Hydro-climatic Impact on Cholera Incidence in Dhaka under Global Warming

by

Salima Sultana Daisy

DOCTOR OF PHILOSOPHY

Institute of Water and Flood Management (IWFM),

Bangladesh University of Engineering and Technology

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Salima Sultana Daisy

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Institute of Water and Flood Management (IWFM)

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This is to certify that this work entitled "**Hydro-climatic Impact on Cholera Incidence in Dhaka under Global Warming**" has been done by me under the supervision of Dr. A.K.M. Saiful Islam, Professor, Institute of Water and Flood Management (IWFM), Bangladesh University of Engineering and Technology (BUET), Dhaka. I do hereby declare that this thesis or any part of it has not been submitted elsewhere for the award of any degree or diploma from any other institution.

Signature of the candidate

(Salima Sultana Daisy)

DEDICATED

TO MY BELOVED FAMILY

(especially to my son Tazwar Tanvir

for always being with me)

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ABSTRACT

Cholera, an acute diarrheal disease spread by lack of hygiene and contaminated water, is a major public health risk in many countries. Bangladesh experiences endemic cholera for more than 2,000 years, where cholera is triggered by environmental conditions influenced by climatic variables. This study employed to establish a correlation between cholera incidence and climatic variables, which would provide an opportunity to develop a cholera forecasting model in densely populated Dhaka megacity. The aim of this study was to predict the potential impact of future climate change on cholera using the consequences of high-end concentration scenario (RCP8.5), and further an adaptation guideline has been described through a systematic review on preparedness practices.

In this study, a time series analysis namely a seasonal-auto-regressive-integrated-moving-average (SARIMA) model as short-term forecasting was used considering the auto-regressive nature and the seasonal behavioral patterns of cholera. As both rainfall ($r=0.43$) and maximum temperature ($r=0.56$) have the strongest influence on the occurrence of cholera incidence, single-variable (SVMs) and multi-variable SARIMA models (MVMs) have been developed and tested for evaluating their relationship with cholera incidence for the period of 2000 to 2013. Low relationship was found with relative humidity ($r=0.28$). Using SVM for 1°C increase in maximum temperature at one-month lead time showed 7% increase of cholera incidence ($p<0.001$). However, MVM (AIC=15, BIC=36) showed better performance than SVM (AIC=21, BIC=39). An MVM using rainfall and monthly mean daily maximum temperature with 1-month lead time showed a better fit (RMSE=14.7, MAE=11) than the MVM with no lead time (RMSE=16.2, MAE=13.2) in forecasting.

In this study, another time series analysis namely Artificial Neural Network (ANN) model was used to compare the performance with SARIMA model and further, to assess the potential impact of climate change on cholera incidence as long-term prediction. Rainfall, maximum temperature and Brahmaputra River discharge (SWAT output) for 11 different climate projections were used as input data to calibrate (1986-2005) and

validate (2006-2013) the cholera prediction model. Then, the calibrated model was used to simulate future impact of cholera for the perspective climate projections, and analyzed the simulated cholera to estimate the future change in different time slices. During the peak of the pre-monsoon season, cholera cases could potentially increase because of climate change by 18% - 80% for 2020-2039, by 24% - 119% for 2040-2059, by 11% - 208% for 2060-2079, and by 36% - 308% for 2080-2099.

Finally, a systematic review has been done on preparedness practices and response plan strategies of combating cholera for different countries of the world to recommend adaptation guideline for Bangladesh. The government of Bangladesh is eager to improve preparedness against waterborne diseases by ensuring safe drinking water all around the year including pre- and post-monsoon seasonal scarcity, which will be benefited by the findings of this study. Still, Bangladesh needs a 'preparedness and response plan' for its endemic cholera outbreaks every year during pre- and post-monsoon. This study proposed a preparedness and response plan as an adaptation guideline to combat cholera in Bangladesh.

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ABBREVIATIONS AND ACRONYMS

ACF	Autocorrelation function
AIC	Akaike Information Criterion
ANN	Artificial Neural Network
BCCSAP	Bangladesh Climate Change Strategy and Action Plan
BDP	Bangladesh Delta Plan
BIC	Bayesian Information Criterion
BMD	Bangladesh Meteorological Department
BWDB	Bangladesh Water Development Board
C5	Combating Cholera Caused by Climate Change
CFR	Case Fatality Rate
CMIP5	Coupled Model Intercomparison Experiment Project Phase 5
CORDEX	Coordinated Regional Climate Downscaling Experiments
CSIRO	Commonwealth Scientific and Industrial Research Organization
EMM	Ensemble mean of models
ENSO	El Niño Southern Oscillation
ESGF	Earth System Grid Federation
GCM	Global Climate Model
GoB	Government of Bangladesh
icddr,b	International Centre for Diarrheal Disease Research, Bangladesh
IEDCR	Institute of Epidemiology, Disease Control and Research of Government of Bangladesh
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error

MPI-CSC	Max Planck Institute-Computational Methods in Systems and Control Theory
MSBC	Multi-segment Statistical Bias Correction
MVM	Multi-Variable model
NAPA	National Adaptation Plan of Action
NGO	Non-Government Organization
nRMSE	Normalized Root Mean Squared Error
NSE	Nash-Sutcliffe Efficiency
ORS	Oral Rehydration Solution
PACF	Partial Autocorrelation Function
RCM	Regional Climate Model
RCP	Representative Concentration Pathway
RMSE	Root Mean Square Error
SARIMA	Seasonal Auto-Regressive Integrated Moving Average
SDG	Sustainable Development Goals
SMHI	Swedish Meteorological and Hydrological Institute
SOI	Southern Oscillation Index
SST	Sea Surface Temperature
SVM	Single Variable model
SWAT	Soil and Water Assessment Tool
T1P6A1	Theme 1 Program 6 Action 1 of
WASH	Water Sanitation and Hygiene
WHO	World Health Organization

CHAPTER ONE

INTRODUCTION

1.1 Background And Present State of The Problem

Cholera is an infection of the small intestine; marked by profuse, watery, secretory diarrhea with or without vomiting; caused by the bacterium *Vibrio cholerae*. This may result in acute dehydration and without treatment, it can even cause death within 24 hours [1]. Cholera bacteria transmission occurs via the faecal-oral route primarily by drinking water or eating food that has been contaminated. Worldwide, about 1.3 billion people are at risk for cholera in endemic countries. An estimated burden of 2.9 million with uncertainty of 1.3 to 4.0 million cholera cases occur annually in endemic countries. Among these cases, there are 95,000 with uncertainty of 21,000 to 143,000 deaths as of 2015 [2]. Cholera is a global killer with the world witnessing an extraordinary rise in cholera infection and transmission since the 1990s [3].

Cholera has been endemic in Bangladesh for more than 2,000 years [3] and is associated with water and sanitation as well as a number of environmental factors (rainfall, temperature, sea surface temperature, etc.). Bangladesh experiences an estimated 300,000-400,000 life-threatening cases of cholera per year, where hydro-climatic processes play a vital role in propagating cholera incidence [4-6]. Cholera has been observed in two seasons in Bangladesh, namely, pre-monsoon (March - May) and post-monsoon (September - November) seasons [4, 7]. Pre-monsoon cholera outbreak in coastal areas of Bangladesh and the capital region of Dhaka is associated with low flow situations in regional rivers, a surrogate for dry season water scarcity; while post-monsoon outbreaks in Dhaka and other inland regions have shown strong links to water abundance in flood-prone areas [4]. During pre-monsoon, there is seasonal safe drinking water scarcity as many hand tube wells go dry due to seasonal declination of groundwater table while salinity encroaches to the coastal region of Bangladesh due to low fresh water river flow. This causes endemic pre-monsoon cholera outbreaks in coastal areas of Bangladesh. On the other hand, during post-monsoon, with encroachment of seasonal flood water in the flood-prone areas of Bangladesh, all type of water-borne disease including cholera take place due to scarcity of safe drinking water when many hand tube wells go under flood water.

Bangladesh is one of the most hazard prone countries in the world and is expected to be one of the worst affected by climate change [8]. Every year, extreme weather events such as flooding, droughts and cyclones have devastating effects, also impacting on water quality, quantity and sanitation infrastructure. As extreme weather events continue to increase with climate change, Bangladesh faces a multitude of adverse health, economic, and livelihood consequences [9].

It is essential to project the potential impact of climate change on meteorologically sensitive diseases for the regions where changes to disease may have adverse health impact [10-12]. Projecting the future risk of cholera involves a number of uncertainties (e.g., vaccination, cultural and behavioral practices, and prevalence of other related diseases) which may change in the future because many factors in addition to climate influence the disease. In spite of such uncertainties this study is useful as it indicates the potential impact of climate change on future cholera burden which inform authorities to develop mitigation and adaptation strategies to protect the vulnerable populations [13]. Therefore, to evaluate the long-term impact of climate change and variability on cholera incidence, very good calibrated models at different scales are necessary for reliable prediction. In this study, we will evaluate the relation between cholera incidence and hydro-climatic variables as well as climate change impact on cholera incidence through developing statistical models in Dhaka megacity using International Centre for Diarrheal Disease Research, Bangladesh (icddr,b) cholera data. icddr,b is known as the only cholera hospital located in Mohakhali, Dhaka, Bangladesh where most cholera patients come for treatment. An appropriate climate change adaptation options will also be recommended for combating cholera caused by climate change in Bangladesh.

1.2 Objectives with Specific Aims And Possible Outcome

The general objective of the study is to evaluate the hydro-climatic impact on cholera incidence under long-term global warming in Dhaka, Bangladesh.

The specific objectives of the study are:

a) To investigate the relationship between cholera incidence and climatic variables;
b) To develop and validate a cholera forecasting model with different lead time;
c) To evaluate the climate change impact on cholera incidence based on Regional Climate Models (RCMs) under different scenarios; and
d) To develop an adaptation guideline related to combating cholera.

The possible outcome will be

- Developing and testing a forecasting model for cholera incidence in Dhaka using time series analysis;
- Impact of future climate change on cholera incidence in Dhaka using the assessment of global climate models available; and
- Combating cholera in Bangladesh: Preparedness and emergency response guidelines

1.3 Organization of The Chapters

This thesis consists of nine chapters. The **Chapter One** describes the background and present state of the problem. It provides major objectives and outcomes of the research. **Chapter Two** includes history of cholera and gives the review of the literatures on linkage between cholera and climatic variables throughout the world. **Chapter Three** describes the study area and the data sets, along with the use of the data in the analysis. **Chapter Four** describes the methodologies and performance indicators regarding the application to short-term cholera forecasting and long-term future impact on cholera incidence. **Chapter Five** presents the first objective which describes the descriptive analysis of cholera incidence and climate variables in Dhaka. **Chapter Six** provides the second objective which describes the development and evaluation of a cholera forecast model. **Chapter Seven** summarizes the results and discussion of projection of future impact of climate change on cholera incidence, which presents the third objective. **Chapter Eight** provides an adaptation guideline related to combating cholera where worldwide cholera preparedness and response plan are summarized here. **Chapter Nine** offers conclusions of this study.

CHAPTER TWO

LITERATURE REVIEW

2.1 History of Cholera Transmission

The *first pandemic* of cholera occurred from 1817 to 1824 and was fairly limited in scope and related to the two wars – the Oman War and the war between Persia and Turkey. Before 1817, cholera was most probably a sporadic, summertime illness, perhaps emerging in its violent epidemic form in the early 19th century.

The *second pandemic* (1829 to 1837) is believed to have instigated in Russia, where citizens of Moscow were particularly hard hit. The pandemic spread across the Atlantic Ocean in 1832 to the Americas, and, ultimately, spreading to New York on 23 June 1832 [14]. The disease spread from New York to Philadelphia in 2 weeks and subsequently along the coast to New Orleans.

The *third pandemic* (1846 to 1860) deeply affected Russia with over one million deaths. The *third pandemic* reappeared in a region of London, close to where Dr. John Snow, physician to Queen Victoria, lived, who determined in 1849 that the spread of the disease was connected to mixing of drinking water and sewage [15].

The *fourth* (1863 to 1875), was followed by the *fifth* (1881 to 1896), and *sixth* (1899 to 1923) *pandemics*. From 1926 to 1960, many believed that cholera would not recur in pandemic form because water supplies had been improved worldwide. Indeed, many parts of the world did become free of cholera. But, nature prevailed in 1961, the *seventh cholera pandemic* started in Indonesia which has been reported in over 50 countries.

2.2 Cholera Transmission

Cholera is an enteric diarrheal disease caused by the gram-negative bacterium *V. cholerae*, which remains to be a worldwide health concern. Without treatment, cholera can result a mortality rates of 50% upwards [16]. *V. cholerae* is transmitted through the fecal-oral route in which fecal may be ingested in a pathway. Wagner, et al. [17] developed these pathways as the F-diagram (Figure 2.1) which demonstrates how the transmission of the pathogen from feces to a new host through fluids, fingers, flies, fields and food. This diagram suggests that improvement in sanitation, water quality, water quantity and hygiene can break all the pathways in the fecal-oral route.

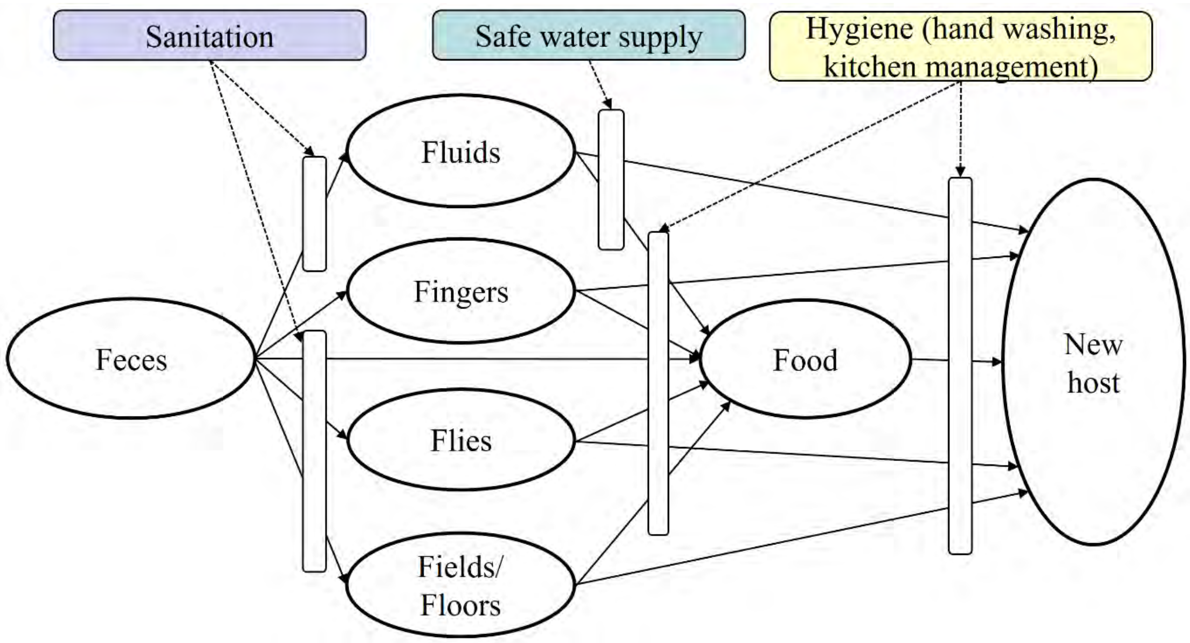

Figure 2.1: The F-diagram which illustrates the fecal-oral transmission route of *V. cholerae* (adapted from Wagner, et al. [17])

The causative agent of cholera in humans *V. cholerae*, is classified into two groups: O1 and non O1 [18]. The O1 serogroup of *V. cholerae* is further classified into two biotypes, namely, the classical and El Tor biotypes [19]. In 1993, an entirely new serogroup O139 made an explosive appearance and caused an epidemic in Bangladesh [20, 21]. Cholera has over 200 identified serotypes based on O-antigen [22], but only O1 and O139 are toxigenic, which are the only reported groups linked to the original epidemics and pandemics globally. Recently, a hierarchical model has been recommended, where the role of environmental, weather and climatic variables in cholera outbreaks has been defined (Figure 2.2).

