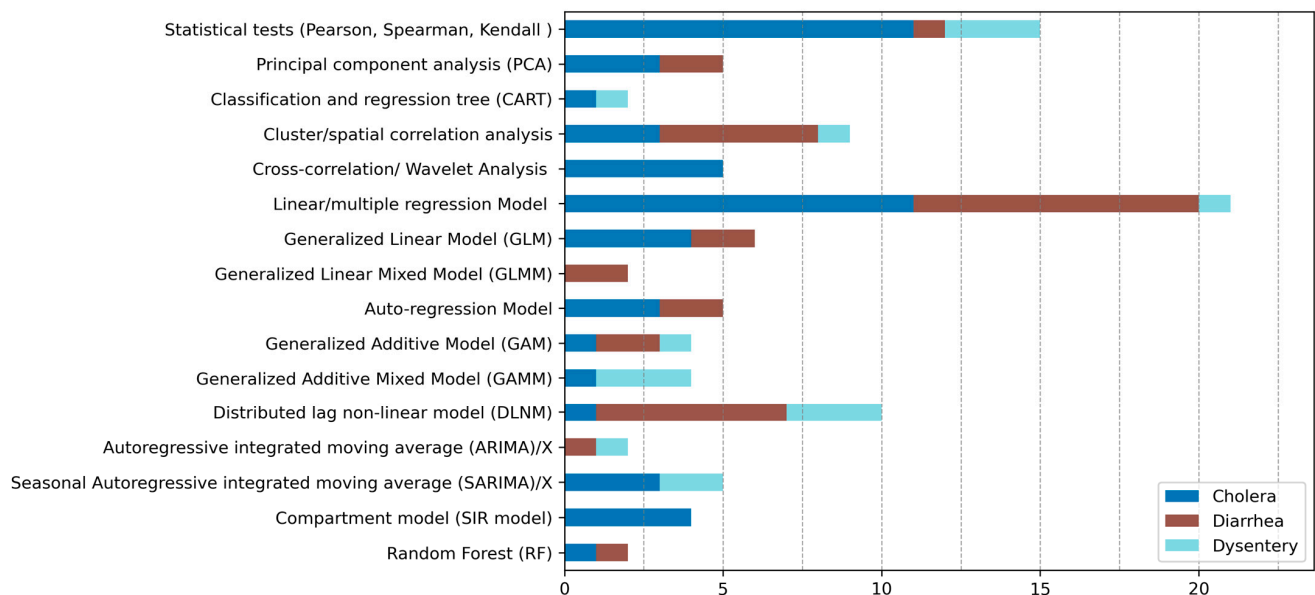


Figure 6. List of data analysis methods used in the relationships between climate variables and waterborne diseases.

Spearman's rank correlation coefficient was frequently employed when the relationships between variables were non-linear or when data did not meet parametric assumptions. This method was particularly useful for detecting monotonic associations and was often combined with other analytical techniques. Studies in Peru, Bangladesh, and China used Spearman correlation to demonstrate associations between sea surface temperature, flooding, and cholera incidence, highlighting both immediate and lagged climatic effects [45,59,73].

Kendall's tau correlation was used less frequently but provided complementary insights by assessing concordant and discordant pairs of observations. In some studies, Kendall and Pearson correlations were jointly applied to examine the role of seasonality, river flow, and flooding in cholera transmission, reinforcing evidence for climate-sensitive disease dynamics [61].

Overall, correlation-based methods were primarily used for hypothesis generation and preliminary screening of climatic variables prior to more advanced modeling.

Multivariate Sensitivity and Variable Screening Techniques

Beyond pairwise correlations, several studies applied multivariate techniques to identify the most influential climatic factors and to address multicollinearity among predictors. These methods were particularly valuable in complex environmental systems, where multiple, interrelated climate variables may jointly influence disease transmission.

