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Climate Change and the Transmission of Vector-Borne Diseases: A Review

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This article reviews studies examining the relationship between climate variability and the transmission of vector- and rodent-borne diseases, including malaria, dengue fever, Ross River virus infection, and hemorrhagic fever with renal syndrome. The review has evaluated their study designs, statistical analysis methods, usage of meteorological variables, and results of those studies. The authors found that the limitations of analytical methods exist in most of the articles. Besides climatic variables, few of them have included other factors that can affect the transmission of vector-borne disease (eg, socioeconomic status). In addition, the quantitative relationship between climate and vector-borne diseases is inconsistent. Further research should be conducted among different populations with various climatic/ecological regions by using appropriate statistical models.

Keywords: climate; dengue fever; HFRS; malaria; Ross River virus

Background

It is now widely acknowledged in the scientific community that Earth's climate system has demonstrably changed since the preindustrial era and that at least some of these changes are due to human activities, especially in recent decades.[1] The impact of climate change on the transmission of infectious diseases, particularly on vector- and rodent-borne diseases, has been studied recently. However, the quantitative relationship between climatic variables and the transmission of vector-borne diseases is still not clear, and the study results are sometimes inconsistent, which may due to many reasons, including the limitations of research methods and data availability. This article systematically reviews the published research articles examining the relationship between climate variations and malaria, dengue fever, Ross River virus (RRV) infections, and hemorrhagic fever with renal syndrome (HFRS)–vector- and rodent-borne diseases that have attracted most research attention recently. The objectives of this review are to summarize what has been done in examining the relationship between climate change and vector-borne diseases worldwide and to give suggestions for future research directions by noting limitations in previous published works.

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Search Strategies

This article reviews recently published studies in this area of climate change and the transmission of infectious diseases. PubMed was the main search database to search for original studies, using combinations of the following keywords (MeSH terms): *malaria*, *dengue fever*, *Ross River virus*, *hemorrhagic fever with renal syndrome* (HFRS), *climate*, *global warming*, *temperature*, *rainfall*, and *El Nino*. Articles had to be published in English, over the period of 1984 to present. Review papers were not included. Using the same criteria, other databases, including AustHealth (a collection of major Australian health databases), Academic Search Elite and CAB Abstracts, and related official Web sites were searched as well, including the World Health Organization, the International Panel on Climate Change (IPCC), and the World Meteorological Organization. Except for unavailable papers, the available full-text papers being reviewed are listed in Table 1 with the evaluation of study design, target population and location, statistical analysis method, and main findings, with comments on the results.

Climate Change

There is abundant evidence to illustrate that climate change has occurred at a global level. According to the IPCC,[1] the global average surface temperature has increased approximately 0.6°C since the 1850s, when temperature records were first kept. Global land precipitation has increased by approximately 2% since the beginning of the 20th century, showing an increase in middle and high latitudes and a decrease in the tropic and subtropical regions.[1] The rate of sea level increase during the 20th century is in the range 1.0 to 2.0 mm per annum.[1]

According to projections, there will be an increase in global average temperatures in the range of 1.4°C to 5.8°C by 2100, indicating that the rate of warming could be up to 10 times that observed during the past century.[1] Global average precipitation and evaporation are also projected to increase from 1% to 9% during the 21st century, depending on different climatic models, and vary by location, with some regions having increased rainfall, whereas others might experience a decrease.[2] In Australia, from 1910 to 1999, the continental-average temperature rose by about 0.7°C.[3] By 2030, there will be 0.3°C to 1.4°C warmer temperatures, 10% to 60% fewer frosts, and 0% to 10% drier winters, and the sea level will rise by 5 to 25 cm.[4]

Impact of Climate Change on Vector/Rodent-Borne Diseases

Climate conditions affect the transmission of vector-borne diseases in 3 ways: altering the distribution of vector species and their reproductive cycles; influencing the reproduction of the pathogens within the vector organism, known as the external incubation period (EIP); and affecting human behaviors and activity.[5] Malaria, dengue fever, HFRS, and Ross River virus are the most commonly investigated climate-related vector/rodent-borne diseases.