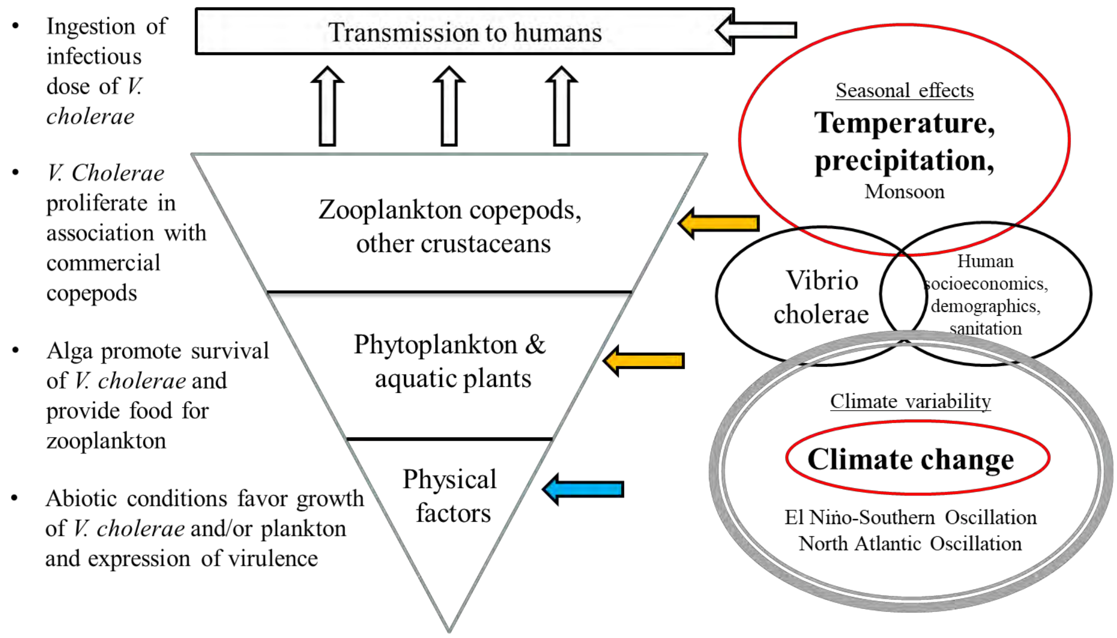

Figure 2.2: Hierarchical model for environmental cholera transmission (source: Lipp, et al. [7])

The global pattern and magnitude of the pandemic suggests that cholera outbreaks primarily originate in coastal environments and then spread inland through secondary means [23, 24]. The cholera-coastal connection is usually explained by the fact that cholera is caused by two particular pathogenic strains of the bacterium *Vibrio cholerae*, which are found mainly in marine plankton [25, 26]. Phytoplankton and zooplankton, by serving as the primary sources of nutrients and also physical carriers of the bacteria, play an important role in facilitating the survival, multiplication, and transmission of *Vibrio cholerae* in the natural aquatic environment [7, 24].

V. cholerae is known to persist in brackish waters, coastal waters and estuarine environments [27]. In these environments, *V. cholerae* is typically associated with copepods that feed on phytoplankton. Many studies have shown that increasing sea surface temperature can promote phytoplankton growth and consequently *V. cholerae* growth; and, although no clear link has been established between cholera incidence and global warming but suggests that variables of climate change and variability e.g., rainfall and temperature might facilitate more frequent cholera outbreaks [28-30]. Besides, social risk factors e.g., poverty, sanitation conditions, and untreated drinking water are playing an important role in transmission and outbreak of cholera [31-34].

2.3 Cholera in Different Countries

After *seven pandemics* (spread along a continent) in the last 200 years, cholera remains endemic (≤1% mortality rate) in many developing countries in Asia, Africa and Latin America. The seventh cholera pandemic began in Indonesia in 1961, but the disease has reemerged as a global killer since the1990s [3]. Recently, mortality rate for epidemic (>3% mortality rate) cholera was recorded as high as 6.4% in 2010 in Haiti, 6% in 2000 in Madagascar, 4.3% in 2008-9 in Zimbabwe, 4% in 2006-7 in Angola, 3.8% in 2010 in Nigeria, and 3.3% in 2006-7 in Sudan [35].

In Peru, cholera epidemics are strictly confirmed to the warm season [36], where the seasonality seems to be related to the ability of vibrio to grow rapidly in warm environmental temperatures [23, 37, 38]. In this study two seasons are also taken into consideration as risk factors to cholera epidemics: the rainy season (humid) and the dry season. The research intends to demonstrate whether there is a relationship between cholera cases and the period of occurrence. A study by Gil, et al. [39] indicated the relationship between cholera incidence and elevated sea surface temperatures as well as cholera incidence and changes of climatic variables during 1997-1998 El Niño in Peru. Furthermore, Pascual, et al. [40] investigated the relationship between El Niño Southern Oscillation (ENSO) and the occurrence of cholera. In 2010, Haiti experienced cholera epidemics as a result of a huge earth quake disaster [41]. Laboratory tests on the cholera strain responsible for the outbreak in Haiti, conducted by the US Centre for Diseases Control and Prevention (CDC) in Atlanta, showed that it is most similar to cholera strains found in South Asia. In endemic areas, annual rates of disease vary widely, probably as a result of environmental and climate changes. Better understanding of the relation to climate would thus allow better planning for epidemics by public-health officials.

In the 21st century, Africa bears the burden of global cholera, where the percentage of people die from reported cholera cases remains higher than elsewhere [42]. Cholera incidence during El Niño years was higher in East Africa with increasing rainfall, and was also higher in some areas with decreasing rainfall, which indicate a complex relationship between rainfall and cholera incidence [43]. In Africa, rainfall, temperature and El Niño play a role on cholera outbreaks e.g., in Great Lakes Region [44], in Tanzania [45], in Zimbabwe [46] and in South Africa [47].

In India, rainfall, temperature and relative humidity influence to increase cholera outbreaks [48, 49], where researchers used SARIMA and GLM methods to model cholera case data.

2.4 Cholera in Bangladesh

Cholera is endemic in Bangladesh, meaning that the country experiences cholera year after year, even while other parts of the world remain free of cholera [7]. However, detailed mechanisms of such endemism are not yet clearly understood [19, 50]. It is estimated that cholera burden is 109,052 cases per year with a case fatality rate of about 3% and about 66.5 million people are at risk in Bangladesh [2]. Generally, cholera outbreaks showed dual peaks annually in some parts of Bangladesh (e.g., in Dhaka and Matlab), while single seasonal peaks in other parts (e.g., pre-monsoon peak in Mathbaria in the southwest coast and post-monsoon peak in Chhatak in the northwest) (Figure 2.3) [4, 5, 51, 52].

It is hypothesized in many studies that hydrological low flow in major rivers and salinity intrusion caused pre-monsoon cholera outbreak while hydrological high flow in major rivers causing seasonal floods all over Bangladesh causes post-monsoon cholera outbreaks in Bangladesh [4, 29]. During pre-monsoon, there is seasonal safe drinking water scarcity as many drinking water sources (e.g., hand tube wells) go dry due to seasonal declination of groundwater table while salinity encroaches to the coastal region of Bangladesh due to low fresh water river flow that provides an optimum environment for growth and increased abundance of *V. cholerae* pathogens [53, 54]. This causes endemic cholera outbreaks in coastal areas of Bangladesh. On the other hand, monsoon floods inundating large inland areas with stagnant water and rain-flushed nutrients provide a growth environment for pathogens [55]. With the recession of seasonal flood water, available water-borne pathogens including cholera in combination with scarcity of safe drinking water when many drinking water sources are contaminated with flood water, cause a second 'post-monsoon' outbreak [4, 5].

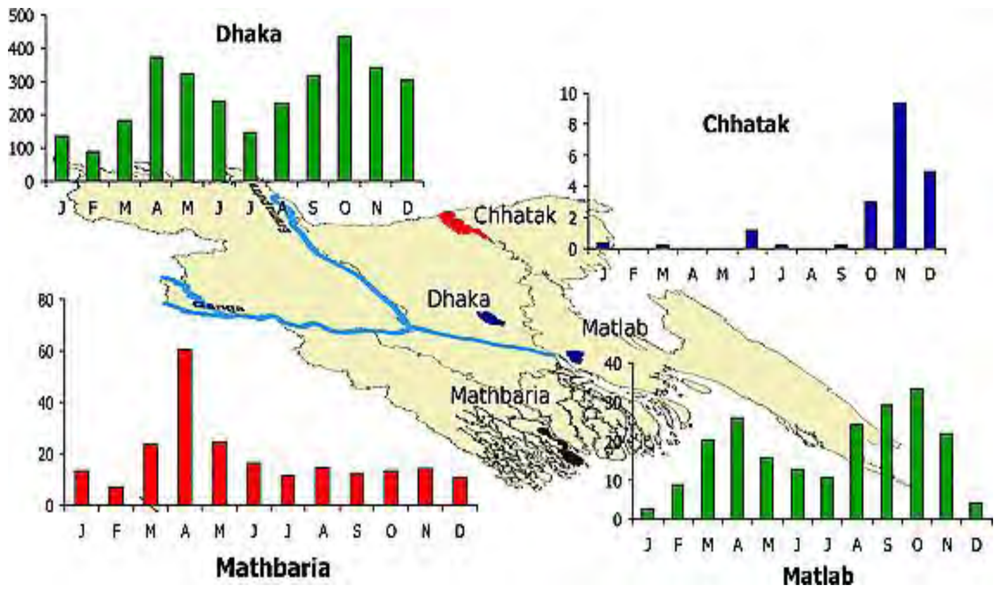

Figure 2.3: Monthly climatology of cholera incidence recorded at International Centre for Diarrheal Disease Research, Bangladesh (icddr,b) surveillance centers in Dhaka, Mathbaria, Chhatak, and Matlab, Bangladesh (source: Akanda, et al. [5])

Cholera has pronounced seasonality. There have been concerns about the recurrence of epidemics of diseases such as cholera, previously thought to be under control [56]. Many scientific studies have been undertaken to study cholera and factors that may contribute to its re-occurrence and spread to new areas. In Bangladesh, where the disease is endemic, two peaks occur each year that corresponds with two warm seasons before and after the monsoon rainfall [57]. Specifically, linkages between environmental conditions and outbreaks of cholera in Bangladesh have been demonstrated by Huq, et al. [58], where the Poisson regression model has been used to model cholera case data.

In laboratory tests, it has been shown that salinity and temperature are important factors for influencing the growth of *V. cholerae* [59], and *V. cholerae* can survive more when aided by copepods [60]. Some environmental indicators such as water temperature and water depth in some water bodies in Bangladesh showed a significant lagged correlation with cholera outbreaks [58]. Moreover, climate variability for example, extreme dry conditions and high temperature leading to droughts, or heavy rainfall leading to floods that occurred caused by El Niño Southern Oscillation (ENSO) may lead to enhance cholera outbreaks in future [61].

2.5 Climate Change General Concept

Climate change occurs when changes in Earth's climate system result in new weather patterns that remain in place for an extended period of time that can be as short as a few decades to as long as millions of years. Scientists have identified many episodes of climate change during Earth's geological history; more recently since the industrial revolution, climate has increasingly been affected by human activities driving global warming [62]. IPCC [63] also stated in its Fifth Assessment Report (AR5) that human influence on the climate system was clear, while the latest anthropogenic emissions of greenhouse gases were the highest in history. Therefore, these climate changes have had widespread impacts on human and natural systems. Figure 2.4 illustrates the multiple observed indicators of climate change globally that are adapted from IPCC [63].

The new climate scenarios of Representative Concentration Pathways (RCPs) that are introduced by Moss, et al. [64], are widely used presently for climate change impact assessment. Four RCPs have been introduced for climate modeling and research, which describe different climate futures, all of which are considered possible depending on how much greenhouse gases are emitted in the years to come. The four RCPs, namely RCP2.6, RCP4.5, RCP6, and RCP8.5, are labelled after a possible range of radiative forcing values in the year 2100 (2.6, 4.5, 6.0, and 8.5 W/m^2, respectively (Figure 2.5)).

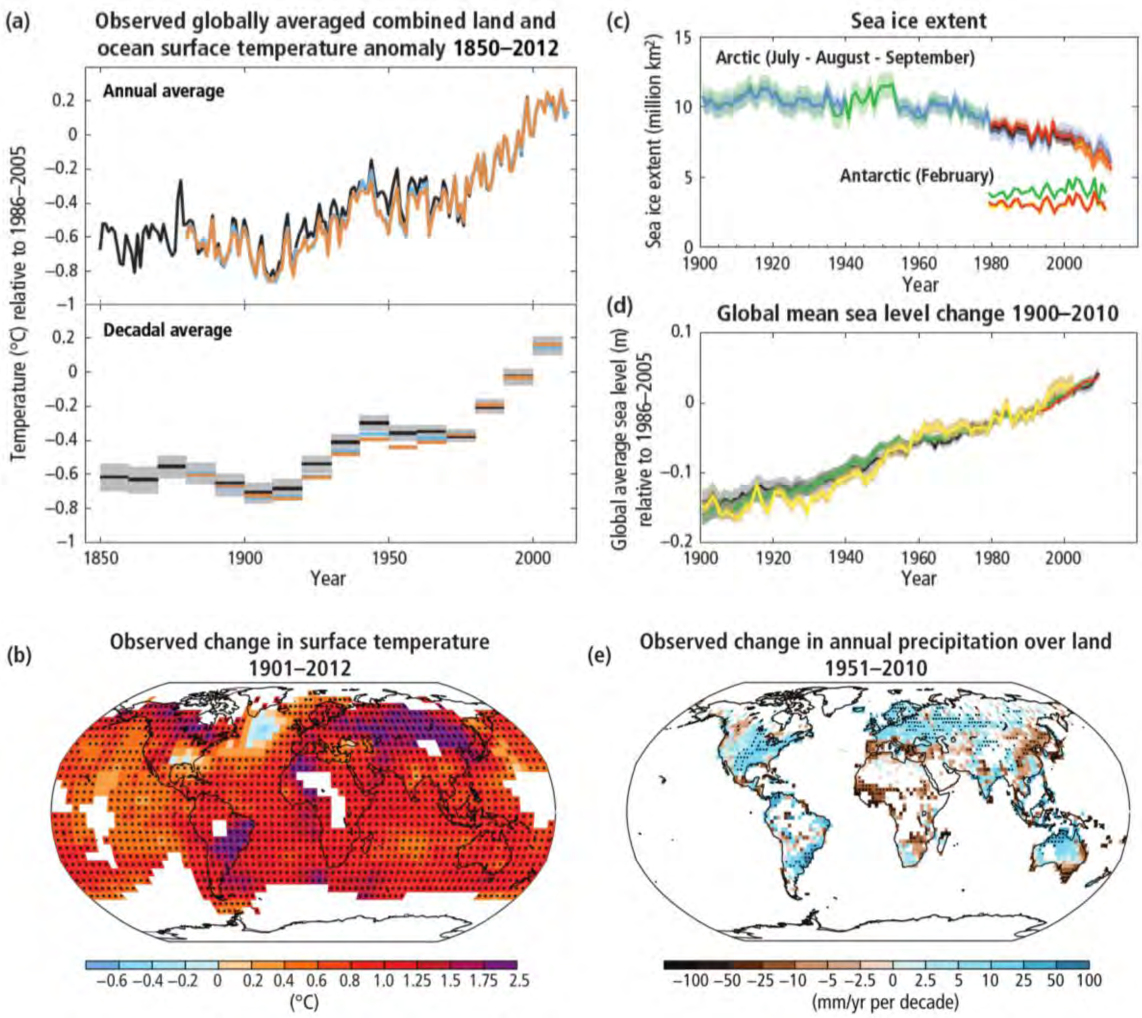

Figure 2.4: Multiple observed indicators of a changing global climate system: (a) observed globally averaged combined land and ocean surface temperature anomalies (relative to the mean of 1986 to 2005 period, as annual and decadal averages) with an estimate of decadal mean uncertainty included for one data set (grey shading); (b) map of observed surface temperature change, from 1901 to 2012, derived from temperature trends; (c) Arctic (July to September average) and Antarctic (February) sea ice extent; (d) global mean sea level relative to the 1986–2005 mean of the longest running data set, and with all data sets aligned to have the same value in 1993, the first year of satellite altimetry data; and (e) map of observed precipitation change, from 1951 to 2010; adapted from IPCC [63]

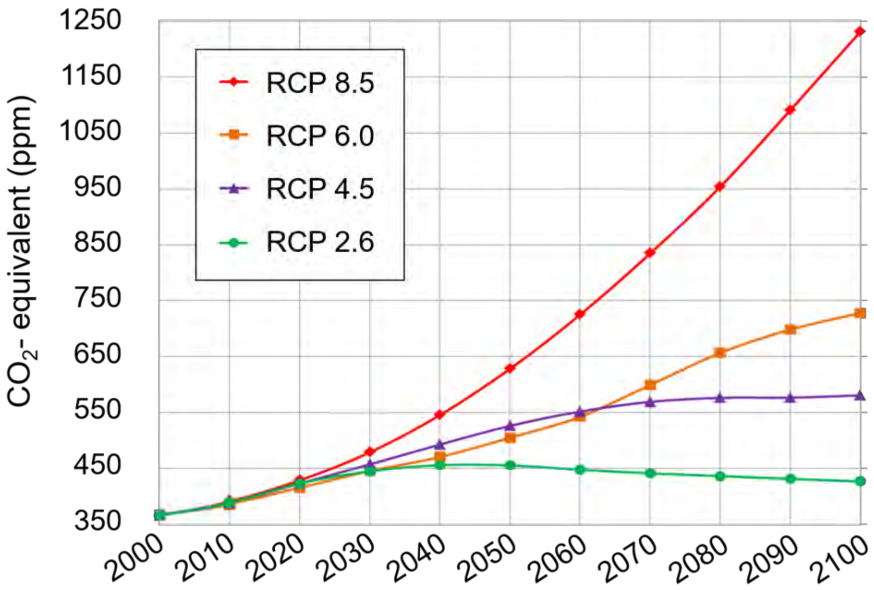

Figure 2.5: Future CO_2 projections, including all forcing agents' atmospheric CO_2-equivalent concentrations in parts-per-million-by-volume (ppmv) according to four RCPs (Representative Concentration Pathways) by Moss, et al. [64]

2.6 Impact of Climate Change on Cholera

According to IPCC [9], climate change is likely to increase the frequency and intensity of drought at regional and global scale; and the increasing frequency and intensity of extreme rainfall is expected which leads flood throughout the 21st century. WHO [12] summarizes the impact of climate change on human health that between 2030 and 2050, climate change is expected to cause approximately 250,000 additional deaths per year globally, from malnutrition, malaria, diarrhea and heat stress where areas with weak health infrastructure – mostly in developing countries – will be the worst able to cope without assistance to prepare and respond.