Principal component analysis (PCA) was widely used to reduce data dimensionality and to transform correlated climatic variables into a smaller set of uncorrelated components [48,75,76]. PCA-based studies in China demonstrated that extreme weather events such as typhoons, tropical storms, and cyclone-induced precipitation significantly increased the risk of diarrheal and dysenteric diseases [48]. Similar findings were reported in other regions, where temperature, rainfall, and humidity emerged as dominant components influencing disease transmission [75,76].

Covariate-adjusted cluster analysis was applied to classify geographic areas or climatic conditions according to shared characteristics. For instance, studies in West Africa used this approach to identify clusters of increased childhood diarrheal risk associated with warmer, drier climates and, in some cases, regions experiencing intense rainfall [77].

Classification and regression tree (CART) analysis was used to explore non-linear interactions and threshold effects among climatic variables. CART models, sometimes combined with PCA, revealed synergistic effects of temperature, sunshine duration, humidity, and air pressure on cholera and other waterborne diseases [36,67]. These methods were particularly useful for identifying critical climatic thresholds associated with abrupt increases in disease incidence.

Collectively, these multivariate approaches supported the identification of key climatic drivers and informed the specification of subsequent statistical and predictive models.

3.3.2. Statistical and Mathematical Models for Inference and Prediction

Most studies investigating climate–waterborne disease relationships relied on statistical or mathematical models to quantify associations, assess lagged and non-linear effects, and generate short- or long-term predictions. These models can be grouped into four main categories: regression-based models, time-series models, non-linear and distributed lag models, and machine learning or mechanistic models.

Regression-Based Models

Regression-based approaches, particularly Poisson regression and generalized linear models (GLM), were widely used to analyze count data on disease incidence. These models were often adapted to account for overdispersion through quasi-Poisson specifications or extended to generalized linear mixed models (GLMMs) to incorporate random effects and spatial or temporal heterogeneity [63,66].

Several studies used Poisson or quasi-Poisson regression models to demonstrate significant associations between temperature, rainfall, flooding, and waterborne disease incidence, often identifying lag periods ranging from days to several months [50,51,62]. GLM-based analyses were also used to examine large-scale climate indices, such as the El Niño–Southern Oscillation (ENSO), revealing delayed and sometimes negative associations with diseases like dysentery [78]. In flood-related studies, regression models highlighted immediate and short-term increases in diarrheal disease risk following extreme precipitation events [22].

Time-Series Models

Time-series models were extensively applied to capture temporal dependence, seasonality, and short-term forecasting of disease incidence. Autoregressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA) models, often extended with exogenous climatic variables (ARIMAX, SARIMAX), were particularly common.

These models were used to assess the effects of temperature, rainfall, and other meteorological variables on cholera and dysentery incidence in Asia and other regions [32,33,55]. SARIMA-based studies consistently demonstrated strong seasonal patterns and significant positive associations between climatic variables and disease incidence [79]. In several cases, time-series models were combined with correlation analyses to improve model specification and interpretability [80]. Overall, ARIMA- and SARIMA-based approaches were valued for their strong short-term predictive performance.

Non-Linear and Distributed Lag Models

To address non-linear exposure–response relationships and delayed climatic effects, many studies employed Distributed Lag Non-Linear Models (DLNMs), Generalized Additive Models (GAMs), and Generalized Additive Mixed Models (GAMMs).

DLNMs were particularly effective in simultaneously modeling non-linearity and lagged effects of temperature and precipitation on diarrheal diseases [31]. Studies across East Asia demonstrated statistically significant lagged associations between extreme temperatures and childhood diarrhea, with lag periods extending up to several weeks [43].

GAM and GAMM approaches allowed flexible smoothing of climatic predictors and were widely used to capture complex, non-linear relationships. GAMMs further enabled the inclusion of random effects, improving model fit and predictive accuracy in multi-site or long-term studies. These models consistently identified temperature, rainfall, and humidity as key drivers of waterborne disease risk, with strong evidence of delayed effects [41,68,81,82].