Malaria

Malaria is considered the most important vector-borne disease, with cases occurring in more than 92 countries in the world.[6] The relationship between malaria and climatic variables has been assessed in many studies, covering Africa, Europe, Asia, South America, and Australia (see Table 1).[7-20] Almost all of these studies have been conducted in Africa and indicate that increases in the incidence of malaria are strongly associated with higher temperatures.

(text continues on p. 72)

Table 1. Review of the Relationship Between Climate Variation and Malaria, Dengue, Ross River Virus, and Hemorrhagic Fever With Renal Syndrome

Reference	Study Population	Study Period	Indicators: Climate	Indicators: Disease	Statistical Methods	Main Results	Comments
Malaria							
Zhou et al (2004)[7]	Seven highlands in East Africa	1978-1988 1989-1998	Monthly temperature, rainfall	Outpatient numbers	Nonlinear regression models	65%-81% of the variance in the number of monthly malaria outpatients can be explained by climatic variables; there was a high spatial variation in the sensitivity of malaria outpatients' number to climate fluctuation.	√ Spatial variation was detected × Vector population dynamics were not examined
Kuhn et al (2003)[8]	43 counties in England	1840-1910	Annual rainfall and temperature	Death rate and case counts	Logistic regression analysis	Rainfall and temperature were associated with year-to-year variability in death rate but not with the long-term malaria trend. By 2050, the increase of temperature may lead to an 8% to 14% increase of malaria transmission.	√ Included areas throughout England × Did not control for autocorrelation × Annual index could be too large
Abeku et al (2003)[9]	Ethiopia	1986-1993	Monthly minimum and maximum temperature, rainfall	Epidemic episode of malaria	Morbidity log-transformed series	Positive association with minimum temperature; no positive association with maximum temperature and rainfall.	√ Potential spatial changes were considered × Only considered morbidity
Tanser et al (2003)[10]	Africa	1920-1980	Mean monthly temperature, rainfall	Person-month exposure of malaria	Projection using IPCC scenarios	Potential increase of 16%-28% in person-months of exposure in Africa by 2100.	√ Produced a validated malaria transmission model for Africa × Did not consider: demographic, socioeconomic status, and malaria control programs

Bi et al (2003)[11]	A temperate county of China	1980-1991	Monthly minimum and maximum temperature, rainfall, relative humidity	Monthly incidence	Spearman correlation analysis; time-series analysis (ARIMA)	Significant association between climate variables and incidence of malaria was observed.	√ ARIMA model applied × Did not take into account socioeconomic factors
Small et al (2003)[12]	Africa	1911-1995	MTCSI[a]: monthly rainfall, mean air temperature, mean diurnal temperature	Monthly incidence	Time-series analysis	Not enough evidence showing a significant association between malaria and climatic data. Rainfall rather than temperature might be more crucial for the transmission of malaria.	√ Considered the whole of Africa × Annual climatic indicators
Singh and Sharma (2002)[13]	Central India	1986-2000 1967-2000	Annual rainfall	Annual parasite incidence	Correlation, linear regression	No relationship between rainfall and incidence was observed.	× The result may be due to a water resources improvement project
Poveda et al (2001)[14]	Colombia	1980-1997	Mean monthly temperature, rainfall, dew point temperature, river discharge	Monthly record for *Plasmodium vivax* malaria	Seasonal cross-correlations, power spectral analysis	Epidemic malaria is highly associated with climatic conditions.	√ Considered many climate variables × No regression analyses were conducted
Kleinschmidt et al (2001)[15]	KwaZulu Natal, South Africa	1994-1995	Daily/monthly temperature, rainfall, seasonal data	Incidence	GIS, Poisson regression analysis	Higher winter rain and higher maximum temperature are associated with the incidence of malaria.	√ Spatial analysis of small area/application of GIS × Study period was short
van der Hoek et al (1997)[16]	Sri Lanka	1979-1995	Mean monthly relative humidity, rainfall	Incidence	Correlation analysis	Weak association between rainfall and incidence; monitoring rainfall alone is not sufficient to predict incidence.	× No regression analysis
Bouma et al (1997)[17]	Colombia	1960-1992	El Nino year, SST	Reported malaria cases	Correlation analysis	Strong association between El Nino, SST, and the incidence of malaria.	√ Investigated the impact of El Nino on malaria × No regression analysis

