The Effect of Global Warming on Infectious Diseases using Survival Analysis Methods

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Abstract

Global warming has various effects on human health. The main indirect effects are related on infectious diseases. The effects on infectious diseases will be detected worldwide and types of effect are different, depending on the location of the respective countries and socio-economical situations. Food-borne diseases, water-borne diseases, tick-borne diseases, rodent-borne diseases and vector-borne diseases are five main categories related to infectious diseases. In this paper, we studied water borne diseases and vector borne diseases are two main categories of infectious diseases. The aim of this paper is to estimate the variability in survival rate of infectious diseases and climate factors. We also studied weather conditions occurring on a particular period influence the diseases observed with to survival time, temperature, humidity and rainfall. Similar results were obtained using cox proportional hazard model, which explores the relationships between the survival and explanatory variables.

Keywords: infectious diseases, climate factors, cox proportional hazard function, survival function, logistic hazard model.

1. Introduction

Global warming is one of the components of climate change and it induces considerable impacts on human health. The emerging evidence of the effect of global warming on human health has been summarized in the fourth report of Intergovernmental Panel on Climate Change (IPCC 2007). Epidemiologic studies have associated health events with climate conditions like global warming and ozone depletion. Data from all over the world indicate that changes in climate affect health in more ways than just promoting the spread of infectious diseases. Global warming can adversely affect health by causing a disruption in food production and economic performance. It may also increase the occurrence of illness, injury and death because of more extreme temperatures, increased floods and severe storms, droughts, increased frequently of and changing patterns in waterborne, foodborne, vector-borne and rodent-borne diseases.

The effect of global warming on human health is dived into two categories: direct effect on the illness such as heat shock and increased mortality in population with other diseases and indirect effect on diseases such as infectious diseases and allergy. The IPCC report states that climate change has altered the distribution of some infectious disease vectors, the seasonal distribution of some allergenic pollen species and increased heatwave related deaths. In the present study, the effect of global warming on infectious diseases is discussed.

2. Effect of Global Warming on Infectious Diseases

It has been assumed that global warming has profound effects on infectious diseases. The effect of global warming on infectious diseases is indirect. There is a well-studied relationship between rainfall and diseases spread by insect vectors which breed in water, and are therefore dependent on surface water availability. The main species of interest are

mosquitoes, which spread malaria and viral diseases such as dengue and yellow fever. There is considerable evidence linking mosquito abundance to rainfall events. Mosquitoes need access to stagnant water in order to breed conditions that may be favoured by both wet and dry conditions. For example, heavy rain can create as well as wash away breeding sites, while in normally wet regions drought conditions can increase breeding sites by causing stagnation of water in rivers. The timing of rainfall in the year and the co-variation of other climate factors also are likely to be important (Kurane 2009).

A vector is an invertebrate animal (example: tick, mite, mosquito, bloodsucking fly) capable of transmitting an infectious agent among vertebrates. A vector can spread an infectious agent from an infected animal or human to other susceptible animals or humans through its waste products, bite, body fluids or indirectly through food contamination. Vector borne diseases kill millions of people in each year. Vectors do not regulate their internal body temperature. In addition, because mosquitoes primarily use shallow pools of rain water for breeding, a time lag between rainfall and diseases associated with mosquitoes is well established. Among infectious diseases food-borne diseases, water-borne diseases, tick-borne diseases, rodent-borne diseases and vector-borne diseases were five main categories that are forecasted to be most affected.

2.1 Effect of Global Warming on Food-borne Diseases

It is observed that bacterial growth flares up in warmer temperatures; hence increase in the average temperature will lead to rapid bacterial growth in foods. This can lead to contamination of food with bacteria such as salmonella. Food-borne illnesses lead to gastrointestinal diseases with symptoms like diarrhoea, dehydration, abdominal cramps and in some severe cases can be even fatal.

Heavy rainfall leading to flood conditions can lead to food contamination. Alternately gastrointestinal infectious diseases can be caused as a result of fresh water being contaminated by sewage water hence in turn contaminating food crops and fresh food supply. Infectious diseases like cholera, typhoid, and salmonella infection can spread due to this food contamination (Hashizume 2007).