Machine Learning and Mechanistic Models

A smaller subset of studies employed machine learning techniques, such as random forest models, to capture complex interactions among climatic variables without strong parametric assumptions. Although less frequently used, these approaches demonstrated promising predictive performance [37,38].

Mechanistic compartmental models, including Susceptible–Infected–Recovered (SIR) frameworks, were applied to simulate disease transmission dynamics under varying climatic conditions [20,30,35,45]. These models provided valuable insights into the underlying processes linking climate variability and disease spread, complementing purely statistical approaches.

3.3.3. Synthesis and Implications for Short- and Long-Term Prediction

Overall, the reviewed literature reveals a methodological gradient aligned with the temporal scale of interest in climate–health analyses (Table 2). Short-term predictions, typically associated with weather variability and seasonal fluctuations, were most effectively addressed using time-series and regression-based models, including Poisson regression, ARIMA/ARIMAX, SARIMA/SARIMAX, and distributed lag non-linear models (DLNM). These approaches are well suited for early-warning systems, as they explicitly account for temporal autocorrelation, seasonality, and delayed effects of meteorological variables such as temperature, rainfall, and flooding. In particular, SARIMA-based models and DLNM demonstrated strong short-term predictive performance in forecasting cholera and diarrheal disease incidence at weekly to monthly horizons, supporting their application in operational public health surveillance.

In contrast, longer-term projections, relevant to climate change impact assessments, relied more heavily on flexible regression frameworks and non-linear models, including generalized additive models (GAMs), generalized additive mixed models (GAMMs), and, to a lesser extent, mechanistic compartmental models. These approaches are better suited to capturing gradual shifts in exposure–response relationships, non-stationarity, and interactions among climatic drivers over multi-year to decadal time scales. GAMs and GAMMs, in particular, were frequently used to explore how sustained changes in temperature, precipitation patterns, and extreme weather frequency may alter baseline disease risk, while mixed-effects structures allowed for spatial heterogeneity and long-term trends.

Table 2. Summary of analytical methods or approaches identified in the studies reviewed, highlighting their main objectives, analytical frameworks, time scales (weather vs. climate), assumptions, limitations, and applications in the study of waterborne diseases.

Method/Model	Analytical Approach	Main Objective	Time Frame (Short/Long-Term)	Key Assumptions	Limitations	Main Use	Reference
Statistical tests (Pearson, Spearman, Kendall)	Bivariate analysis	Measure the strength and direction of the association between climate and health variables.	Short-term/long-term	Pearson: linearity, normality; Spearman/Kendall: monotonic relationships.	Lags, seasonality, spatiality, prediction, causality	Useful for an initial exploration of the relationships between climate and health variables, but insufficient on their own.	[15,17,23,24,45,47,70,83–88]
Principal component analysis (PCA)	Multivariate analysis	Reduce dimension and identify dominant environmental gradients.	Short-term/long-term	Linearity and multicollinearity	Difficulty of interpretation, loss of information	Complementary exploratory tool highlighted to reveal the dominant structures associated with risks.	[19,36,48,75,89]
CART (Classification and regression tree)	Multivariate analysis	Classify or predict incidence and risk.	Short-term/long-term	Relative independence of observations	Instability, overfitting	Good exploratory tool for identifying decision rules that influence diseases.	[36,67]
Cluster/spatial correlation	Multivariate and spatial analysis	Identify clusters based on their similarity.	Short-term/long-term	Measurement of similarity, stationarity, spatial dependence	Sensitive to the chosen scale, data noise	Shows the heterogeneity and spatial trend of health risks.	[54,77,90–95]
Cross-correlation/Wavelet	Multivariate, temporal and frequency Analysis	Identify temporal dependencies, periodicities and transient modes of variability.	Short-term/long-term	Existence of a relationship (linear or otherwise) and a measure of similarity	Sensitive to outliers /edge effects ('cone of influence')	Useful for quickly quantifying the response time between environmental variables and diseases.	[16,17,54,69,96]
Linear/multiple regression Model	Multivariate analysis	Identify and quantify the influence of variables on diseases.	Short-term/long-term	Linearity, independence, homoscedasticity, normality, absence of multicollinearity	Excessive simplification, sensitivity to outliers, causality	Provides a simple estimate of the effects of environmental variables on diseases.	[8,14,18,25,26,46,49–52,57,62,70,74,75,88,92,97–100]
GLM	Multivariate analysis	Quantify and predict the relationship between a climate variable and diseases.	Short-term/long-term	Specific distribution of residues, independence, linearity	Complex relationships, stationarity	Improves modeling and estimation of disease cases.	[21,22,27,43,60]
GLMM	Hierarchical/mixed multivariate analyses	Quantify and predict the relationship between a climate variable and diseases.	Short-term/long-term	Residual independence, specific distribution of residuals, linearity	Complexity, sensitivity to the choice of random effects structure	Robust spatio-temporal approach to estimating disease cases.	[63,66]
Autoregressive models	Multivariate analyses	Capture temporal dependence, understand dynamics and predict diseases.	Short-term/long-term	Stationarity, linearity, independence of residuals	Poor performance for non-linear relationships, sensitivity to missing data	Robust method for statistical disease prediction.	[32–34,99,101]