In the future, even if global warming is kept to 1.5°C, warming in the mountains of Hindu Kush Himalaya region will likely be at least 0.3°C higher and in the northwest Himalaya at least 0.7°C [65]. While Fahad, et al. [66] found that at the end of this century the mean temperature increase over Bangladesh will vary from 3.2 - 5.8°C where spatially southwest and south central parts of Bangladesh will experience a greater temperature rise than other parts. Such large warming could trigger a multitude of biophysical and socio-economic impacts such as increased glacial melting which may affect the annual water budget i.e. less predictive water availability during pre-monsoon and increasing frequency and severity of floods, therefore, the endemic cholera outbreaks both at pre- and post-monsoon may increase largely.

Mohammed, et al. [67] showed that floods in Brahmaputra basin are likely to become more frequent in the future, and their magnitude will also become more severe due to climate change high-end scenario (RCP 8.5) while hydrological droughts are projected to become less frequent in the future and their magnitude to become less severe, however, the average timing of both floods and hydrological droughts is projected to shift earlier compared to the present hydrological regime i.e., early onset of both drought and flood, therefore, this time change may also affect adversely on dual cholera outbreaks annually that may prolong the cholera outbreaks.

2.7 Gap Analysis in the Context of This Study

From the above discussion, no forecasting model and/or prediction model considering climatic variables has been developed previously. The studies so far conducted are not enough for cholera forecasting at the short-term. For example, the latest study on Dhaka, Martinez, et al. [68] developed a forecast model for a small area of Dhaka (Mirpur) considering the influence of only ENSO, however, influence of ENSO on rainfall pattern is yet to establish over the Indian sub-continent region [69-72] while the rainfall affects positively on cholera incidence in Dhaka [73]. In other previous studies, no study developed a cholera forecast model, instead only relationships between cholera incidence and climatic variables are shown for Dhaka, Bangladesh. Therefore, it is necessary to develop a short-term forecasting model at least for Dhaka city on the basis of that model a short-term preparedness can be taken into consideration.

The literature also shows that as far our knowledge only one study has been done in any location of the world on climate change impact assessment on cholera incidence in northern Nigeria by Abdussalam [74]. Therefore, a long-term prediction of cholera incidence is required to be done based on climatic variables under global climate change and variability on the basis of which, a long-term preparedness and emergency plan may be taken into consideration for combating cholera for Dhaka megacity as well as for whole Bangladesh wherever cholera outbreaks occur.

For cholera planning, there is no cholera preparedness and response plan for whole Bangladesh although there is one emergency response plan for water, sanitation and hygiene (WASH) for Bangladesh during disaster periods and icddr,b follows an emergency medical service for cholera patients at one location in Dhaka only. Therefore, if cholera outbreaks increase widespread in Bangladesh in future, a guideline of preparedness and emergency response plan would be required that has been proposed after revisiting the existing related plans of Bangladesh and the cholera response plans by different countries of the world.

CHAPTER THREE

STUDY AREA AND DATA

3.1 Study Area

Dhaka is a densely-populated megacity with the population of 14.2 million in 2011; the 2001 population was 9.7 million, therefore, the decadal growth rate was 46% [75]. Dhaka has a tropical wet and dry climate which has a distinct monsoonal season with an annual average temperature of 26.1°C and rainfall of 2,149 mm based on last 30 years of data [76]. During January 2000 to December 2013, the mean (± SD) monthly rainfall, maximum temperature, minimum temperature, and relative humidity of 164 (± 177) mm, 30.7 (± 3.3) °C, 22.1 (± 4.5) °C, and 82 (± 6.4) %, respectively indicate that Dhaka has generally warm and humid weather.

Dhaka cholera incidence data has been used for this study because: (i) Dhaka is at high risk of endemic cholera because of high population density as well as seasonal flooding and proximity to Bay of Bengal; (ii) Dhaka received dual peak of cholera incidence annually like Matlab for which a similar study has been conducted by Ali, et al. [28] where single variable SARIMA model with minimum temperature and SST were found triggering cholera outbreaks that compared for addressing in Chapter Six; and (iii) long-time series continuous cholera incidence data is available from International Centre for Diarrheal Disease Research, Bangladesh (icddr,b), which receives most cholera patients in and around Dhaka megacity (Figure 3.1).

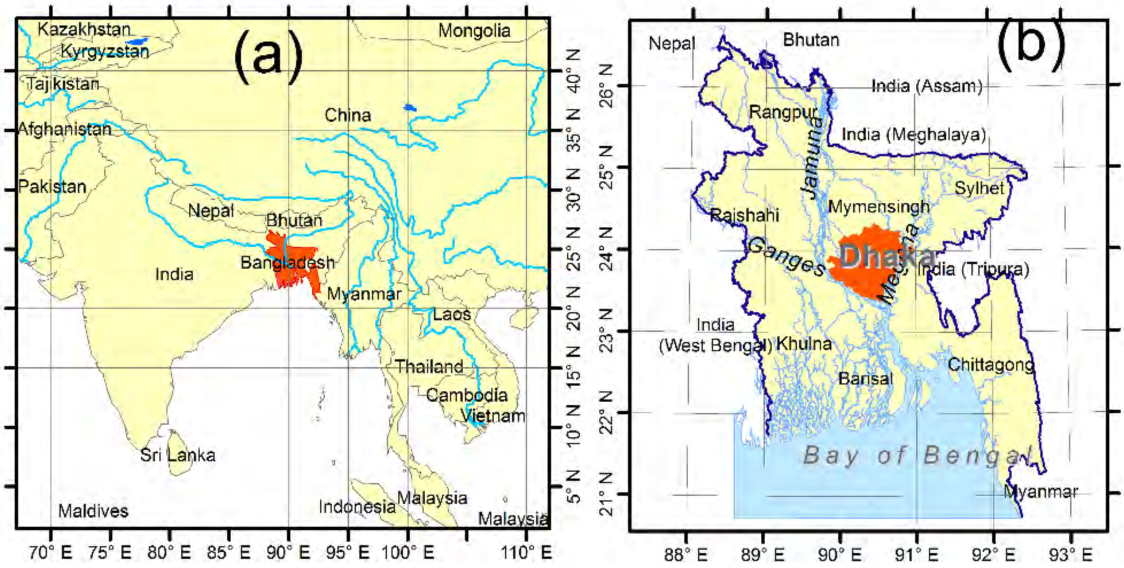

Figure 3.1: (a) Location map of Bangladesh; (b) Location map of Dhaka

3.2 Meteorological Data

To fulfill the investigation of the relationship between cholera incidence and climatic variables; and the development and validation a cholera forecasting model, three-hourly local meteorological data of Dhaka station was used. The meteorological data such as rainfall, maximum temperature, minimum temperature and relative humidity was collected from Bangladesh Meteorological Department (BMD) which was summarized as monthly data for the last 14 years from January 1, 2000 to December 31, 2013. The weather station is located at latitude 23°46′N, longitude 90°23′E. There was no missing data during the study period. In Dhaka district, there are two meteorological stations by BMD, one at Tejgaon which is at the center of Dhaka city and another at Dhaka international airport located at the northern part of Dhaka. The Tejgaon station's data is used here as this is more reliable than the airport station's data as suggested by BMD. Satellite-derived ENSO [77] and SOI [78] at the index Niño 3.4[1] were also used in this study.

[1] Niño 3.4 (5N-5S, 170W-120W) anomalies may be thought of as representing the average equatorial sea surface temperatures (SSTs) across the Pacific from about the dateline to the South American coast. The Niño 3.4 index typically uses a 5-month running mean, and El Niño or La Niña events are defined when the Niño 3.4 SSTs exceed +/- 0.4°C for a period of six months or more. For more information please refer to https://climatedataguide.ucar.edu/climate-data/nino-sst-indices-nino-12-3-34-4-oni-and-tni

3.3 Hydrologic Data

Time series daily discharge data from the Bahadurabad gauging station (SW46.9L) on the Brahmaputra River was collected from Bangladesh Water Development Board (BWDB) for the period 1986-2005. These observed discharge data have been used to compare with historical RCM simulations.

3.4 Hydro-Climatic Data

To evaluate the climate change impact on cholera incidence, the outcome of the Soil Water Assessment Tool (SWAT) hydrological modelled discharge from Mohammed, et al. [67] of 11 independent climate projections (Table 3.1) were used to calibrate/validate the ANN models. After calibration and validation, the calibrated models were used to simulate future cholera incidence.

A bias-corrected climate projections for rainfall and maximum temperature with a multisegment statistical bias correction (MSBC) from Fahad, et al. [66] was used where the reference data set was the hybrid data set of WATCH forcing data [79] which was applied to ERA-Interim data [80] that are described in detail in Grillakis, et al. [81]. The reference period for bias correction was 1986 – 2005 while correction period was 2006 – 2100. The raw regional climate model (RCM) outputs of daily rainfall and maximum temperature at Dhaka were retrieved from repositories of Earth System Grid Federation (ESGF) website (https://pemdi.llnl.gov/projects/esgf-llnl/) and Indian Institute of Technology Madras Centre for Climate Change Research website (http://cccr.tropmet.res.in/cccr/home/index.isp). These ESGF RCMs were driven from CMIP5 global climate models (GCMs). Details of RCMs obtained for predicted variables for input for cholera case are listed in Table 3.1.

Among four representative concentration pathways (RCPs) of climate projection scenarios of IPCC [9], the high emission scenario RCP8.5 was chosen for this study to predict the climate anomaly in different times in 21st century. Time series were selected as base period (1986 - 2005), and four future times of 2030s (average of 2020 - 2039), 2050s (2040 - 2059), 2070s (2060 - 2079), and 2090s (2080 - 2099).

Table 3.1: List of regional climate models obtained for input variables of cholera cases

Modeling centre/ Institute	GCM	RCM	Driving ensemble member	Resolution (degrees)	RCP	Corresponding ANN model
CSIRO	ACCESS 1.0	CCAM-1391M	r1	0.5	8.5	M1
CSIRO	CCSM 4.0	CCAM-1391M	r1	0.5	8.5	M2
SMHI	CNRM-CERFACS-CNRM-CM5	RCA4	r1i1p1	0.5	8.5	M3
CSIRO	CNRM-CM5	CCAM-1391M	r1	0.5	8.5	M4
SMHI	ICHEC-EC-EARTH	RCA4	r12i1p1	0.5	8.5	M5
SMHI	IPSL-CM5A-MR	RCA4	r1i1p1	0.5	8.5	M6
SMHI	MIROC-MIROC5	RCA4	r1i1p1	0.5	8.5	M7
CSIRO	MPI-ESM-LR	CCAM-1391M	r1i1p1	0.5	8.5	M8
MPI-CSC	MPI-M-MPI-ESM-LR	REMO2009	r1i1p1	0.5	8.5	M9
SMHI	MPI-M-MPI-ESM-LR	RCA4	r1i1p1	0.5	8.5	M10
SMHI	NOAA-GFDL-GFDL-ESM2M	RCA4	r1i1p1	0.5	8.5	M11

Note: CSIRO = Commonwealth Scientific and Industrial Research Organization; SMHI = Swedish Meteorological and Hydrological Institute; MPI-CSC = Max Planck Institute-Computational Methods in Systems and Control Theory; GCM = Global Climate Model; RCM = Regional Climate Model; RCP = Representative Concentration Pathway

3.5 Cholera Incidence Data

Laboratory-confirmed cholera patients data of the icddr,b were used for the same period of January 2000 to December 2013. icddr,b is commonly known as the 'cholera hospital' where most severely cholera patients in and around Dhaka megacity come to this cholera hospital for treatment. Monthly counts of cholera incidence data of icddr,b (Figure 3.2) were extracted using ArcGIS 10.3 for the period of January 1984 to December 1999 from Figure 2 of Hashizume, et al. [82].

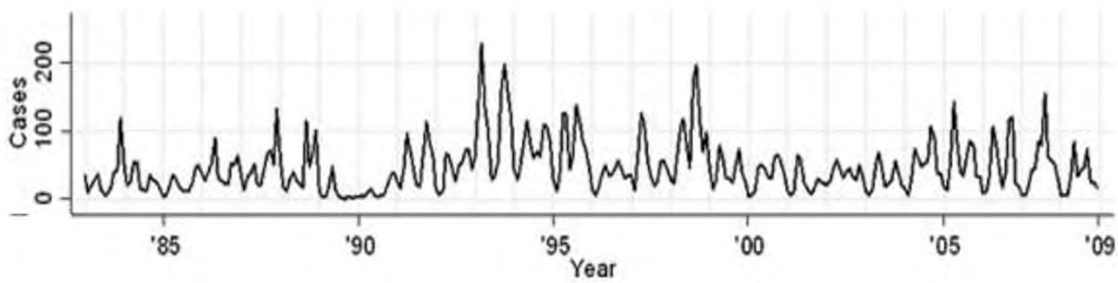

Figure 3.2: Monthly total cholera cases data for Dhaka icddr,b (source: Hashizume, et al. [82])

CHAPTER FOUR

METHODOLOGIES AND PERFORMANCE INDICATORS

4.1 Seasonal Auto-Regressive Integrated Moving Average (SARIMA)

4.1.1 Introduction

A class of time series techniques, namely ARIMA, can be active for the short-term forecasting. ARIMA is a method first introduced by Box and Jenkins [83] and has now become one of the most popular methods for time series forecasting. Here, a variation of the classical ARIMA model, namely the seasonal ARIMA model (i.e. SARIMA) is used, in order to account for the inherent seasonal effect of the output. The seasonal ARIMA model is generally referred to as SARIMA $(p,d,q)(P,D,Q)_s$, where p, d, q and P, D, Q are non-negative integers that refer to the polynomial order of the autoregressive (AR), integrated (I), and moving average (MA) parts of the non-seasonal and seasonal components of the model, respectively. **Auto-Regression (AR)** is a regression model that uses the dependencies between an observation and a number of lagged observations. **Integration (I)** is to make the time series stationary by measuring the differences of observations at different time. **Moving Average (MA)** is an approach that takes into accounts the dependency between observations and the residual error terms when a moving average model is used to the lagged observations.

The SARIMA model is described mathematically as follows:

$$\varphi_p(B)\Phi_P(B^s)\nabla^d\nabla_s^D y_t = \theta_q(B)\Theta_Q(B^s)\varepsilon_t \tag{4.1}$$

where:

y_t is the forecast variable

$\varphi_p(B)$ is the regular AR polynomial of order p

$\theta_q(B)$ is the regular MA polynomial of order q

$\Phi_P(B^s)$ is the seasonal AR polynomial of order P

$\Theta_Q(B^s)$ is the seasonal MA polynomial of order Q

∇^d is the regular differentiating operator

∇_s^D is the seasonal differentiating operator

B is the backshift operator, which operators on the observation y_t by shifting it one point in time (i.e. $B^k(y_t) = y_{t-k}$). The term ε_t follows a white noise process and s defines the seasonal period. The polynomials and all operators are defined mathematically as follows:

$$\varphi_p(B) = 1 - \sum_{i=1}^{p} \varphi_i B^i \quad (4.2)$$

$$\theta_q(B) = 1 - \sum_{i=1}^{q} \theta_i B^i \quad (4.3)$$

$$\nabla^d = (1 - B)^d \quad (4.4)$$

$$\Phi_P(B^s) = 1 - \sum_{i=1}^{P} \Phi_i B^{s,i} \quad (4.5)$$

$$\Theta_Q(B^s) = 1 - \sum_{i=1}^{Q} \Theta_i B^{s,i} \quad (4.6)$$

$$\nabla_s^D = (1 - B^s)^D \quad (4.7)$$

The model development was based on the Box-Jenkins methodology, which consists of four iterative steps: a) Identification, b) Estimation, c) Diagnostic checking, and d) Forecasting.

4.1.2 Development of the SARIMA model

The overall flow chart of how SARIMA models were developed in this study is shown in Figure 4.1, where the Box-Jenkins modelling approach [83] was used to conduct a time series analysis. The mean-range plot (the range is plotted against the means for each seasonal period) of untransformed and logarithm or square root transformed series was done to stabilize variance of cholera incidence. The logarithm transformation is needed when the mean-range plots display random scatter about a straight line [84]. Seasonal patterns of a time series can be examined by box-plot or autocorrelation plot. As cholera incidence showed the seasonality, a seasonal-auto-regressive-integrated-moving-average (SARIMA) model as a time series analysis tool was used which estimates the effects of climatic variables on cholera incidence and makes the appropriated model for forecasting cholera transmission in this area [85, 86]. The non-seasonal (p,d,q) and seasonal (P,D,Q) order of the model was determined by: (i) the differencing order determined by checking stationarity from unit root test; (ii) the order of autoregressive by partial autocorrelation (PACF); and (iii) the order of moving average by autocorrelation (ACF) functions.