(*continued*)

Table 1. (continued)

Reference	Study Population	Study Period	Indicators		Statistical Methods	Main Results	Comments
			Climate	Disease			
Bryan et al (1996)[18]	Australia	NA	Ecoclimatic index	NA	CLIMEX[b]	Potential distribution of *Anopheles Farauti* extends a further 800 km south in coastal Queensland.	√ Prediction of malaria distribution in 2030 × Only considered vector density
Bouma M and van der Kaay (1996)[19]	India and Sri Lanka	1868-1943	El Nino year, SST, monthly rainfall	Case counts	Correlation analysis	Significant correlation between SST anomalies and malaria cases was found.	√ Investigated the relationship between El Nino and malaria × No regression analysis
Dengue							
Yi et al (2003)[25]	Guangdong, China	NA	Average of lowest/highest air temperature, sunlight, rainfall, relative humidity, Breteau Index (an index of vector intensity)	Case counts	Correlation analysis, stepwise regression, logistic regression	Lowest air temperature, rainfall, and relative humidity were associated with cases of dengue fever.	√ Considered density of vectors √ Built a predictive model × Time-series study was not applied
Hales et al (2002)[27]	A global study	1975-1996	Monthly vapor pressure, rainfall, temperature	Outbreak (author defined)	Projection for 2055 and 2085, GIS, logistic regression	Annual vapor pressure was the most important indicator of dengue fever (OR = 1.3)	√ Sensitivity analysis was applied × Only considered outbreaks
Hales et al (1999)[30]	Fourteen island nations of the South Pacific	1973-1994			Correlation analysis	Positive correlations between SOI and dengue in 10 countries; positive correlations between dengue cases and local temperature and rainfall in 5 countries.	× Only correlation analysis was applied

Schreiber et al (2001)[31]	Puerto Rico	1988-1993	Daily rainfall, maximum and minimum temperature, water budget indicators (evaporation and water storage)	Incidence, daily running average of suspected dengue	Correlation and regression model	Water budget and traditional climate measures over 8-week period were related with dengue.	√ Different models show intra- and interannual variations × Did not consider other coexchanging factors
Bi et al (2001)[29]	Queensland, Australia	1992-1993	Monthly maximum/minimum temperature, relative humidity, precipitation	Outbreak, attack rate	Graphic assessment, Spearman correlation analysis, ARIMA model	Monthly mean minimum temperature with 4-month lagged effect was the strongest predictor of dengue fever.	√ Applied time-series analysis to control confounders × Only 1-year study period
Pontes et al (2000)[28]	A Brazilian city	1986-1998	House Index (the density of the vector found in a cycle during every 3 months of work)	Outbreak	Descriptive study	Heavy rainfall did not correlate with elevated vector density and dengue incidence; periods of droughts were associated with dengue outbreaks.	√ Evaluated local intervention programs × Not enough statistics
Li et al (1985)[26]	Malaysia	1973-1982	Monthly rainfall, *Aede* House Index	Case counts	NA	300 mm or more rainfall will lead to 120% increase of dengue cases.	× Only rainfall considered
Cazelles et al (2005)[34]	Thailand	1983-1997	SOI, rainfall, temperature	Monthly dengue incidence	Wavelet approaches	Strong association between incidence and dynamics of El Nino	√ Both transient and long-term relationships
Ross River virus infection							
Kelly-Hope et al (2004)[44]	Australia	Over 100 years	SOI, percentage of rainfall for the 3 preceding months and the month of onset	Historical outbreak	*t* test	SOI is important but only for Murray Darling River areas.	√ Study across Australia × Simple statistical methods × Did not define *outbreak*

(*continued*)

Table 1. (continued)