Table 2. Cont.

Method/Model	Analytical Approach	Main Objective	Time Frame (Short/Long-Term)	Key Assumptions	Limitations	Main Use	Reference
GAM	Multivariate analyses	Model and predict non-linear relationships between environmental factors and disease.	Short-term/long-term	Stationarity, additivity, data distribution	Concurvity, limited interactions, multicollinearity	Method for analyzing non-linear relationships in environmental and climate data for disease prediction.	[13,28,41,66]
GAMM	Multivariate analyses	Model and predict non-linear relationships between environmental factors and disease, taking random effects into account.	Short-term/long-term	Additivity, data distribution, residual independence	Computational complexity, more complex interpretation	Method well suited to environmental and climate data for disease prediction.	[68,81,82,90]
DLNM	Multivariate analyses	Estimate delayed or non-delayed effects between environmental and climatic factors and disease.	Short-term/long-term	Delay effect, adjustment of factors, stationarity	Over-adjustment, model complexity	Identify critical thresholds and essential temporal vulnerability windows associated with diseases for the implementation of early warnings.	[28–31,43,102–106]
ARIMA/X	Univariate/multivariate analyses	Predict disease cases and outbreaks based on historical data or environmental and climatic variables.	Short-term/long-term	Stationarity, linearity, residual independence	Seasonality, long-term forecasting	Reliable short-term forecasts that are useful for disease monitoring and early-warning systems.	[38,55]
SARIMA/X	Univariate/multivariate analyses	Identify patterns, trends, and seasonality to predict disease cases based on historical data or environmental and climatic variables.	Short-term/long-term	Stationarity, linearity, residual independence	Parameter complexity, long-term forecasting	Reliable short-term forecasts that are useful for monitoring diseases, especially seasonal ones, and setting up early-warning systems.	[32–34,80,87]
Compartmental models (SIR)	Univariate/multivariate analyses	Understand disease transmission dynamics.	Short-term/long-term	Homogeneous population, constant parameters	Excessive simplification, dependence on data	Approach linking climate, transmission and disease spread dynamics, providing information for public health policy.	[20,30,35,45]
Random forest (RF)	Univariate/multivariate analyses	Predict disease cases while identifying the most important variables in the prediction.	Short-term/long-term	Independence of samples, uncorrelated variables between trees, data quality	Complexity and interpretability, computational intensity	Robust prediction models that generally offer excellent predictive performance for disease cases.	[37,38]

Mechanistic models, such as SIR-type compartmental frameworks, offer additional advantages for long-term climate change scenarios by explicitly representing transmission processes and enabling simulation under hypothetical climatic conditions. However, their use remains limited, partly due to data requirements and model complexity. Machine learning approaches, while showing promise for short-term prediction, were infrequently applied to long-term climate projections, highlighting an important methodological gap.