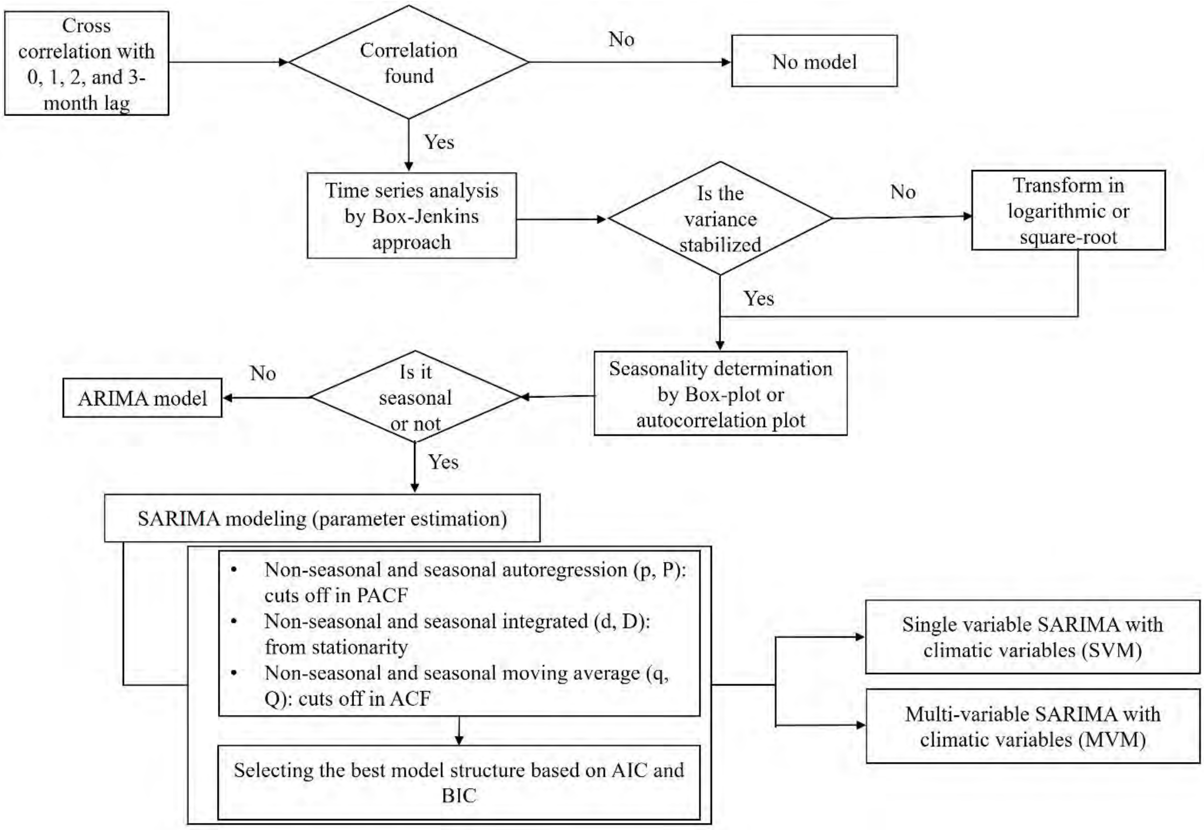

Figure 4.1: Flow chart of evolution of SARIMA model

4.1.3 Goodness of fit

Akaike Information Criterion (AIC) [87] and Bayesian Information Criterion (BIC) [88] were used to assist in the goodness-of-fit of penalizing the model parameters. The lower the AIC and BIC (Eq. 4.8 and 4.9) indicate a better model. Goodness of fit was examined using both ACF and PACF [89] of the residuals of the model and checking Portmanteau test [90, 91] for white noise in residuals and a scatter plot of residuals versus predicted values.

$$AIC = -2 * \ln(maximum\ likelihood) + 2\kappa \tag{4.8}$$

$$BIC = \ln(n)\kappa - 2 * \ln(maximum\ likelihood) \tag{4.9}$$

where,

κ is the number of independently adjusted parameters within the model; and

n is the total number of observations.

4.1.4 Model forecasting

The cholera incidence data was divided into two: data of 2000 - 2011 was used for the model development, and data of 2012 and 2013 for model forecasting. Root mean squared error (RMSE), mean absolute percentage error (MAPE) and mean absolute error (MAE) (described in 4.3 section) were used to verify the forecasting ability of the models [92].

4.2 Artificial Neural Network (ANN)

4.2.1 Introduction

Nowadays, artificial neural networks (ANNs) are considered to be one of the most useful tools to understand the complex problems and have been widely used in the medical and health field [93-95]. ANNs have the ability to learn and model non-linear and complex relationships, which is really important because in real-life, many of the relationships between inputs and outputs are non-linear as well as complex. Researchers have used these models for analyzing different types of regression problems in different situations. To the best knowledge of the author, there is no works available that has been carried out to utilize the ANNs method in predicting cholera. In this study, an attempt has been made to establish an ANN model to predict cholera in Dhaka with a set of climatic variables as predictors. In 1943, Warren McCulloch and Walter Pitts developed the original concept of an ANN, who proposed the conceptualization of human brain function based on a network of interconnected cells [96].

An ANN is formed from a series of information processing elements referred to as nodes or neurons which are highly interconnected. ANNs are arranged into a series of layers: an input layer; one or more hidden layers; and one output layer (Figure 4.2). These layers are then associated with the nodes of successive layers through weights (coefficients), which represents the magnitude or strength of that connection. Each processing element has weighted inputs, transfer function and one output. A weight matrix and an activation or transfer function is associated with each hidden layer [97].

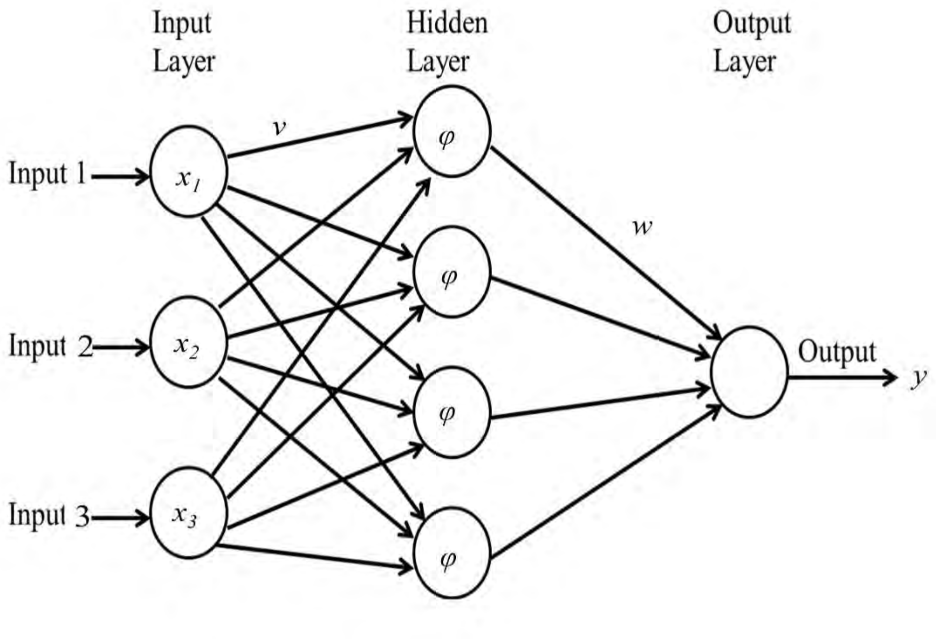

Figure 4.2: Diagram of a typical artificial neural network

The input layer is where external information is received and provided to the network (e.g. rainfall or maximum temperature or river discharge) while the output layer produces the prediction (e.g. cholera incidence). Each node is connected with all other nodes of the previous and the next layer. The most well-known training algorithm in neural network is feed forward (Figure 4.2) in which the information flows in a forward direction through the network and there are no feedback effects. The output of each node is obtained by computing the value of the activation function with respect to the product of the input vector and the weight vector associated with that node.

The relationship between the output and the inputs has been shown in the following mathematical representation:

$$y = f(x_i) = w_0 + \sum_{j=1}^{m} w_j \, \varphi\left(\sum_{i=1}^{n} (v_{ij} x_i - b_j)\right) - b \tag{4.10}$$

where,

m = the number of hidden nodes,

w_j = the weights between the j-th hidden node and the output node,

v_{ij} = the weight between the i-th input node, x_i and the j-th hidden node,

b_j = the biases for the j-th hidden nodes,

b = the biases for the output node,

φ = the transfer function of the hidden set in which the sigmoid function is used.

Models are usually calibrated with a portion of the observed dataset and validated with the remaining portion.

4.2.2 Development of an ANN Model

Developing an ANN follows mainly three steps. **Firstly, variable selection,** the input variables important for modeling variable under study are selected by suitable variable selection procedures. **Second, formation of training, testing and validation sets,** to achieve an acceptable level of generalization by the ANN, the data set is usually divided into three subsets called training, testing and validation sets. The training set is the largest set and is used by neural network to learn patterns present in the data. The testing set is used to evaluate the generalization ability of a supposedly trained network. A final check on the performance of the trained network is made using validation set. **Finally, neural network architecture** is defined its structure including number of hidden layers, number of hidden nodes and number of output nodes etc.

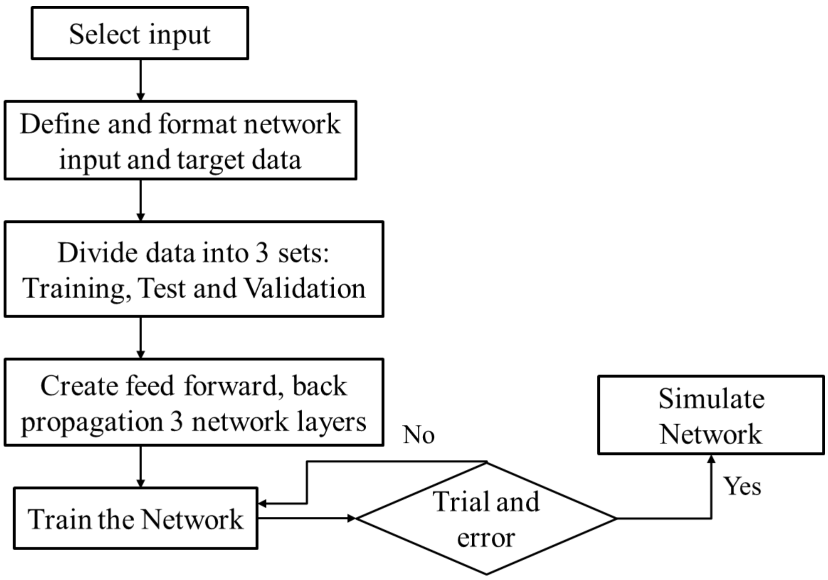

Figure 4.3: Flow chart of Artificial Neural Network (ANN) model.

To fulfill the objective of long term prediction of cholera, the Neural Network Toolbox of MATLAB was used to develop the ANN models (Figure 4.3). The feedforward architecture was selected for the ANNs with three layers, i.e. an input layer, a hidden layer and an output layer. The Levenberg-Marquardt (LM) was chosen for the training algorithm [98], a tan-sigmoidal transfer function in the hidden layer, and a linear activation function (Purelin) in the output layer. The number of nodes in the hidden layer was estimated through trial and error. In this study, the ‘training’ dataset of ANN will be referred as ‘calibration’ dataset, and the ‘validation’ and ‘testing’ dataset as the combined ‘validation’ dataset. Finally, the ratio of the data in the ANN models was 71.4% (20 years) for calibration and 28.6% (8 years) for validation.

4.2.3 Model input and output parameters

It is an important task to select the input parameters before the neural network modeling, whether to choose a set of input variables which can best reflect the reason for desired output changes is directly related to the performance of neural network prediction. In this study, the input parameters affecting cholera are monthly values of rainfall, maximum temperature and Brahmaputra river discharge. Rainfall and maximum temperature were selected as the effect of these variables has been established when fulfilling the second objective (Chapter 6). And according to Akanda, et al. [5], river discharge as hydro-climatic variable helps to propagate the cholera transmission in Dhaka. The output parameter is the monthly number of cholera incidence.

4.2.4 Calibration, validation and prediction

The first 20 years (1986-2005) of the observed cholera incidence data were used for calibration, and the remaining 8 years (2006-2013) were used for validation. To assess the performance of the models during calibration and validation, the coefficient of determination (R^2), normalized root-mean squared error (nRMSE), Nash-Sutcliffe Efficiency (NSE) and skill score (described in 4.3 section) were used. In the analysis of future impact on cholera incidence, four time slices were considered, which are the baseline period (1980-2009), the 2020s (2010-2039), the 2050s (2040-2079), and the 2080s (2080-2099).

4.3 Comparative Analysis of Using SARIMA And ANN

Both SARIMA and ANN are useful tools for time series analysis ([99]). SARIMA is normally used for short term forecasting which is used for short-term forecasting study in Chapter 6. When SARIMA is run for long-term prediction, it does not provide good results with a fixed upper and lower bounds of cholera incidence in future. Whereas, ANN can be used for long-term prediction e.g., climate change impact for hundred years although ANN is a black box model of which accuracy of simulated values with observed ones is lower than SARIMA but closer. More detail accuracy measurements are shown in Chapter 6 (Table 6.5).

4.4 Performance Indicators

In this thesis, the following performance indicators were applied for different model evaluation:

4.4.1 Root Mean Squared Error (RMSE)

The root mean squared error (RMSE) is defined by Wallach and Goffinet [100] as:

$$RMSE = \sqrt{\sum_{months=1}^{n}(Observed - forecasted)^2 / Number\ of\ months} \quad (4.11)$$

RMSE is a measure between values predicted by a model or an estimator and the observed values. RMSE represents the sample standard deviation of the differences between predicted values and observed values. RMSE has the same unit as the variable and as an error measure, 0 is the optimum value.

4.4.2 Mean Absolute Percentage Error (MAPE)

Mean absolute percentage error is a measure of prediction accuracy of a forecasting method in statistics. It measures the size of the error in percentage terms, and is defined by;

$$MAPE = \frac{100}{number\ of\ months} \sum_{months=1}^{n} |(observed - forcasted)/observed| \quad (4.12)$$

The lower the MAPE, the better fit the model.

4.4.3 Mean Absolute Error (MAE)

It is calculated as:

$$MAE = \sum_{months=1}^{n} |(observed - forcasted)|/number\ of\ months \qquad (4.13)$$

MAE is a measure of difference between predicted and observed values. MAE can range from 0 to ∞ and are indifferent to the direction of errors, and as an error measure, 0 is the optimum value.

4.4.4 Nash-Sutcliffe Efficiency (NSE)

NSE is defined as the proportion of the total variance of observed data explained by Nash and Sutcliffe [101]:

$$NSE = 1 - \frac{\sum_{months=1}^{n}(Observed - predicted)^2}{\sum_{months=1}^{n}(Observed - Observed_{mean})^2} \qquad (4.14)$$

NSE is a normalized statistic which determines the relative magnitude of the residual variance compared to the observed data variance. NSE can range from -∞ to 1. An efficiency of 1 (NSE=1) corresponds to a perfect match of modeled value to the observed data.

4.4.5 Normalized Root Mean Squared Error (nRMSE)

The normalized root mean square error is defined as:

$$nRMSE = \frac{\sqrt{\sum_{months=1}^{n}(Observed - predicted)^2/Number\ of\ months}}{Observed_{mean}} \qquad (4.15)$$

4.4.6 Coefficient of determination (R^2)

Coefficient of determination determines how well the modeled data is fit to observation data, and can be defined as:

$$R^2 = \frac{[\sum(Observed - Observed_{mean})(Predicted - Predicted_{mean})]^2}{\sum(Observed - Observed_{mean})^2 \sum(Predicted - Predicted_{mean})^2} \tag{4.16}$$

R^2 is represented as a value between 0 and 1. The closer the value is to 1, the better the fit, or relationship, between observed and predicted values.

4.4.7 Skill score (SS):

Skill score provides a measure of the prediction accuracy of the models by comparing the models' predicted MAE, MAE_{pre} with that of a reference model MAE_{ref}, written as:

$$Skill\ score = \frac{MAE_{pre}}{MAE_{ref}} \tag{4.17}$$

In this case, MAE_{pre} represents the MAE of the monthly model-predicted cases compared to the observed cases, while E_{ref} represents the MAE of the long-term monthly mean of the observed cholera cases, also compared to the observed cases for each month.

CHAPTER FIVE
RELATION BETWEEN CHOLERA INCIDENCE AND HYDRO-CLIMATIC VARIABLES

5.1 Introduction

In this chapter, a thorough review on the relationship between cholera incidence and the climatic variables by using different statistical methods in different locations of the world has been shown in Table 5.1. In the review, climatic variables rainfall, maximum temperature, minimum temperature, relative humidity, ENSO and Southern Oscillation Index (SOI) were found statistically significant relationship with cholera incidence. After selecting the climatic variables, the cross correlation analysis has been done to investigate the effects of the climatic variables on the cholera incidence. The overall flow chart of how this chapter was done, has been shown in Figure 5.1.