2.2 Effect of Global Warming on Water-borne Diseases

There can be flood like conditions prevailing due to heavy rainfall which can cause fresh water supply to be contaminated with sewage water. This can cause water-borne diseases like giardiasis, cholera and other gastrointestinal illnesses. Symptoms like diarrhoea, vomiting, headache and abdominal discomfort can be seen in people infected with these illnesses (Hashizume 2008).

2.3 Effect of Global Warming on Tick-borne Diseases

Tick-borne diseases like Lyme's disease cause symptoms such as fever, rash, headache and joint pain, as temperature and humidity impacts the tick's life cycle. Rise in the temperatures is going to affect the geographic location of ticks as they will continue their range of spread to the north side of the globe (Haines 2004).

2.4 Effect of Global Warming on Rodent-borne Diseases

Climatic changes are going to cause extremes in the weather leading to heavy rainfall. This weather condition can lead to increase in the spread of rodent-borne diseases like leptospirosis.

2.5 Effect of Global Warming on Vector-borne Diseases

The vector borne transmission of diseases particularly, diseases such as malaria and dengue are understudied when it comes to their relation to rising sea-levels which in turn are caused by global warming (Craig 2004). In a study which had several hypotheses related to the vector tolerance such as abilities of mosquitoes to adapt to changes in the salinity levels in sea water as well as fresh waters , researchers tried to address some of the existing issues in vector related disease transmission in humans.

In this paper, we studied water borne diseases and vector borne diseases are two main categories of infectious diseases.

3. Materials and Methods

In water-borne diseases data, yearly cases of hospital admissions data from 2011 to 2017 for diarrhoea and cholera diseases were obtained from **www.nvbdcp.gov.in**.

In vector-borne diseases data, yearly cases of hospital admissions data from 2011 to 2017 for malaria, dengue, chikungunya, Japanese encephalitis and acute encephalitis syndrome data were obtained from **www.nvbdcp.gov.in.**

In monthly observations of environmental factors data such as maximum temperature (^{o}C), minimum temperature (^{o}C), average temperature (^{o}C), rainfall (mm) and humidity (%) were obtained from **www.worldweathearonline.com**.

3.1 Analysis of the influence of weather conditions and Infectious Diseases

In order to investigate the relationships between climate factors and diseases survival rates, we combined three statistical methods which are described below. These methods were chosen for their power and suitability in survival analysis, related to the time series of explanatory weather variables.

3.2 Discrete hazard and survival functions

We used the framework of survival analysis to analyse the influence of weather conditions and infectious diseases. While analysing the influence on diseases of factors that vary in time, lifetime observations could not be used as a target variable to be explained and a regression model was required.

To model the effect of some continuous variables X_1, …, X_k on the dummy variable Y, associated with the risk of infectious diseases, we used the binary logistic regression (Agresti 2002). As well as proportional hazard modelling. To analyse the influence of climate and infectious diseases, we used the framework of survival analysis (Lawless 2003), the branch of statistics dealing with diseases in biological organisms and in particular the concepts of survival and hazard rate functions. The survival function, conventionally denoted by s, is defined as $s(t) = 1-F(t)$, where $F(t)-P(T \leq t)$ is the cumulative probability function, with t the random variable denoting the time of diseases. The hazard function is defined as the event rate at time t, conditional on survival until time t or later: $P(t \leq T < t + \delta t \mid T \geq t$. Implementing this framework, we estimated an empirical hazard function. The proportional hazards models are a class of survival models in statistics. Survival models relate the time that passes before some event occurs to one or more covariates that may be associated with that quantity (Comfort 1979).

In a proportional hazards model, the unique effect of a unit increase in a covariate is multiplicative with respect to the hazard rate. Survival models can be viewed as consisting of two parts: the underlying hazard function, often denoted $h_0(tj)$, describing how the hazard (risk) changes over time at baseline levels of covariates, and the effect parameters, describing how the hazard varies in response to explanatory covariates. The proportional hazards condition (Breslow 1975) states that covariates are multiplicatively related to the hazard. However, the covariates are not restricted to binary predictors and in the case of a continuous covariate Xi, the hazard responds logarithmically. Thus, each unit increases in Xi results in proportional scaling of the hazard. The effect of covariates estimated by any proportional hazards model can thus be reported as hazard ratios. Cox (1972) observed that if the proportional hazards assumption holds (or is assumed to hold), then it is possible to estimate the effect parameters without any consideration of the hazard function. This approach to survival data is an application of the Cox proportional hazards model, sometimes abbreviated to Cox model or to proportional hazards model.