Reference	Study Population	Study Period	Indicators: Climate	Indicators: Disease	Statistical Methods	Main Results	Comments
Woodruff et al (2002)[45]	Southeastern Australia	1991-1999	Mean monthly temperature, rainfall	Epidemic year, seasons	Logistic regression analysis	A prediction model was set up.	√ Considered the socioeconomic situation × Lost information when transferring numeric data into categorical data
Bi et al (2002)[41]	Queensland, Australia	1985-1996	Seasonal data of temperature, rainfall, relative humidity, and mean high tide	Incidence	NA	The incidences of RRV infection differ the in northern, central, southern coast, and inland regions; the differences in rainfall, relative humidity, and mean high tide were possible contributors to the variation.	√ Considered different climatic regions × Nonmeteorological factors were not considered
Lindsay et al (1993)[46]	Western Australia	1988-1989 1991-1992	Mean sea level, daily tide height, rainfall, SOI	Case attack rate	NA	Unusual heavy rainfall and a sea level rise may contribute to the epidemics.	× No statistical analysis applied
Tong et al (2002)[38]	Inland and coastline in Queensland, Australia	1985-1996	Monthly rainfall, temperature, relative humidity, high tide, sea level	Monthly cases and incidence	Time series adapted for Poisson model	There was a different association between inland and coastline in the relationship between climate variables and malaria.	√ Considered confounders: seasonality and secular change √ Analysis of spatial difference
Tong et al (2004)[37]	Townsville	1985-1996	Monthly rainfall, temperature, relative humidity, high tide, sea level	Monthly cases and incidence	Cross-correlation; SARIMA	Significant association between these climatic variables and malaria cases and incidence was found with various lag times.	√ Population growth was considered √ Time-series analysis applied √ Control of seasonality, lag time √ Considered high tide and sea level × Other cochange factors (eg, socioeconomic status) were not controlled

Tong et al (2002)[39]	Queensland	1985-1996	Monthly rainfall, temperature, relative humidity, high tide, sea level	Monthly cases and incidence	Spearman's rank correlation analysis; ARIMA	Rainfall and high tide were significantly related with malaria.	
Tong et al (2001)[40]	Cairns	1985-1996	Monthly rainfall, temperature, relative humidity, high tide, sea level	Monthly cases and incidence	ARIMA	Maximum temperature, rainfall, and relative humidity were related with malaria.	
Hu et al (2004)[52]	Brisbane	1985-2001	Monthly maximum and minimum temperature, precipitation, relative humidity, high tidal level	Monthly cases	SARIMA	Monthly precipitation was significantly associated with RRV; no significant association between temperature and humidity.	√ Controlled seasonality × Did not control outbreaks
HFRS							
Bi et al (1998)[51]	A low-lying region of China	1983-1995 1961-1963 1964-1977	Seasonal rainfall, water level	Incidence of HFRS	Correlation analysis; multiple linear regression; log-transformation of the incidence rate of HFRS	There was an inverse relation between water level, farmland inundated, and the incidence of HFRS.	√ Density of mice, seasonality, and occupational index were considered
Bi et al (2002)[49]	Yingshang County, China	1980-1996	Mean of temperature, rainfall, relative humidity, SOI (July to September)	Notified data of HFRS	Correlation analysis; multiple regression	Rainfall, the density of mice, and autumn crop production were correlated with the incidence of HFRS.	√ Density of mice, seasonality, and occupational index were considered √ SOI was used to show relation between El Nino and HFRS
Bi and Parton (2003)[53]	China	1970-1996	SOI	Annual incidence of HFRS	Correlation analysis	There was an inverse correlation between the SOI and the incidence of HFRS.	× No regression analysis

ARIMA, autoregressive integrated moving average model; SOI, southern oscillation index; OR, odds ratio; SARIMA, seasonal autoregressive integrated moving average model; SST, sea surface temperature; IPCC, International Panel on Climate Change; GIS, geographic information systems; MTCSI, malaria transmission climate suitability index; RRV, Ross River virus; HFRS, hemorrhagic fever with renal syndrome.

a. MTCSI model: a model transforms temperature and rainfall into an index of transmission based on the biological constraints of climate on malaria vectors.

b. CLIMEX: an empirical-statistical model in the study of the relationship between malaria and climate change.