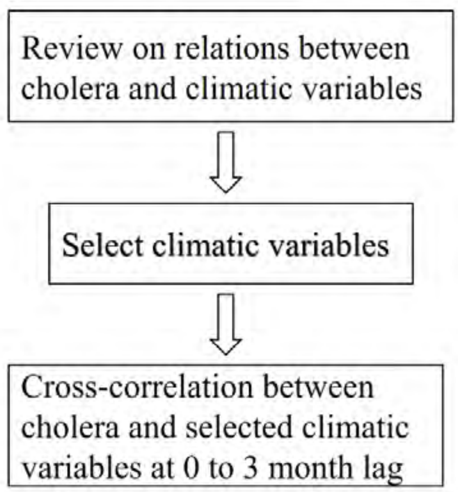

Figure 5.1: Flow chart of the selection of the climatic variables on cholera incidence

5.2 Descriptive Statistics

The descriptive analysis for the disease notification and climatic variables of the study area during 2000 to 2013 are presented in Table 5.2. During this period, out of all diarrheal

Table 5.1: Studies of relations of cholera incidences and climatic variables with different statistical method

Variables	Type of statistical analysis	Location; time, reference	Findings
Rainfall; Southern Oscillation Index (SOI)	Cross-correlation analysis	Africa - Ghana; 1975-1995, (De Magny et al.[102])	Strong statistical association between cholera outbreak and climatic variables under scrutiny
Mean temperature; rainfall; relative humidity	Generalized Additive Modeling (GAM) and Multiple Linear Regression (MLR)	Africa - Nigeria; 1990-2011, (Leckebusch & Abdussalam [103])	Climatic variables most especially temperature and rainfall play an important role in explaining the cholera dynamics
Rainfall	Cross-correlation analysis	Africa - Senegal; May 10- December 31, 2005, (de Magny et al. [104])	The influence on cholera transmission of the intense rainfall over a densely populated and crowded region was detectable for both Dakar and Thiès, Senegal
Maximum temperature; Rainfall	Poisson autoregressive model	Africa - Lusaka, Zambia; 2003-2006, (Luque Fernández et al. [105])	1°C rise in temperature 6 weeks before the onset of the outbreak explained 5.2% of the increase in the cholera cases and a 50 mm increase in rainfall 3 weeks before explained an increase of 2.5%
Minimum temperature; rainfall;	SARIMA model	Africa - Zanzibar; 2002-2008, (Reyburn et al. [106])	1°C rise in temperature at 4 months lag resulted in a 2-fold increase of cholera cases, and an increase of 200 mm of rainfall at 2 months lag resulted in a 1.6-fold increase of cholera cases
Mean temperature; SST	Poisson regression model	Africa - Southeastern Africa; 1971-2006, (Paz [107])	Annual mean temperature and SST had significant impact on cholera incidence during the studied period
Rainfall	Multivariate Poisson	America - Haiti; October 2010 – December 2011, (Righetto et al. [108])	A clear correlation between rainfall events and cholera outbreaks

Variables	Type of statistical analysis	Location; time, reference	Findings
Rainfall	Quantitative analysis using a combination of statistical and dynamic models	America - Haiti; 2010, (Eisenberg et al. [109])	Increased rainfall was significantly correlated with increased cholera incidence 4-7 days later
Maximum temperature; rainfall; relative humidity	SARIMA model	Asia - Vellore, India; 2000-2010, (Sebastian et al. [49])	50% decrease of cholera cases from 2000-2004 to 2005-2010. During 2000-2004, there was a positive significant association between rainfall and cholera cases ($r=0.51$, $p<0.001$) and this was not observed in 2005-2010
Mean temperature; relative humidity; rainfall	SARIMA and GLM	Asia - Kolkata, India; 1996-2008, (Rajendran et al. [48])	Cholera was associated higher RH (>80%) with 29°C temperature with intermittent average (10 cm) rainfall
Rainfall; mean temperature	Poisson regression model	Asia - Dhaka, Bangladesh; 1996-2002, (Hashizume et al. [73])	Weekly cholera cases increased and decreased by 14% and 24% respectively for 45±10-mm of rainfall over 0-8 and 0-16 weeks lag
ENSO (El Niño/Southern Oscillation)	Scale-dependent correlation (SDC) analysis, Singular spectrum analysis (SSA)	Asia - Bangladesh; 1980-2001, (Rodó et al. [110])	A strong and consistent association between cholera levels and ENSO is apparent in the last two decades
Minimum temperature; maximum temperature; rainfall and SST	SARIMA model	Asia - Matlab, Bangladesh; 1988-2001, (Ali et al. [28])	6% increase in cholera incidence with a minimum temperature increase of 1°C

patients recorded in icddr,b, 19% were identified as cholera patients (5,939 out of 30,984). Of all cholera patients, 55% were less than 5 years of age, 6% were 5 to 15 years of age, and 39% were of greater than 15 years of age. Greater number of cholera patients was male (56%), while the rest (44%) was female. The average monthly cholera patients recorded in icddr,b and related climatic variables during 2000-2013 depicted the well-known bimodal distribution (Figure 5.2) pattern over an annual cycle: one occurred in the month of March-May (pre-monsoon) and the other in the month of September-November (post-monsoon). The pre-monsoon peak was higher than the post-monsoon peak during the studied period.

Table 5.2: Descriptive statistics for the disease and climatic variables in Dhaka, Bangladesh, during 2000-2013

Variables (monthly average)	***n* (months)**	**Mean**	**SD**	**Minimum**	**Maximum**
Cholera incidence	168	35	30	0	145
Total rainfall (mm)	168	164	177	0	839
Minimum Temperature (°C)	168	22.1	4.5	11.7	27.4
Maximum Temperature (°C)	168	30.7	3.3	21.1	35.4
Relative humidity (%)	168	81.7	6.4	60.8	90.8
ENSO	168	-0.13	0.76	-1.92	1.72
SOI	168	0.34	0.93	-3.1	2.9

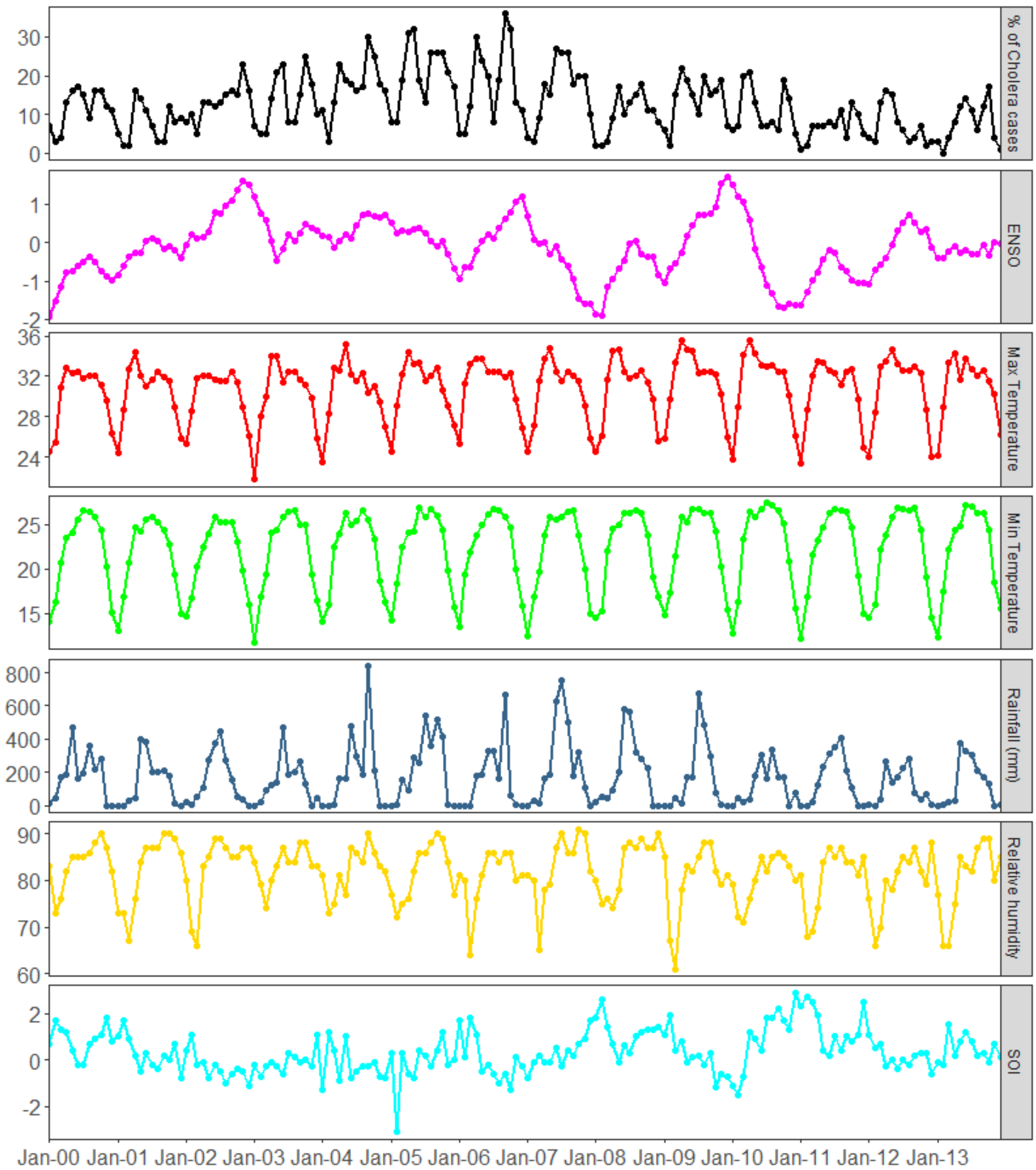

Figure 5.2: Time series plot of percentage (%) of cholera cases obtained from total patients visiting in icddr,b, Dhaka, ENSO, average monthly maximum temperature (°C), minimum temperature (°C), total rainfall (mm), relative humidity (%),and SOI during 2000-2013

5.3 Cross-correlation Analysis

To investigate delayed effects on cholera incidence, climate variables were temporally lagged by 0, 1, 2 and 3 months by cross correlation analysis. Lagged association of climatic variables with cholera incidence is necessary for developing a forecasting model. Table 5.3 shows the cross-correlation of climatic variables with log-transformed monthly cholera incidence at 0, 1, 2, and 3 months lag which provides the information on selecting the variables for detail modelling with SARIMA. The results showed positive and high association with rainfall (r=0.43 at 0-month lag), maximum temperature (r=0.61 at 1-month lag) and minimum temperature (r=0.56 at 0-month lag), while relative humidity (r≤0.28), ENSO (r≤0.21) and SOI (r≤-0.06) showed low association with cholera incidence.

Table 5.3: Cross-correlation analysis of climatic variables (Pearson's correlation coefficient) and log-transformed cholera incidence in Dhaka with a lag 0 - 3 months

Lag (month)	0	1	2	3
Rainfall	0.43	0.38	0.24	0.07
Minimum Temperature	0.56	0.53	0.23	-0.12
Maximum Temperature	0.56	0.61	0.31	-0.10
Relative Humidity	0.28	-0.06	-0.25	-0.25
ENSO	0.21	0.16	0.09	0.03
SOI	-0.23	-0.17	-0.12	-0.06

Table 5.4: Inter-correlations between climatic variables, Dhaka, Bangladesh

	Minimum Temperature	Maximum Temperature	Relative humidity	ENSO	SOI
Rainfall	0.672***	0.445***	0.533***	0.092	-0.132*
Minimum Temperature		0.904***	0.374***	0.119	-0.125
Maximum Temperature			0.058	0.093	-0.092
Relative humidity				0.115	-0.181**
ENSO					-0.709***

ENSO = El-Niño Southern Oscillation; SOI = Southern Oscillation Index

*p < 0.1; **p < 0.05; ***p < 0.001

Covariates indicating significant correlation (Table 5.4) are: rainfall with positive minimum temperature ($p < 0.001$), positive maximum temperature ($p < 0.001$) and positive relative humidity ($p < 0.001$); minimum temperature with positive maximum temperature ($p < 0.001$) and positive relative humidity ($p < 0.001$); relative humidity with negative SOI ($p < 0.05$), and ENSO with negative SOI ($p < 0.001$).

5.4 Discussion

Among various climatic variables, there is a significant association of rainfall and temperature (Table 5.3) with cholera incidence. These results are consistent with other studies (e.g., Colwell, 2002 [111] in Dhaka, Bangladesh; Reyburn *et al.*, 2011 [106] in Zanzibar, Tanzania). Although very low positive effect of relative humidity ($r = 0.28$) was found at current month (lag 0) and negative values at lags of 1, 2 and 3 months (Table 5.3).

These analyses help to select the input variables to develop a forecast model of the cholera incidence. The lagged relationship also provides the information whether the cholera incidence can be forecasted or not.

CHAPTER SIX

DEVELOPING A CHOLERA FORECAST MODEL

6.1 Introduction

Considering the studies relevant to Bangladesh and other countries as summarized in Table 5.1, the following research questions are yet to be addressed: (1) which climatic variable, single- or multi-variable can predict better cholera incidence especially in densely populated Dhaka megacity?; (2) will it be possible to develop a cholera forecast model based on this correlation and how much forecast lead-time is possible?; and (3) is there any location dependent correlation between cholera incidence and climatic variables, or not? This chapter, therefore, aims at addressing the above research questions for better predicting cholera incidence and preparedness can be taken into consideration in a more comprehensive way than at present. For doing so, a regression model seasonal autoregressive integrated moving average (SARIMA) was found suitable for this study which refers a relevant method for time series analysis due to its forecasting capability and better information on time-related changes [112]. ANN has also been compared the forecasting capability with SARIMA results.

6.2 Evolution of SARIMA Models

By plotting the mean-range for each seasonal period (12 months), the logarithmic transformation was necessary to stabilize the variance of cholera incidence (Figure 6.1). All statistical analyses were performed on the logarithmically transformed cholera incidence.

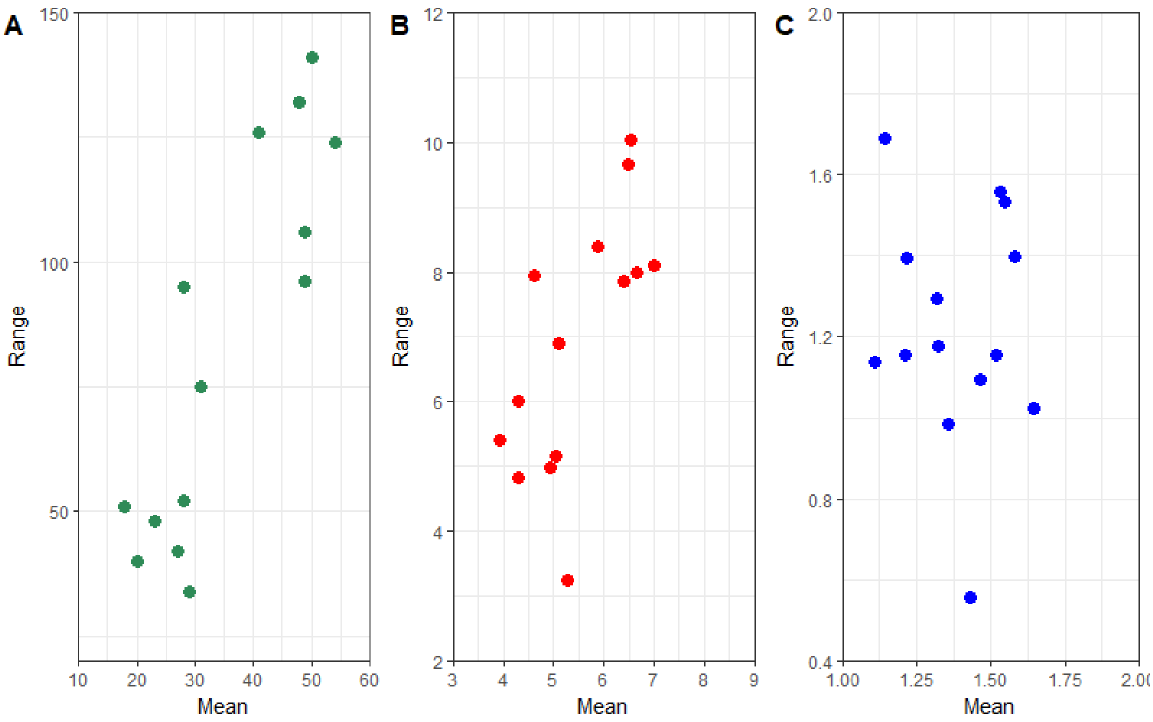

Figure 6.1: Mean-range plot of cholera incidence for (A) non-transformed data, (B) square-root transformation data, (C) log-transformed data

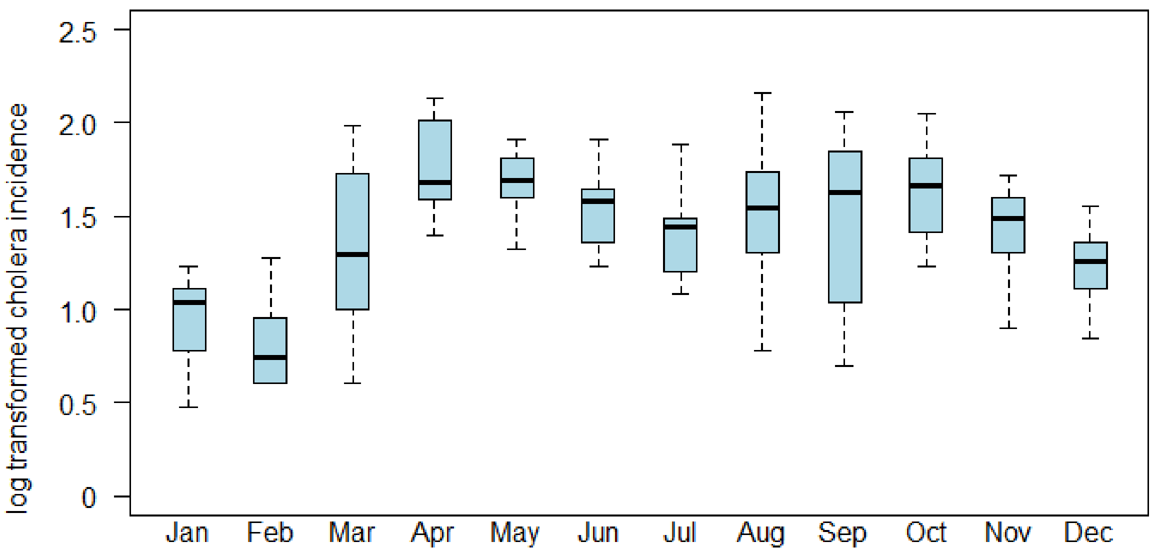

Figure 6.2: Box-plot of log-transformed cholera incidence in icddr,b, Dhaka, 2000-2013

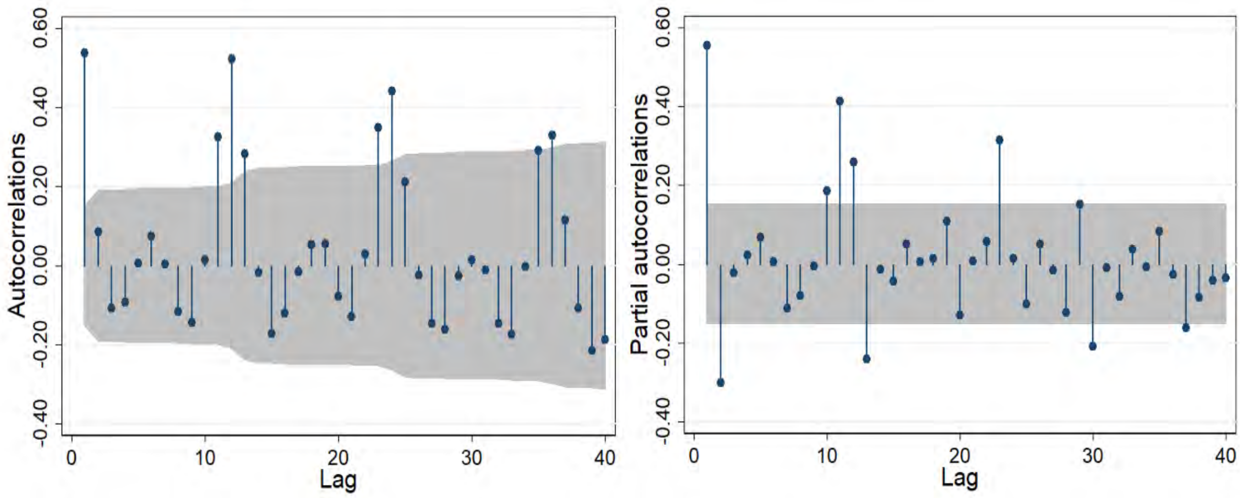

Figure 6.3: Autocorrelation function and partial autocorrelation plots with 5% significant limits of cholera incidence in Dhaka, 2000-2013

The seasonal pattern is quite evident in the box-plot (Figure 6.2) of the cholera incidence, where the incidence in April and May showed the pre-monsoon peak and in September and October the post-monsoon peak. The autocorrelation plot (Figure 6.3) showed the highest peak (0.54) at lag 12 which indicates annual seasonality. On the basis of Augmented Dickey-Fuller (Fuller, 2009) unit root test (test statistic = -6.77, whereas 0.01 = -3.49, 0.05 = -2.89, 0.1 = -2.58), the monthly cholera incidence showed stationary i.e., the differencing order for non-seasonal and seasonal (d, D) is zero. Finally, after checking ACF and PACF plots, the SARIMA (1,0,0) $(1,0,1)_{12}$ was the best fitted model based on the lowest AIC and BIC values.