3.2 The logistic hazard model

Cox (1972) proposed an extension of the proportional hazards model to discrete time by working with the conditional odds of dying at each time tj given survival up to that point, the model is given by:

$$\frac{h_T(t_j \mid X_t)}{1-h_T(t_j \mid X_j)} = \frac{h_0(t_j)}{1-h_0(t_j)} \exp\{X_i \beta\} \qquad (1)$$

where $h_T(t_j \mid X_i)$ is the hazard at time t_j for an individual with covariate values X_i, $h_0(t_j)$ is the baseline hazard at time t_j and exp $\{X_i\beta\}$ is the relative risk associated with covariate values X_i. Taking logs, we obtain a model on the logit (l) of the hazard or conditional probability of dying at t_j given survival up to that time: $l[h_T(t_j \mid X_i)] = \alpha_j + X_i\beta$, where $\alpha_j = l[h_0(t_j)]$ is the logit of the baseline hazard and $X_i\beta$ is the effect of the covariates on the logit of the hazard. Note that the model essentially treats time as a discrete factor by introducing one parameter α_j for each possible time of death t_j. Interpretation of the parameters β associated with the other covariates follows along the same lines as in the logistic regression. Time-varying covariates and time-dependent effects can be introduced in this model along the same lines as before. In the case of time-varying covariates, note that only the values of the covariates at the discrete times

$t_1 < t_2 < \ldots < t_j\text{-}1 < t_j$ are relevant. Time-dependent effects are introduced as interactions between the covariates and the discrete factor (or set of dummy variables) representing time (Therneau and Grambsch 2000).

The logistic regression analyses binomially distributed data, where the numbers of Bernoulli trials n are known and the probabilities of success p are unknown. The model proposes for each trial that there is a set of explanatory variables that might inform the final probability. The model then takes the form:

$$P = E\left(\frac{Y}{n} \mid X_1, X_2, ..., X_k\right) \qquad (2)$$

One can transform the output of a linear regression to be suitable for probabilities by using a logit link function. The logit, natural logs of the odds, of the unknown binomial probabilities are modelled as a linear function of the explained variables $X_1,\ldots,X_k$:

$$l[P] = h\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 X_1 + ... + \beta_k X_k \quad (3)$$

or a real-valued explanatory variable X_1, the intuition is that a unit additive change in the value of the variable should change the odds by a constant multiplicative amount. The logit function is invertible, so

$$P = \frac{e^{(\beta_0+\beta_1 X_1+....+\beta_k X_k)}}{1+e^{(\beta_0+\beta_1 X_1+....+\beta_k X_k)}} \quad (4)$$

The parameters of the model $\{\beta_0, \beta_1, \ldots, \beta_k\}$ are estimated by the principle of maximum likelihood based on the data. So, the binary logistic regression is a useful way to describe the relationship between one or more independent variables and a binary response variable, expressed as a probability. The logistic function is defined as

$$f(z) = \frac{e^z}{e^z + 1} = \frac{1}{1+e^{-z}} \quad (5)$$

The input is z and the output is f(z), which is confined to values between 0 and 1; f(z), represents the probability of a particular outcome, given that set of explanatory variables. The variable z is a measure of the total contribution of all the independent variables used in the model and is known as the logit. In this study the variable z was defined as $z = \beta_0 + \beta_1 X_1 + \ldots + \beta_k X_k$.

From a technical point of view, there is no error term in a logistic regression, unlike in classic linear regression. The logistic regression is useful when we are predicting a binary outcome from a set of continuous predictor variables. It is frequently preferred over discriminant function analysis because of its less restrictive assumptions.