However, extremely high temperatures might have a negative impact on the growth of mosquitoes. In terms of the effect of rainfall, the results are not consistent. Some of them claimed that rainfall significantly affects the incidence of malaria,[7-9,11,12,14] whereas others did not detect a significant association.[13,16] Besides tropical areas such as Africa, it is noticed that malaria could be a serious public health issue in current malaria-free countries. In Australia, for example, the length and intensity of wet seasons have a significant effect on the distribution of the main vector, *Anopheles farauti*.[20] Climate modeling shows that global warming will enlarge the potential range of this vector, which could extend, by 2030, to a location 800 km south of its present limit.[18] Although these analyses only considered the vector density and did not include other factors that may affect malaria transmission (eg malaria control program and socioeconomic status), it should be looked as a warning signal of potential risks of malaria in temperate climatic zones.

Biases may exist in the published studies on climate variation and malaria transmission. For instance, most studies do not treat the vector as an independent variable in analyses (eg, the density of mosquitoes) due to the unavailability of data. Socioeconomic status, which plays an important role in malaria transmission, was not taken into account.[7,10,11] Autocorrelation among both dependent and independent variables in the time-series data and the impact of seasonality were not controlled well in most studies.[8,17] Some studies only conducted correlation analyses, which might have been insufficient (see Table 1).[16,17,19]

Recently, new methods have been adopted in this study area, providing more evidence for the association between climate and vectors. For example, geographic information systems (GIS) and remote sensing (RS) were used to study the environmental determinants of malaria.[21] These methods have their advantages, particularly to identify the spatial variation across different climatic zones in a large geographic area such as Africa. In addition, early warning systems, which are very important for public health practices, need to be explored. Online operational rainfall monitoring has been recently developed in Africa, which can generate a more contextual perspective of current rainfall estimates that compare previous seasons.[22]

Dengue Fever

Dengue is the most common arboviral infection in the world, with 4 distinct virus serotypes.[23] *Aedes aegypti,* the principal vector, has adapted well to urban environmental conditions such as poor housing, overcrowding, and inadequate sanitation.[24] The association between climatic variables and dengue fever has also been documented in south China, Malaysia, South Pacific, Puerto Rico, and Australia,[25-31] but the vector population may develop independently from rainfall,[28] which could be due to the characteristics of the vector, *A. aegypti*, in the urban environment. Using logistic regression analysis, Hales et al[27] found that the annual vapor pressure (humidity) was the most important indicator of dengue fever outbreak globally. This study was the only one to point out the very important effect of vapor pressure (odds ratio 1.3) on dengue transmission, which indicated that the incidence of dengue fever for the people living in humid areas could be 30% higher than people living in areas with less humidity.

Climate change, particularly for a warm climate, may increase the area of land suitable for *A. aegypti*. Accordingly, a slight increase in temperatures could result in epidemics of dengue in the world. Recently, a series of papers studying the association between climatic factors and dengue in Thailand have been published, which suggest a nonstationary influence of climatic situation on dengue epidemics in Thailand.[32-34] However, more work needs to be conducted to confirm the relationship between dengue fever and climate variability in different ecological conditions. Variables such as vector index and socioeconomic factors should be taken into account in analyses. Suitable time-series statistical methods (eg, the seasonal autoregressive integrated moving average [SARIMA] model)[29] could be used to investigate the relationship between weather variables and the diseases because the SARIMA models have intrinsic functions that can be used to effectively control the autocorrelations and seasonal variations among dependent and independent variables.

Ross River Virus Infection

Ross River virus (RRV) is the most common mosquito-borne pathogen in Australia, where approximately 5000 cases are notified annually.[35] There are more than 40 species of mosquitoes, with *Aedes vigilax, Aedes camptorhynchus* (saltmarsh along coastline), and *Culex annulirostris* (inland) being the most important.[36] The influences of temperature, rainfall, and tides on the transmission of RRV vary within regions due to different vector species and ecological situations.