The plots of the ACF and PACF of the residuals of the chosen model showed no significant temporal correlation between residuals at different lags, and the scatter plot of the predicted values against the residuals showed no apparent pattern (Figure 6.4). Portmanteau Q statistics was 31.04 (p = 0.84), i.e., the regression model is quite acceptable.

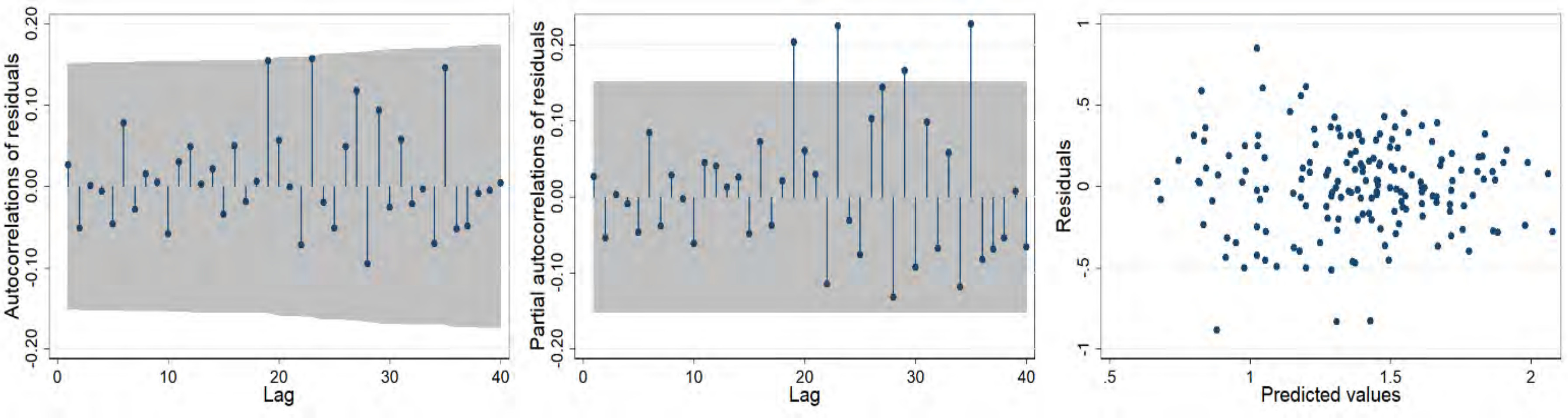

Figure 6.4**:** ACF and PACF plots of the residuals at different lags and scatter plot of residuals against predicted values of the SARIMA model

From the cross correlation analysis (Table 5.3), the results showed positive and high relationship with rainfall, minimum temperature and maximum temperature. Besides, SARIMA models were run with all the variables individually as single variable SARIMA models (SVMs) mentioned in Table 6.1 with lag of 0, 1, 2 and 3 months to check if there is any high association (low AIC and BIC values) can be made not depending on the cross-correlation values only, however, no high association was found for the later three variables (relative humidity, ENSO and SOI) in Table 6.1.The relation of cholera incidence with maximum (AIC=47, BIC=66) and minimum temperature (AIC=46, BIC=65) showed better at the temporal lag 1 month and with rainfall (AIC=52, BIC=71) at the temporal lag 0.

The single variable (SVM) SARIMA models (Table 6.1) show that an increase of previous month (lag 1) 1°C maximum temperature resulted an increase of 7% cholera incidence ($p<0.001$; AIC = 47, BIC = 66). At the temporal lag 0, an increase of 100 mm in rainfall resulted in 4% increase of cholera incidence ($p = 0.04$; AIC = 52, BIC = 71) and an increase of 1°C in minimum monthly temperature at 1-month lag in a 5% increase of cholera incidence ($p < 0.001$; AIC = 46, BIC = 65). However, multi-variable SARIMA model (MVM) has been found better than the SVM in terms of error measurement of AIC and BIC which is shown in Table 6.1 and 6.2.

Table 6.1: Results of single variable SARIMA models (SVMs) for the period of 2000-2013.

Climatic variables	Lag (month)	p-value	AIC	BIC
Rainfall	0	0.04	52	71
	1	0.07	53	72
	2	0.787	58	77
	3	0.094	56	75
Maximum temperature	0	0.002	51	69
	1	<0.001	47	66
	2	0.074	55	74
	3	0.342	57	76
Minimum temperature	0	<0.001	47	66
	1	<0.001	46	65
	2	0.751	58	77
	3	0.901	58	77
Relative humidity	0	0.361	57	76
	1	0.940	58	77
	2	0.259	56	75
	3	0.495	56	76
ENSO	0	0.214	57	76
	1	0.183	56	75
	2	0.260	57	76
	3	0.918	58	77
SOI	0	0.089	54	73
	1	0.388	58	77
	2	0.441	58	77
	3	0.929	58	77

Table 6.2: Results of multi-variable SARIMA models (MVMs) for 0-month lag

Climatic variables	**p-value**	**AIC**	**BIC**
Rainfall, and maximum temperature	0.008 (Rainfall), <0.001 (Maximum temperature)	42	64
Rainfall, and minimum temperature	0.049 (Rainfall), 0.001 (Minimum temperature)	44	66
Minimum temperature, and maximum temperature	0.055 (Minimum temperature), 0.598 (Maximum temperature)	49	70
Rainfall, minimum temperature, and maximum temperature	0.027 (Rainfall), 0.322 (Minimum temperature), 0.190 (Maximum temperature)	44	69

Table 6.3: Four combinations of multi-variable SARIMA models used in forecasting

Model name	**Variables used in model**
A	Cholera incidence with 0-month lagged rainfall and maximum temperature
B	Cholera incidence with 1-month lagged rainfall and maximum temperature
C	Cholera incidence with 2-month lagged rainfall and maximum temperature
D	Cholera incidence with 3-month lagged rainfall and maximum temperature

Table 6.4: Regression coefficients of the fitted SARIMA $(1,0,0)(1,0,1)_{12}$ (models A, B, C, D) during 2000-2011 in Dhaka, Bangladesh; β = co-efficient; SE = standard error; AR = auto-regression; SAR = seasonal auto-regression; SMA = seasonal moving average

Model Parameter	Model A[1]			Model B[2]			Model C[3]			Model D[4]		
	β	**SE**	**p-value**	**β**	**SE**	**p-value**	**β**	**SE**	**p-value**	**β**	**SE**	**p-value**
AR	0.453	0.073	<0.001	0.464	0.072	<0.001	0.52	0.076	<0.001	0.553	0.075	<0.001
SAR	0.833	0.091	<0.001	0.728	0.165	<0.001	0.896	0.061	<0.001	0.880	0.061	<0.001
SMA	-0.53	0.140	<0.001	-0.462	0.198	0.02	-0.572	0.12	<0.001	-0.553	0.12	<0.001
Rainfall	0.00048	0.0002	0.016	0.0004	0.0002	0.03	0.00004	0.0002	0.788	-0.0002	0.0002	0.187
Maximum Temperature	0.062	0.016	<0.001	0.07	0.015	<0.001	0.026	0.022	0.242	-0.033	0.02	0.107

[1] log-likelihood = -2, AIC = 19, BIC = 39; [2] log-likelihood = -1, AIC = 15, BIC = 36;

[3] log-likelihood = -10, AIC = 34, BIC = 55; [4]log-likelihood = -10, AIC = 34, BIC = 55;

The data of monthly rainfall and minimum temperature showed the best result in studies by Ali, et al. [28] and by Reyburn, et al. [106]; however, in this study, the combination of rainfall and maximum temperature (Table 6.3) fitted the best result. Therefore, finally, four combinations of MVMs A, B, C and D were fitted as listed in Table 6.3. The models with climatic variables were run with different time lags to check the effect of climatic variables on cholera incidence at lags of 0, 1, 2, and 3 months. Based on AIC and BIC (during 2000-2011), model B showed better fit (AIC = 15, BIC = 36) than other three models (Table 6.4). That means, the interaction of rainfall ($p<0.05$) and maximum temperature ($p<0.001$) at 1-month lag yielded a significant association with cholera.

6.3 Model Forecast

The performance of models has been shown in Figure 6.5 (SARIMA) and Figure 6.6 (ANN) where first 12-year (1 January 2000 – 31 December 2011) shows at the model developing stage, while the later 2-year (1 January 2012 – 31 December 2013) forecasted model. Model B (1-month lag with rainfall and maximum temperature) follows better the observed cholera incidence than the other models (A, C and D) (Figure 6.5). The error measurements also indicated that model B (RMSE=14.7, MAE = 11) showed more improved fitting comparing to other models (Table 6.5). Using ANN, error measurements (RMSE, MAPE and MAE) of model A and B are quite close to SARIMA, but performance of model C and D is quite lower than SARIMA (Figure 6.6 and Table 6.5). Therefore, SARIMA was used for short-term forecasting, while ANN was used for long-term prediction for evaluating impact of climatic variables by climate change on cholera incidence.

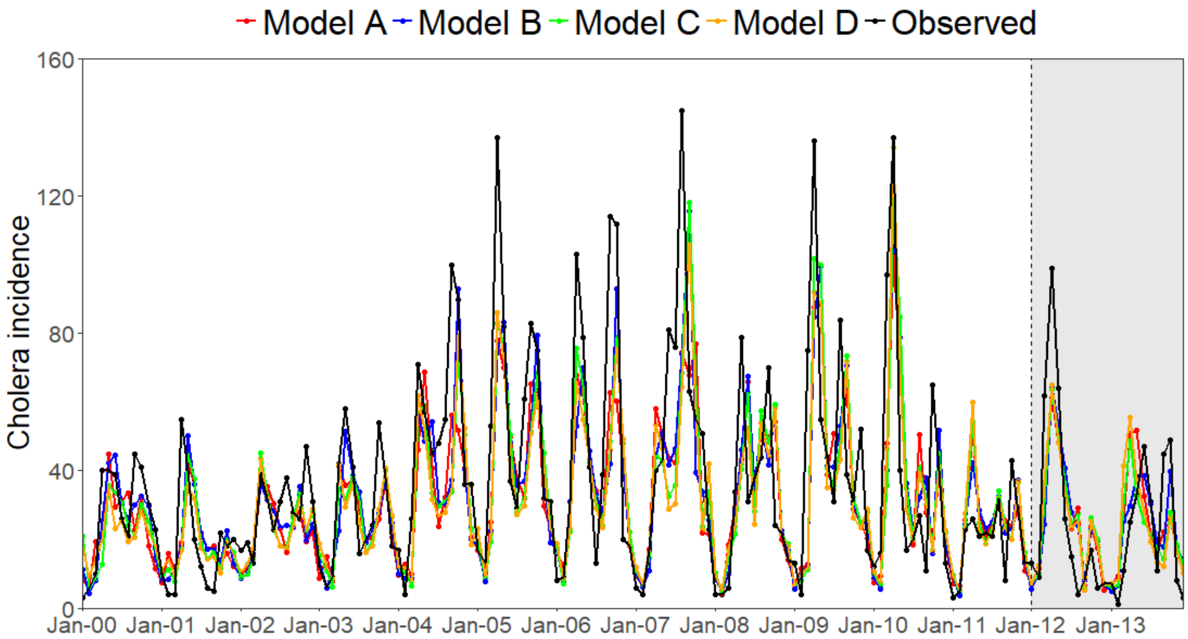

Figure 6.5: SARIMA model of forecasting of cholera incidence in Dhaka

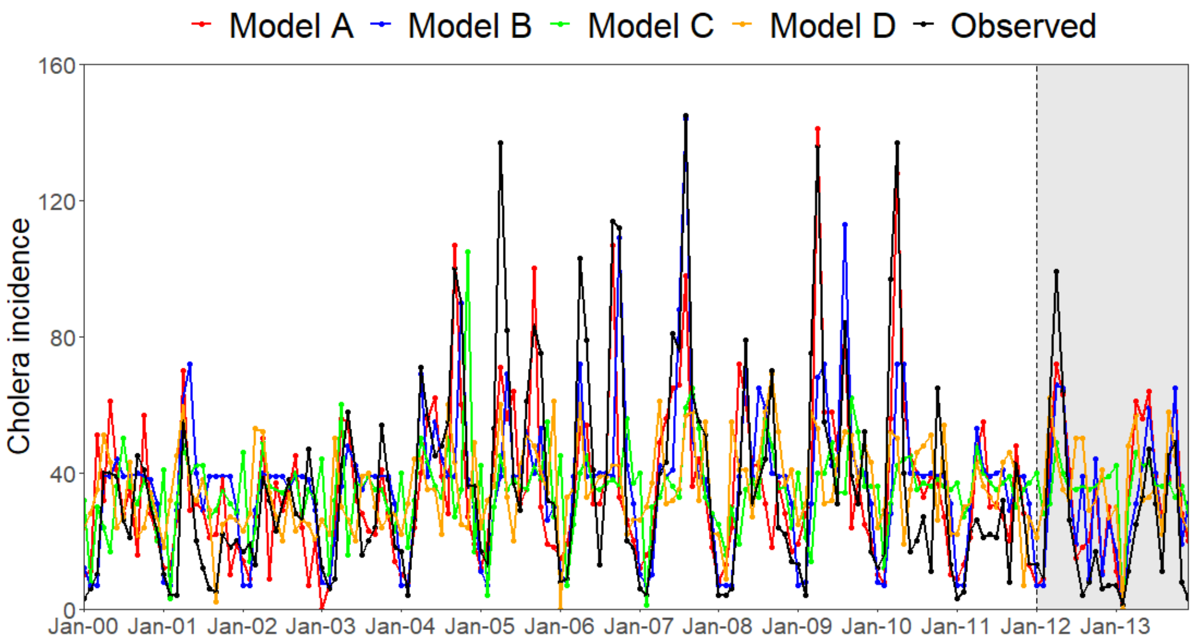

Figure 6.6: Forecasting of cholera incidence by ANN in Dhaka

Table 6.5: Forecasting accuracy of SARIMA and ANN models for cholera; RMSE – root mean squared error; MAPE – mean absolute percentage error; MAE – mean absolute error

Error measurement	**SARIMA**				**ANN**			
	Model A	**Model B**	**Model C**	**Model D**	**Model A**	**Model B**	**Model C**	**Model D**
RMSE	16.2	14.7	16.7	17.2	16.3	15.7	24.4	24.3
MAPE	1.22	1.04	1.13	1.18	1.14	1.30	2.19	2.04
MAE	13.2	11	13.2	13.4	13.4	12.1	21.6	19.6

6.4 Discussion

The results of this study illustrate that there is distinct seasonality (Figure 6.2) observed in *V. cholerae* signatures throughout the world. The results show the similar on both the cross correlation analysis and SARIMA model, like no significant effect of humidity could be found by time series analysis with SARIMA model (Table 6.1) and cross correlation analysis (Table 5.3). This result (effect of humidity on cholera transmission) is also consistent with other studies e.g., Islam, et al. [113] in Matlab.