3.3 The Cox proportional hazard model

Cox proportional-hazards regression allows analysing the effect of several risk factors on survival. The probability of the endpoint (diseases) is called the hazard. The hazard function for the Cox proportional hazard model is,

$$h_T(t_j \mid X_i) = h_0(t_j)\exp\{X_j \beta\} \quad (6)$$

where X_i is a collection of predictor variables and $h_0(t_j)$ is the baseline hazard at time t_j, representing the hazard for a sample unity with the value 0 for all the predictor variables. By dividing both sides of the above equation by $h_0(t_j)$ and taking logarithms, we obtain:

$$\ln\left[\frac{h_T(t_j \mid X_i)}{h_0(t_j)}\right] = \beta_0 + \beta_1 X_1 + ... + \beta_k X_k \quad (7)$$

One calls

$$\frac{h_T(t_j \mid X_i)}{h_0(t_j)} \quad (8)$$

the hazard ratio. The coefficients $\{\beta_0, \beta_1, \ldots, \beta_k\}$ are estimated by Cox regression and can be interpreted in a similar manner to that of multiple logistic regressions. Suppose the covariate is discrete, then the quantity $\exp\{X_i, \beta\}$ is the instantaneous relative risk of an event, at any

time, for an individual with an increase of one-unity in the value of the covariate compared with another individual, given both individuals are the same on all other covariates.

The Cox proportional regression model assumes that the effects of the predictor variables are constant over time. Furthermore there should be a linear relationship between the endpoint and predictor variables. Predictor variables that have a highly skewed distribution may require logarithmic transformation to reduce the effect of extreme values. This model is robust and a safe choice of a model in many situations. Because of the model form

$$h_T\left(t_j \mid X_i\right) = h_0\left(t_j\right) \underset{\geq 0}{\exp}\left\{X_i \beta\right\} \tag{9}$$

the estimated hazards are always non-negative. Even though $h_0(t_j)$ is unspecified, we can estimate $\{\beta_0, \beta_1, \ldots, \beta_k\}$ and thus compute the hazard ratio. The $h_T(t_j \mid X_i)$ and $S_T(t_j \mid X_i)$ can be estimated for a Cox model using a minimum of assumptions. In survival analysis, the Cox model is preferred to a logistic model, since the latter one ignores survival times.

The proportional hazard model is the most general of the regression models because it is not based on any assumptions concerning the nature or shape of the underlying survival distribution. The model assumes that the underlying hazard rate, rather than survival time, is a function of the independent variables (covariates), and no assumptions are made about the nature or shape of the hazard function. Thus, Cox's regression model may also be considered as a nonparametric method. The model may be written as:

$$h(t) = h_0(t)\exp\left\{\beta_X\right\} = h_0(t)\exp\left\{\beta_1 X_1 + \ldots + \beta_k X_k\right\} \tag{10}$$

where h(t) denotes the resultant hazard, given the values of the k covariates for the respective case ($X_1, \ldots, X_k$) and the respective survival time (t). The term $h_0(t)$ is called the baseline hazard, the hazard for the respective individual when all independent variable values are equal to zero. The baseline hazard is an unspecified function that does not depend on X but only
on t. The exponential involves the X but not t; X are time-independent. Similar to ordinary linear regression in the logistic hazard model, the unknown parameters $\{\beta_0, \beta_1, \ldots, \beta_k\}$are usually estimated by maximum likelihood.

Although the Cox model is non-parametric to the extent that no assumptions are made about form of the baseline hazard, there are still a number of important issues which need be assessed before the model results can be safely applied. First, they specify a multiplicative relationship between the underlying hazard function and the log-linear function of the covariates. This assumption is also called the proportionality assumption. In practical terms, it is assumed that, given two observations with different values for the independent variables, the ratio of the hazard functions for those two observations does not depend on time. The second assumption is that there is a log-linear relationship between the independent variables and the underlying hazard function

An hypothesis of the proportional hazard model is that the hazard function for an individual depends on the values of the covariates and the value of the baseline hazard, $h_0(t)$. Given two individuals with particular values for the covariates, the ratio of the estimated hazards over time will be constant, hence the name of the method: the proportional hazard model. The validity of this hypothesis may often be questionable.