Taken together, the findings suggest that no single modeling framework is optimal across all temporal scales. Time-series and DLNM approaches are most appropriate for short-term, weather-driven prediction and outbreak preparedness, whereas GAMs, GAMMs, and mechanistic models are more suitable for assessing long-term climate change impacts on waterborne disease dynamics. Future research would benefit from hybrid modeling strategies that integrate short-term predictive accuracy with long-term scenario-based inference, thereby strengthening climate-informed public health decision-making.

4. Recommendations

Based on the findings in this review, we recommend the following aspects for future studies.

- (1) Climate change variables (meteorological, hydrological, oceanic) as well as extreme events must be taken into account in impact studies relating to diarrheal diseases and waterborne diseases. This would make it possible to better identify the most important and sensitive predictive factor(s) for the prediction of climate–disease relationships on the transmission dynamics of these diseases.
- (2) It is necessary to carry out spatiotemporal studies over as long a period as possible in order to better identify the impacts of climate change on these diseases, while taking account of socio-economic development and population growth.
- (3) All climate factors or events that have been identified as influencing disease incidence in a study area should be systematically considered, if possible, in the same area in future studies. The results of this study could support a more efficient selection of variables.
- (4) It is essential to select appropriate methods of analysis (mathematical models) for the impact study to be carried out, considering the data/variables available, and the disease(s) of concern to make an accurate projection over time.
- (5) Applying several methods or combinations or associations of models could also be used to improve accuracy and reliable prediction of events and health risks.

5. Conclusions

This systematic review is a synthesis of 78 international research studies on the associations and impacts of climate change on water-related and climate-sensitive diseases. Changes in climate variables and events (temperature, precipitation, humidity, sunshine duration, flooding, drought, atmospheric pressure), hydrodynamic variables (water temperature, river flow, nutrients, water level, salinity, chlorophyll, turbidity) and oceanic variables (SST, SSH, chlorophyll) can affect the presence and/or abundance and transmission dynamics of diseases such as diarrheal disease caused by a range of pathogens, cholera and dysentery through mechanisms involving, e.g., vectors, pathogens and the ecosystem. Several methods of analysis and study of impacts (sensitivity analyses and mathematical models) are adopted to study the different associations between the presence or abundance of diseases according to climate change variables. Sensitivity analysis methods are those used to detect the sensitivity of different diseases to climate change, based on correlations. Mathematical models, on the other hand, provide more quantitative representations of the correlations between different climate variables and diseases, and enable the effects of

different factors to be assessed. However, various analytical approaches have been used to study these associations. Sensitivity analyses help identify correlations and assess the responsiveness of specific diseases to climate variables. Mathematical models provide more robust quantitative frameworks for assessing the impact of multiple climate factors on epidemiological patterns. Combining models, such as GAMs with GAMMs or GLMs with SARIMA, has proven particularly effective in capturing complex dynamics and improving forecast accuracy. Indeed, despite the rise of machine learning methods, explanatory models remain essential for epidemiological interpretation and public health decision-making. Most of these modeling approaches offer valuable short- and long-term forecasts that can help public health services and policy makers develop early-warning systems and timely interventions to mitigate health and environmental risks. In the future, further research should deepen qualitative and quantitative investigations into the mechanisms underlying these impacts. Particular attention should be paid to improving the accuracy of predictive models to strengthen the ability to anticipate epidemics and inform proactive risk management strategies.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/w18141753/s1>. Table S1: Distribution of studies by waterborne disease syndromes included in the review. Table S2: Distribution of studies by climate variables included in the review. Table S3: Distribution of studies by analysis methods included in the review. Table S4. PRISMA 2020 checklist.

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