The probability of cholera incidence is high with high rainfall in Nha Trang, Vietnam and in Matlab, Bangladesh as documented by Emch, et al. [114]; however, in Dhaka, Bangladesh, Hashizume, et al. [73] summarized that the risk of cholera may increase with both high and low rainfall. Although Hashizume, et al. [73] didn't provide a quantitaive analysis, rather they described a hypothetical pathway of increasing cholera cases due to high rainfall causing flooding condition in Dhaka which may cause for exposure to contaminated water with *V. cholerae*. However, flooding does not only depend on high rainfall but also the upstream river discharge as most areas of Bangladesh lies at the downstream of three large rivers of South Asia namely Ganges, Brahmaputra and Meghna. Low rainfall may also increase the incidence of cholera as hypothesized by [73] where they argued that due to low rainfall there might be water scarcity to a certain proportion of people of Dhaka city who rely on surface water for washing and bathing; therefore, the likelihood of multiple uses in water bodies may increase.

Temperature and increase of cholera incidence has a strong relationship, which is well documented in many studies e.g., in [19, 38, 58, 115]. This relationship might be due to the multiplication of *V. cholerae*, which directly influences the abundance and toxicity of *V. cholerae* in aquatic environments [73]; alternatively, high temperature may also have an indirect influence on p^H levels or nutrients as an effect of increased growth of aquatic plant [7] because, it has already been documented in many studies e.g., in [28, 115] that the increase of sea surface temperature in the Bay of Bengal causes for plankton bloom, which is a favorable condition for multiplication of *V. cholerae*.

The combined effect of rainfall and minimum temperature on cholera showed significant result at 1-month lag in Zanzibar of Tanzania while the individual effect of 200 mm rainfall resulted 1.6% increase of cholera at 2-month lag and 1°C increase of minimum temperature at 4-month lag in 2% increase of cholera [106]. In Matlab of Bangladesh, no combined effect was shown by Ali, et al. [28], however, individually significant relationship was found with minimum temperature of 1°C at 0-month lag with 6% increase of cholera. For Dhaka (this study), correlation of cholera with maximum temperature (at 0 and 1-month lag), minimum temperature (0 and 1-month lag) and rainfall (0-month lag) individually showed better results (based on AIC and BIC in Table 6.1) than other climatic variables i.e., relative humidity, ENSO and SOI. The model run with combined effect of rainfall and maximum temperature (Table 6.2) showed better results (low AIC and BIC) than individual effects of climatic variables (Table 6.1), that means, the performance of a multi-variable model (MVM) showed better results than a single variable model (SVM) which answers research question-1 (Page 39).

This study also illustrates that previous month's rainfall and maximum temperature showed a better fit in forecasting (Table 6.5); that means cholera incidence can be forecasted one month earlier that answers research question-2 (Page 39). However, the rainfall and maximum temperature data should be measured accurately for getting an accurate forecasting of cholera outbreaks.

In Zanzibar, Tanzania and Matlab, Bagladesh, minimum temperature is a factor for cholera forecasting with both SVM and MVM. However, in Dhaka (this study), the combined effect of (i) rainfall and minimum temperature; or (ii) maximum and minimum temperature was found insignificant in MVMs (Table 6.2) while SVM with minimum temperature showed significant but higher AIC and BIC (Table 6.1) than MVMs. That means, it is always not necessary that the same climatic variable should always have similar results rather effect of different climatic variables on cholera incidence are site specific which answers the research question-3 (Page 39). Therefore, for any specific area, individual cholera forecasting models should be developed and tested for better preparedness.

CHAPTER SEVEN

PREDICTION OF FUTURE IMPACT OF CLIMATE CHANGE ON CHOLERA

7.1 Introduction

In this chapter, the potential impact of future climate change on the occurrence of *V. cholerae* in Dhaka was assessed using the consequences of the high-end concentration scenario, namely RCP8.5. It is aimed that this high end RCP8.5 climate scenario will advise policy makers on the possible consequences in case on lower atmospheric concentration levels are not achieved. In this study, existing socio-economic drivers and conditions have been assumed as fixed as present conditions for future impact of climate change on cholera outbreaks. RCP8.5 is a high-emission scenario, which assumes that radioactive forcing due to greenhouse gas emission will continue to increase strongly throughout the 21st century [116]. The scenario 8.5 is the highest CO_2 concentrations in the atmosphere and highest temperature rise globally among four concentration scenarios defined in the Intergovernmental Panel on Climate Change [9]. The broad goals described in this chapter were to (1) calibrate and validate the ANN model for the cholera incidence separately for 11 different climate projections using the baseline-period data of each individual climate projection, (2) use the calibrated models to simulate future impact of cholera for the respective climate projections, (3) analyze the simulated cholera to estimate the future change in mean monthly cholera.

7.2 Climate Change Experiments

Monthly output from 11 RCMs are employed (model details in Table 3.1), obtained from the Coordinated Regional Climate Downscaling Experiments (CORDEX) South Asia database. To get better results for the uncertainties due to different GCMs and RCMs, an ensemble of 11 climate projections generated by a combination of eight GCMs and three RCMs was taken from CORDEX-South Asia database, which includes high-resolution climatic data between 1971 and 2100 with a grid resolution of 0.5° (~50 km). In this study RCP8.5 scenario for 2006-2100 were used which is known as extreme climate

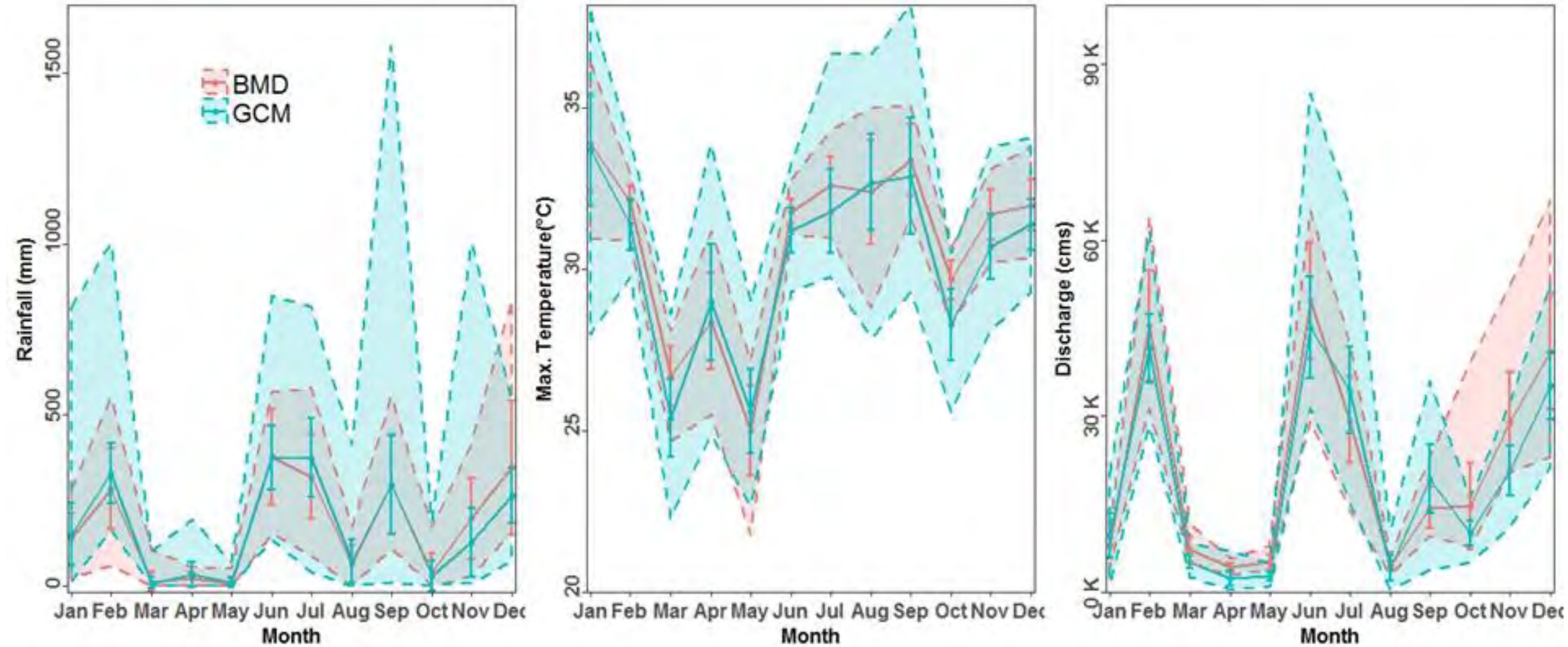

Figure 7.1: Annual cycle of the observed present day (1986-2005) monthly total rainfall (mm), mean maximum temperature (°C), and discharge (m^3/sec) in comparison with the ensemble of historical RCM simulations for the same 20-year period. The thick lines and shaded red and blue areas represent the mean and range of the observed monthly values and RCM simulations, respectively. The vertical lines represent ±1 standard deviation from the mean values.

change scenario. A comparison of the annual cycle of the historical simulations versus observations for some climatic variables relevant to the present study has been shown in Figure 7.1. Although the range of historical simulations is large, the ensemble mean captures the observed seasonal cycle and magnitude, which gives confidence to simulate the climate of the capital of Bangladesh Dhaka. The models show a larger standard deviation and range than the observations because there are 20 data points for each month (because there are 20 years of data for 1986-2005). There are 11 times more data points for the models as there are 11 models. In summary, the models are able to capture the seasonal cycle and magnitude of the climatic variables that impact cholera, even though with some small biases. River's discharge can be changed in the changing of frequency and magnitude of rainfall over river basin, which dominates the change of intensity of floods and droughts [117]. Increased floods and droughts have the obvious potential to cause adverse health impact.

7.3 Calibration And Validation of ANN Model

The calibrated and validated models using ANN has been shown in Figure 7.2 to 7.12, in which the first 20 years (1986-2005) of the observed cholera incidence (recorded in icddr,b) has been used for calibration, and the remaining 8 years (2006-2013) for validation. Statistical indicators evaluating the performances of calibration and validation all the models and ensemble mean of the models (EMM) have been given in Table 7.1. The models have a tendency to underestimate for both calibration and validation. The ensemble mean model showed better performance ($R^2 = 0.34$, nRMSE = 0.65, NSE=0.21, skill score (MAE) = 0.31 for calibration; and $R^2 = 0.47$, nRMSE = 0.70, NSE = 0.25, skill score (MAE) = 0.39 for validation) than other models (Table 7.1). However, the models mostly show underestimate for both high and low peaks, which will be the same for future periods.

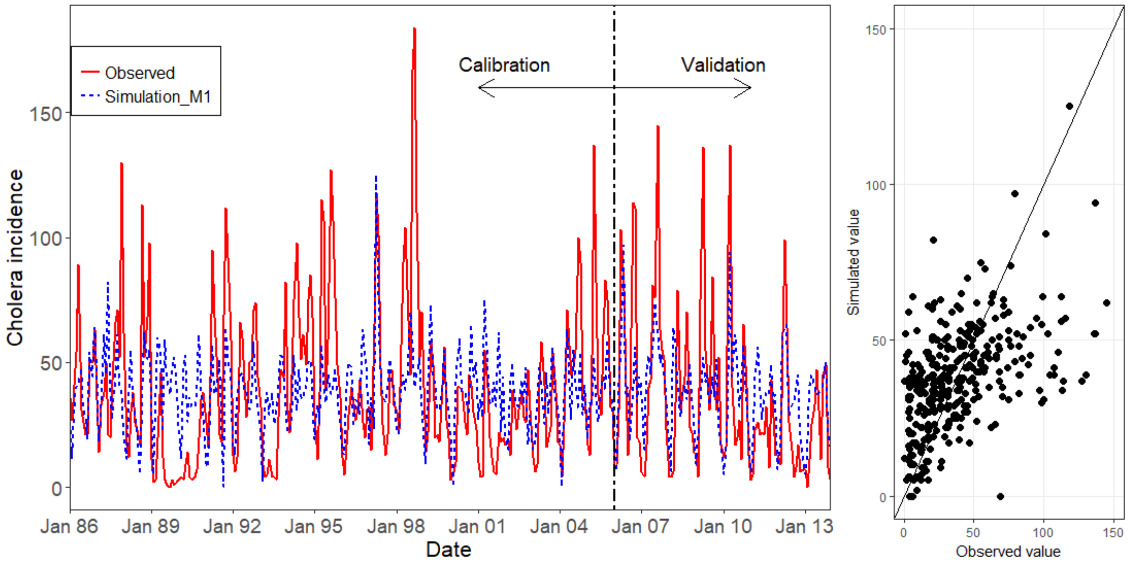

Figure 7.2: Comparison and scatter plot of observed and simulated cholera cases for Model M1 during calibration and validation periods

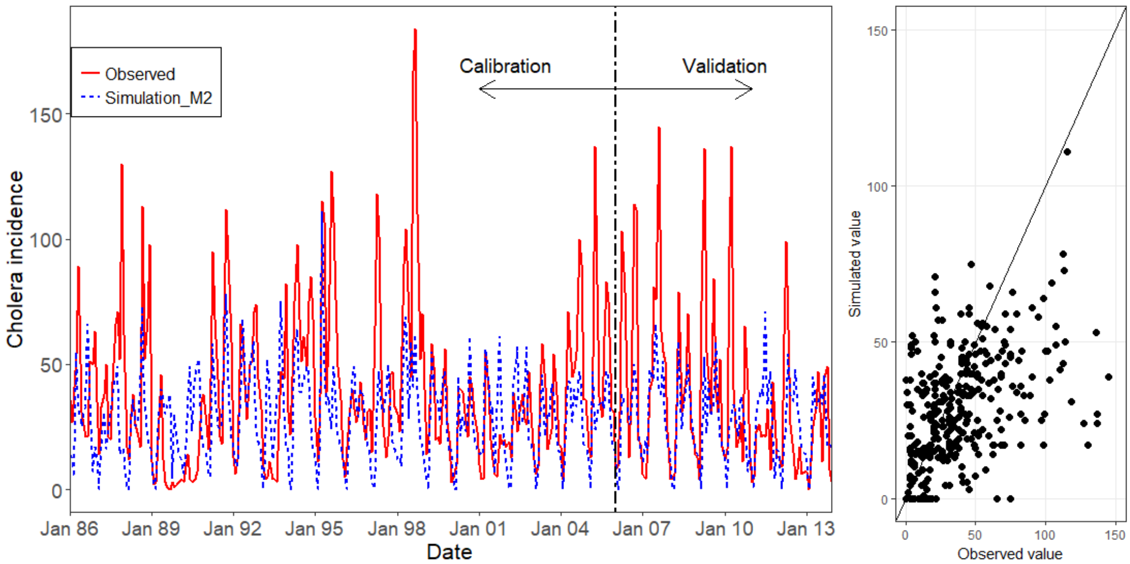

Figure 7.3: Comparison and scatter plot of observed and simulated cholera cases for Model M2 during calibration and validation periods

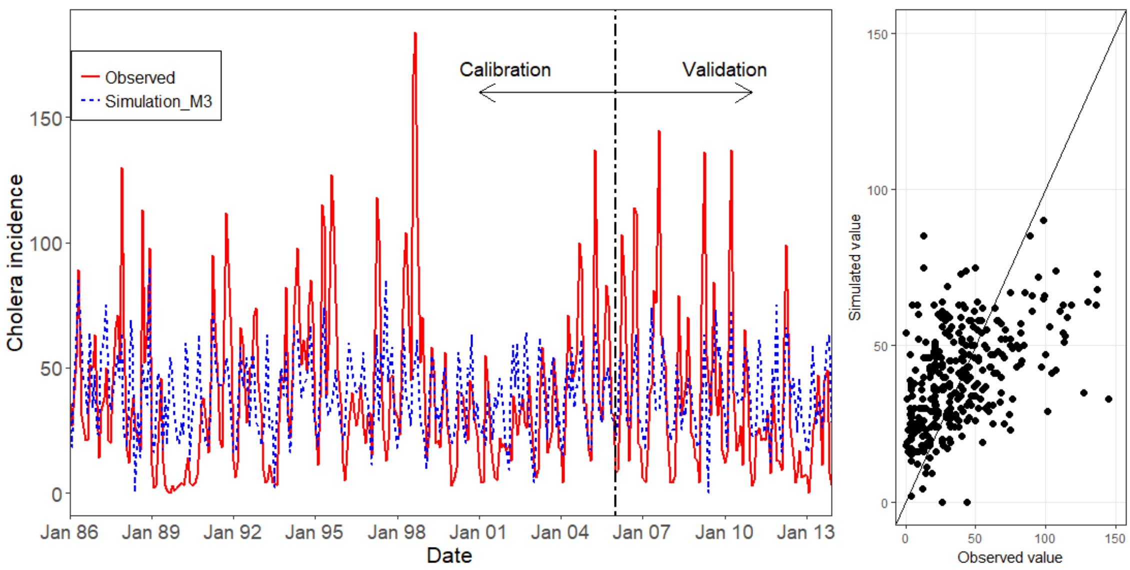

Figure 7.4: Comparison and scatter plot of observed and simulated cholera cases for Model M3 during calibration and validation periods