After the data compilation for all individuals, we submitted an application of the logistic regression to the dataset, using all available climate variables at a time as a predictor, to analyse their effect separately. We also considered potential delayed effects of predictors by applying the regression to lagged variables (Martinussen and Scheike 2006), with lag ranging from one to five days. Finally, we considered cumulative effects using the sum of the variable over the past two to five days as a predictor.

Following the statistical analysis, we estimated the logistic regression coefficients for the daily weather attributes on the complete sample. For this, we have chosen the model by the Akaike Information Criterion (AIC) in a stepwise algorithm (Venables and Ripley 2002), where the seasonal effect was statistically significant. It is worthwhile to note that multicollinearity in the logistic regression model (as well as in the Cox model) is a result of strong correlations between explanatory variables.

4. Results and Discussions

Hospital admissions with principal diagnoses of infectious diseases during the year of 2010 to 2017.

4.1 The Association of Climate Factors on Water-borne Diseases

The descriptive statistics for during the years 2010 to 2017 of the study, there were water-borne diseases, such as cholera, diarrhoea diseases hospital admissions and corresponding environmental factors data are shown in Table 1.

Table 1: Descriptive analysis of Water-borne diseases and Climate Factors.

Characteristics	Minimum	Maximum	Mean	Std. Dev	Skewness	Kurtosis
Cholera	3.00	70.00	23.91	8018.81	4.6210	29.9548
Diarrhoea	7.00	580.00	191.30	8018.82	4.6210	29.9548
Max. Temp.	30.00	41.00	34.60	4.6733	1.2286	0.7799
Min. Temp.	20.00	31.00	25.07	14.3839	9.1543	99.0281
Rainfall	0.00	366.06	60.58	46.7894	5.4446	52.9845
Humidity	51.00	74.00	62.67	22.5005	2.2729	7.8945

4.1.1 Association of Climate Factors and Water-borne Diseases using Logistic Regression Model

Logistic regression model indicated that the concentrations of climate factors were significantly associated with monthly hospital admissions due to water-borne diseases shown in Table 2.

Table 2: Association of hospital admissions in Climate Factors using Logistic Regression Model

Variables	RR	LCL	UCL	P – Value
Cholera Cases				
Maximum Temperature	1.0317	0.9758	1.0907	0.2714
Minimum Temperature	0.9666	0.9282	1.0059	0.0980
Rainfall	1.0009	0.9998	1.0019	0.0880
Humidity	1.0348	1.0132	1.0566	0.0013
Diarrhoea Cases				
Maximum Temperature	1.0100	0.9905	1.0298	0.0010
Minimum Temperature	1.0377	1.0244	1.0511	0.3140

Rainfall	1.0024	1.0021	1.0028	0.0010
Humidity	1.0328	1.0250	1.0406	0.0010

In the logistic regression, among the cholera cases, the highest association between Humidity and hospital admissions RR value is 1.0348 and 95% CI value is [1.0132 to 1.0566] statistically significant (P=0.0013). The diarrhoea cases, the highest association between minimum temperature and hospital admissions RR value is 1.0377 and 95% CI value is [1.0244 to 1.0511] not statistically significant (P=0.3140).

4.1.2 Association of Climate Factors and Water-borne Diseases using Cox Proportional Hazard Regression Model

Cox proportional hazard regression model indicated that the concentrations of climate factors were significantly associated with monthly hospital admissions due to water-borne diseases shown in Table 3.

Table 3: Association of hospital admissions in Climate Factors using Cox Proportional Hazard Regression Model

Variables	RR	LCL	UCL	P – Value
Cholera Cases				
Maximum Temperature	1.0247	0.9233	1.1373	0.6466
Minimum Temperature	0.9646	0.8924	1.0134	0.3388
Rainfall	1.0010	0.9988	1.0032	0.3724
Humidity	1.0298	0.9905	1.0710	0.1431
Diarrhoea Cases				
Maximum Temperature	0.9639	0.8036	2.5298	0.6937
Minimum Temperature	1.1176	0.9622	1.1573	0.0904
Rainfall	1.0028	0.9983	1.3008	0.1608
Humidity	1.0279	0.9615	1.1004	0.4374

In the cox proportional regression, among the cholera cases, the highest association between Humidity and hospital admissions RR value is 1.0298 and 95% CI value is [0.9905 to 1.0710] not statistically significant (P=1.1431). The diarrhoea cases, the highest association between minimum temperature and hospital admissions RR value is 1.1176 and 95% CI value is [0.9622 to 1.1573] not statistically significant (P=0.0904).