Tong et al[37-40] studied the relationship between RRV and climate variability in Queensland, Australia, from far north to south and found that variations in rainfall, temperature, and tides have been associated with the monthly incidence of RRV infections. In addition, they claimed that climate variability might be a contributor to the spatial change of the disease in Queensland over the period from 1986 to 1995. The response of RRV to climate variability between coastline and inland regions might be different.[38,41]

A recent study in Queensland confirmed the various associations, depending on different environmental conditions.[42] Kelly-Hope et al[43] found that the environmental risks of RRV outbreaks varied among different regions throughout Australia and that the southern oscillation index (SOI) could be a predictor only for the southeast temperate region.[44] Projections of RRV epidemics from regional weather data were conducted in different areas.[45] In Western Australia, for example, predicted climatic changes, especially the rise of sea level and greater rainfall and flooding, might significantly increase RRV activity.[46,47] During 1988-1989, epidemics of RRV infection in Western Australia were noted after unusually heavy rainfall and higher tide heights.[46] The various ecological situations in Australia could result in the transmission of RRV infections being different across the states. Therefore, a systematic ecological study across the whole of Australia, noting the relationship between environmental factors and RRV infections, will lead to a deeper understanding of RRV transmission and control strategies.

In examining this association, time-series data are always used. Several issues should be kept in mind when coping with time-series data, which include long-term trend, seasonal variation, and autocorrelation. Some RRV studies used the autoregressive integrated moving average (ARIMA) or seasonal ARIMA models to deal with time-series data.[37-40] Others used logistic regression analysis, in which the continuous variables (incidence of the disease) were converted into a categorical variable (epidemic or not).[39] However, information could be lost in such a transformation. Besides these ecological studies, a case control study has been tried for the first time in tropical Queensland to explore individual risk of RRV, but there was no climatic variable included.[48]

Hemorrhagic Fever With Renal Syndrome (HFRS)

Hemorrhagic fever with renal syndrome is a zoonosis caused by the Hantaan or Hantaan-related virus. Rodents, mostly mice, act as a reservoir and the source of infection.[49] Humans are infected when they come into contact with excreta from infected rodents. The epidemic situation is serious in China, with more than 1 million cases being reported between 1950 and 1996.[50] The transmission of HFRS is influenced by environmental, occupational, and reservoir factors. Few quantitative estimates have been made to study the possible impact of climate variations on the disease transmission. A significant inverse association between the amount of precipitation and the incidence of HFRS was found in low-lying areas of China when the density of rodents and the degree of contact were considered.[49,51] Heavy rainfall in these low-lying areas could reduce the density of mice and thus the incidence of the disease. However, these studies were only conducted in low-lying regions, and further research needs to be conducted in other ecological situations.

Conclusion

Most of the published studies have only answered the question, "Is there an association between climate variability and disease incidence or mortality?" Few studies have defined how much of the burden of such infectious diseases can be attributed to climate change. Second, causal contribution would be enhanced by studies conducted in different population settings, which would include various climatic/ecological regions, especially in developing countries. Third, the quantitative relationship between climate variability and disease transmission in previous studies was inconsistent in some studies and needs to be further examined. Fourth, other potential risk factors (eg, socioeconomic status) have not been included in previous analyses. Fifth, the availability and quality of data, both health outcomes and climatic variables, restrict the precision of such analysis (eg, onset dates rather than notified dates are not available for most infectious disease surveillance systems). Monthly data rather than weekly data are often used in the analysis. Underreporting of infectious diseases is inevitable. Finally, attention must be given to the study design and statistical analysis methods as commented in Table 1. Regression models should be adopted in addition to correlation analysis to investigate this type of association. Time-series regression models (eg, ARIMA), with the consideration of long-term interannual trend, seasonality, autoregression, and lag time effects, would be an appropriate method to quantify the relationship compared with traditional regression models.

Therefore, further research should be performed involving different populations in various climatic/ecological regions to confirm the association between climate variation and the transmission of infectious diseases; predictive models should be made on different climatic scenarios; research should be conducted in developing countries such as China and India, which have the largest populations in the world, with appropriate statistical methods; and the burden of infectious disease attributed to climate change should be identified and projected.

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