4.2 The Association of Climate Factors on Vector-borne Diseases

The descriptive statistics for during the years 2010 to 2017 of the study, vector-borne diseases, such as malaria, dengue, chikungunya, Japanese Encephalitis and acute encephalitis syndrome diseases hospital admissions and corresponding environmental factors data are shown in Table 4.

Table 4: Descriptive analyses of vector-borne diseases and Climate Factors

Variables	Min	Max	Mean	Std. Dev	Skewness	Kurtosis
Dengue	0	23035	2307.82	3781.30	2.85	9.89
Chikungunya	0	31644	1138.84	3317.33	5.74	40.45
Japanese Encephalitis	0	761	60.85	135.95	3.09	9.71
Acute Encephalitis	0	4693	427.27	856.30	2.81	8.03
Maximum Temperature	15.67	39.50	31.03	4.63	1.30	1.06

Minimum Temperature	0.83	178.30	21.58	11.27	10.45	147.23
Rainfall	6.01	569.96	52.73	47.07	5.80	57.16
Humidity	33.58	171.25	62.95	22.33	2.38	8.45

4.2.1 Association of Climate Factors and Vector-borne Diseases using Logistic Regression Model

Logistic regression model indicated that the concentrations of climate factors were significantly associated with monthly hospital admissions due to vector-borne diseases shown in Table 5.

Table 5: Association of hospital admissions in Climate Factors using Logistic Regression Model

Variables	RR	LCL	UCL	P – Value
Malaria Cases				
Maximum Temperature	0.000698	0.000609	0.000707	1.00
Minimum Temperature	0.000940	0.000892	0.000966	1.00
Rainfall	4.406000	4.398000	4.410000	1.00
Humidity	4.833000	4.821000	4.840100	1.00
Dengue Cases				
Maximum Temperature	0.000752	0.000739	0.000931	1.01
Minimum Temperature	0.001026	0.000953	0.001042	1.02
Rainfall	4.406453	4.397861	4.435120	0.04
Humidity	4.833759	4.548951	5.021691	0.02
Chikungunya Cases				
Maximum Temperature	0.001865	0.001609	0.001907	0.90
Minimum Temperature	0.001040	0.000992	0.001266	0.92
Rainfall	3.146000	3.098000	3.162678	0.01
Humidity	2.832300	2.820100	2.892480	0.02
Japanese Encephalitis Cases				
Maximum Temperature	0.002098	0.001990	0.002207	1.24
Minimum Temperature	0.001942	0.001895	0.002201	1.10
Rainfall	3.416548	3.398002	3.395487	0.03
Humidity	3.898452	3.861258	3.910002	0.10
Acute Encephalitis Cases				
Maximum Temperature	0.001987	0.001899	0.002014	1.00
Minimum Temperature	0.002654	0.002592	0.002789	1.02
Rainfall	3.546590	3.498269	3.653548	0.00
Humidity	3.189343	3.082257	3.274609	0.06

In the logistic regression, among the malaria cases, the highest association between Humidity and hospital admissions RR value is 4.833000 and 95% CI value is [4.821000 to 4.840100] not statistically significant (P=1.00). The dengue cases, the highest association between Humidity and hospital admissions RR value is 4.833759 and 95% CI value is [4.548951 to 5.021691] statistically significant (P=0.02). The Chikungunya cases, the highest association between rainfall and hospital admissions RR value is 3.146000 and 95% CI value is [3.098000 to 2.892480] statistically significant (P=0.02). The Japanese Encephalitis cases,

the highest association between Humidity and hospital admissions RR value is 3.898452 and 95% CI value is [3.861258 to 3.910002] not statistically significant (P=0.10). The Acute Encephalitis cases, the highest association between rainfall and hospital admissions RR value is 3.546590 and 95% CI value is [3.498269 to 3.653548] statistically significant (P=0.00).

4.2.2 Association of Climate Factors and Vector-borne Diseases using Cox Proportional Hazard Regression Model

Cox proportional hazard regression model indicated that the concentrations of climate factors were significantly associated with monthly hospital admissions due to vector-borne diseases shown in Table 6.

Table 6: Association of hospital admissions in Climate Factors using Cox Proportional Hazard Regression Model

Variables	RR	LCL	UCL	P – Value
Malaria Cases				
Maximum Temperature	0.846	0.814	0.880	0.000
Minimum Temperature	1.009	0.998	1.021	0.092
Rainfall	0.994	0.989	0.998	0.006
Humidity	1.002	0.994	1.009	0.640
Dengue Cases				
Maximum Temperature	0.848	0.818	0.878	0.000
Minimum Temperature	1.009	0.993	1.025	0.287
Rainfall	1.002	0.999	1.004	0.180
Humidity	1.002	0.996	1.008	0.512
Chikungunya Cases				
Maximum Temperature	0.903	0.871	0.937	0.000
Minimum Temperature	1.003	0.987	1.018	0.748
Rainfall	0.998	0.995	1.001	0.242
Humidity	0.997	0.991	1.003	0.280
Japanese Encephalitis Cases				
Maximum Temperature	0.983	0.934	1.033	0.494
Minimum Temperature	1.010	0.999	1.020	0.068
Rainfall	1.000	0.997	1.003	0.957
Humidity	1.004	0.997	1.012	0.245
Acute Encephalitis Cases				
Maximum Temperature	0.979	0.929	1.031	0.425
Minimum Temperature	1.011	1.000	1.022	0.045
Rainfall	1.000	0.998	1.003	0.757
Humidity	1.004	0.998	1.011	0.177

In the Cox proportional hazard regression, among the malaria cases, the highest association between minimum temperature and hospital admissions RR value is 1.009 and 95% CI value is [0.998 to 1.021] not statistically significant (P=0.092). The dengue cases, the highest association between minimum temperature and hospital admissions RR value is 1.009 and 95% CI value is [0.993 to 1.025] not statistically significant (P=0.287). The Chikungunya cases, the highest association between minimum temperature and hospital admissions RR value is 1.003 and 95% CI value is [0.987 to 1.018] not statistically significant (P=0.748). The Japanese Encephalitis cases, the highest association between minimum temperature and

hospital admissions RR value is 1.010 and 95% CI value is [0.999 to 1.020] not statistically significant (P=0.068). The Acute Encephalitis cases, the highest association between minimum temperate and hospital admissions RR value is 1.011 and 95% CI value is [1.000 to 1.022] statistically significant (P=0.045).

5. Conclusions

In conclusions, many studies have suggested that climate change has various negative effects on human health including infectious diseases. However, it should be noted that the levels of the impacts of climate change on various factors, such as maximum temperature, minimum temperature, rainfall and humidity.

In our study the association of climate factors to hospital admissions for water-borne diseases. In the logistic regression, we observed that cholera cases the largest association between humidity and hospital admissions RR value is 1.0348 with statistically significant and diarrhoea cases the largest association between minimum temperature and hospital admissions RR value is 1.0377 was not statistically significant. We also observed that cox proportional regression, cholera the largest association between humidity and hospital admissions RR value is 1.0298 was not statistically significant and diarrhoea the largest association between minimum temperature and hospital admissions RR value is 1.1176 was not statistically significant.

The association of climate factors to hospital admissions for vector-borne diseases. In the logistic regression, we observed that malaria, dengue, Japanese encephalitis cases the largest association between humidity and hospital admissions RR value is 4.833000, 4.833759, 3.898452 with not statistically significant and chikungunya, acute encephalitis cases the largest association between rainfall and hospital admissions RR value is 3.146000, 3.546590 was statistically significant. We also observed that cox proportional regression, malaria, dengue, chikungunya, Japanese encephalitis, acute encephalitis the largest association between minimum temperature and hospital admissions RR value is 1.009, 1.009, 1.003, 1.010, 1.011 was not statistically significant.

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