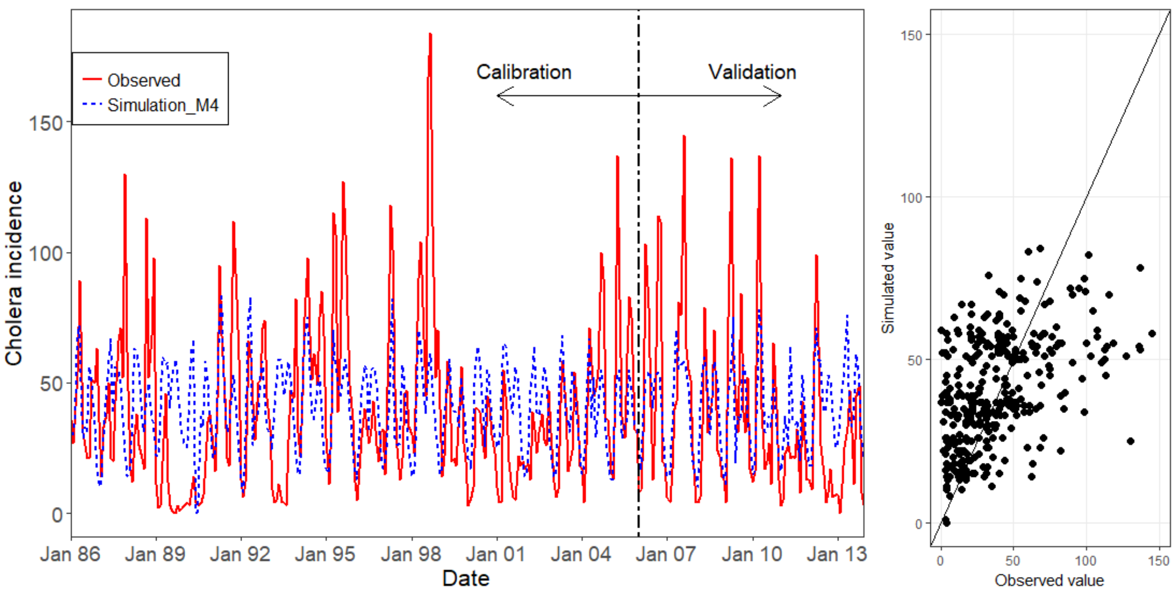

Figure 7.5: Comparison and scatter plot of observed and simulated cholera cases for Model M4 during calibration and validation periods

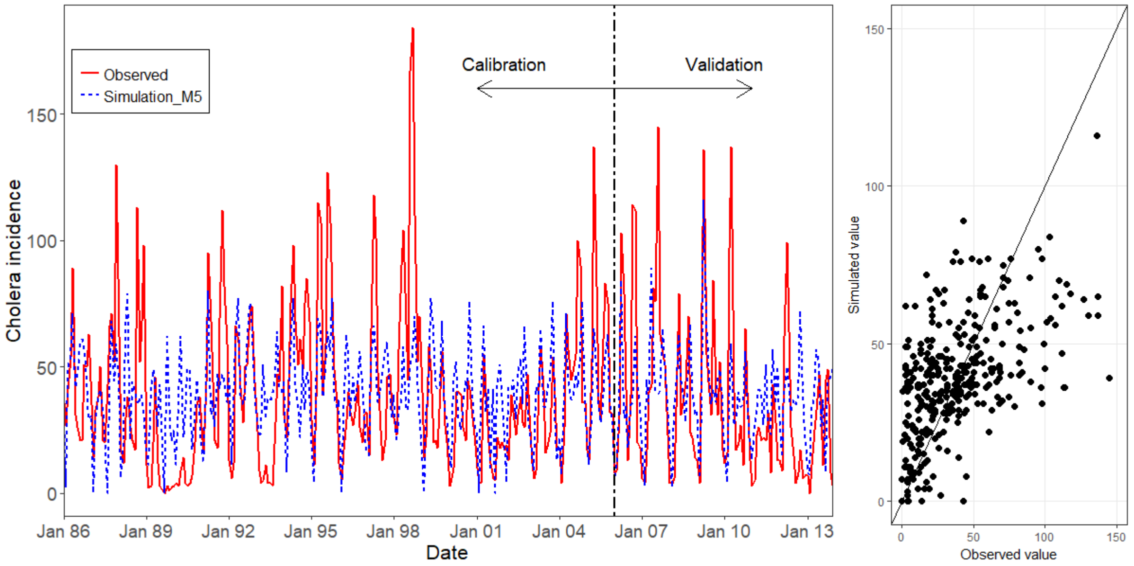

Figure 7.6: Comparison and scatter plot of observed and simulated cholera cases for Model M5 during calibration and validation periods

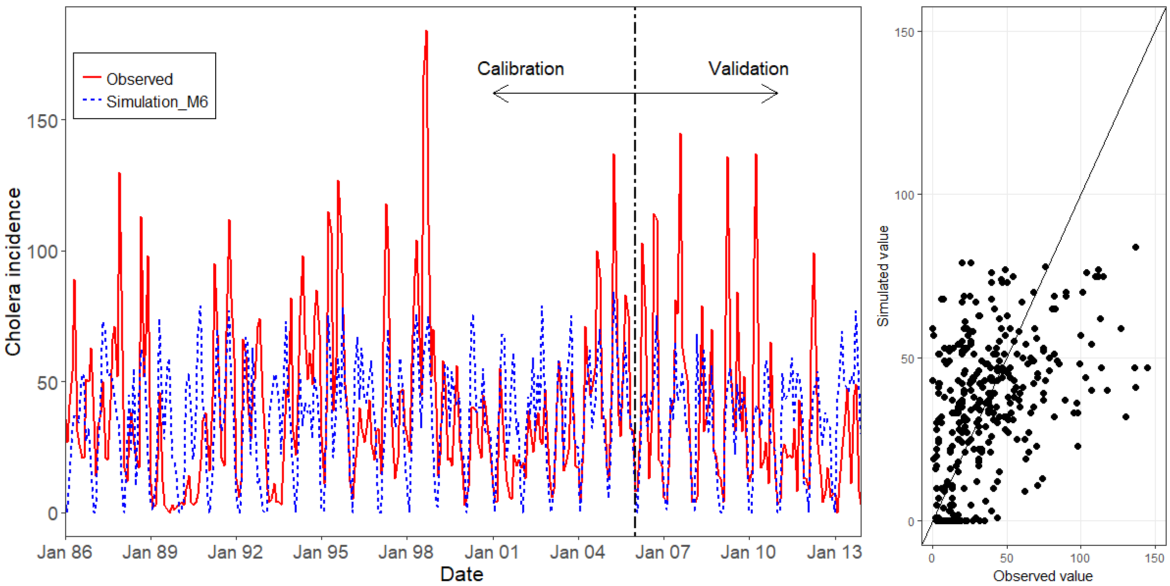

Figure 7.7: Comparison and scatter plot of observed and simulated cholera cases for Model M6 during calibration and validation periods

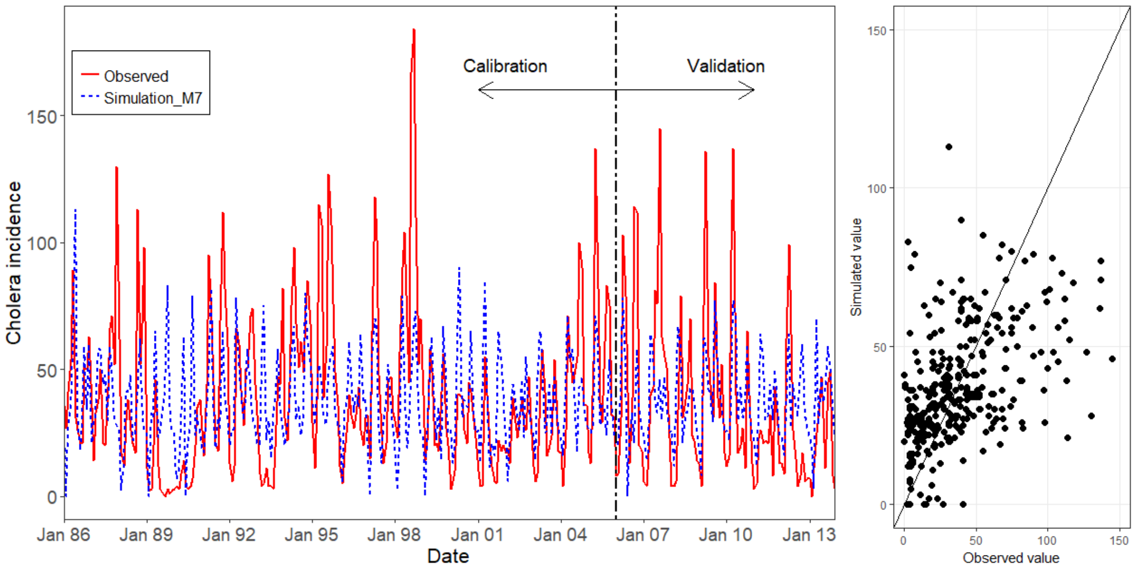

Figure 7.8: Comparison and scatter plot of observed and simulated cholera cases for Model M7 during calibration and validation periods

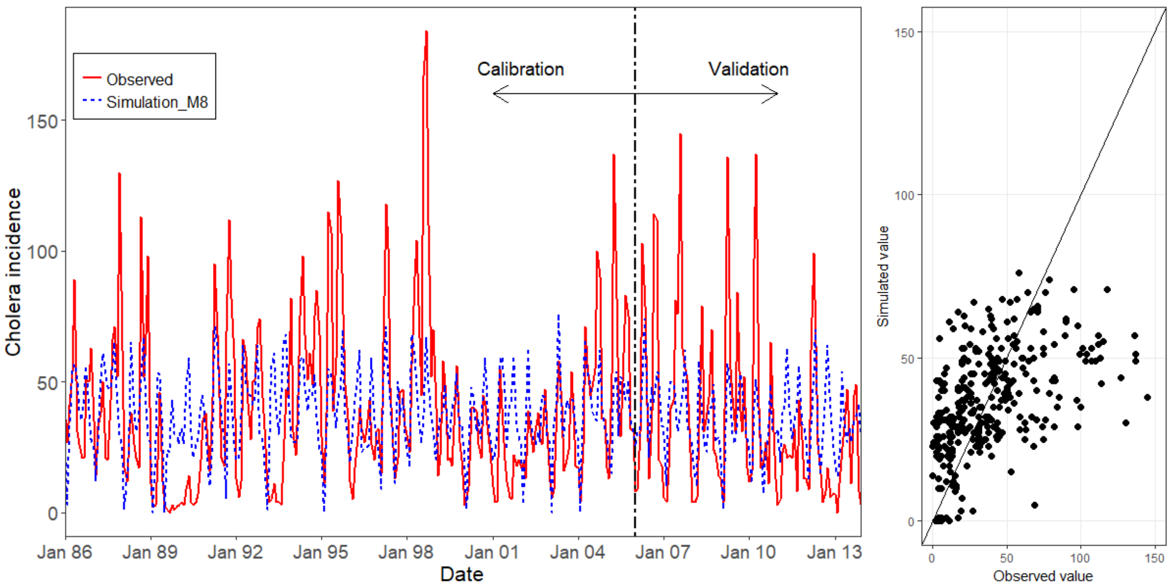

Figure 7.9: Comparison and scatter plot of observed and simulated cholera cases for Model M8 during calibration and validation periods

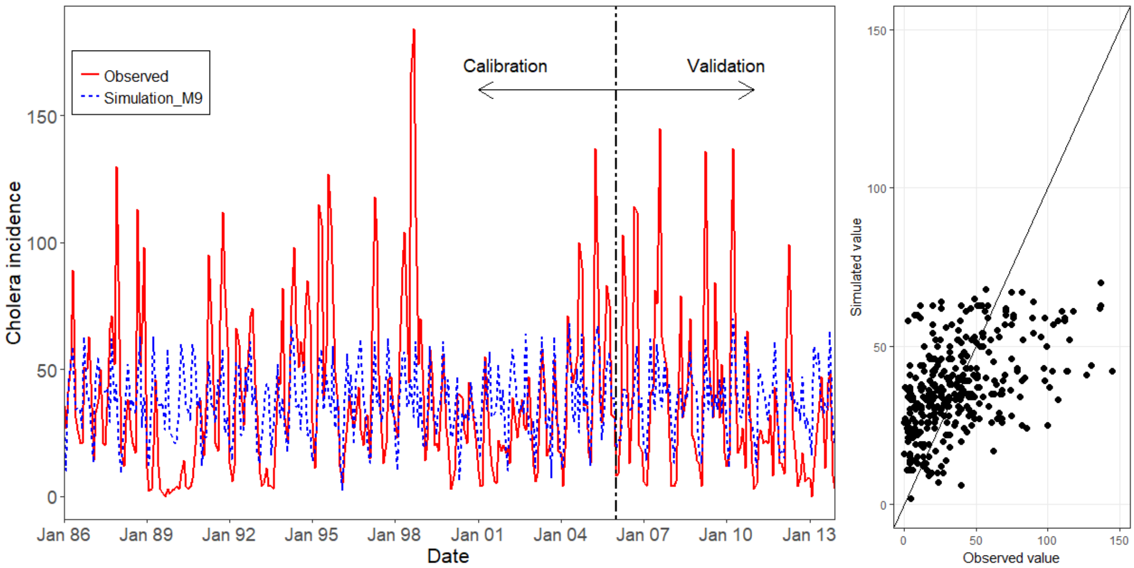

Figure 7.10: Comparison and scatter plot of observed and simulated cholera cases for Model M9 during calibration and validation periods.

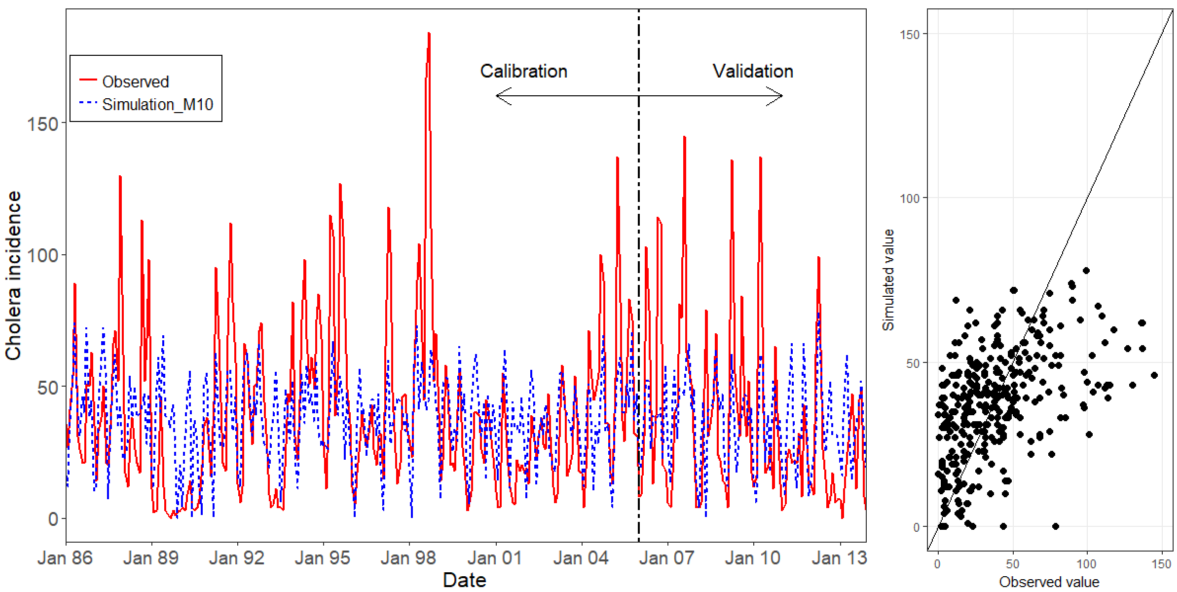

Figure 7.11: Comparison and scatter plot of observed and simulated cholera cases for Model M10 during calibration and validation periods

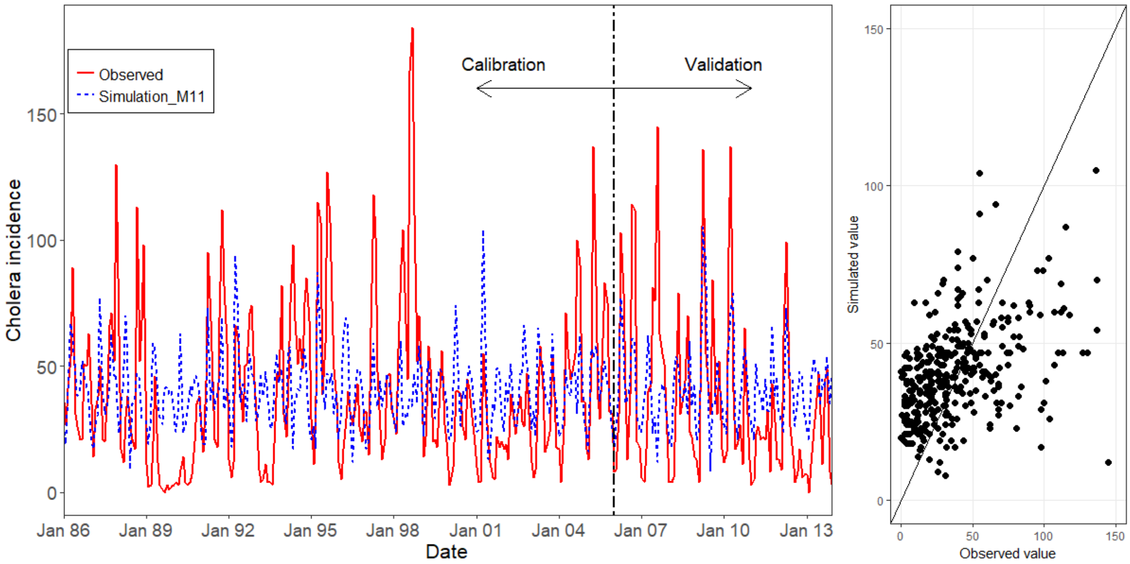

Figure 7.12: Comparison and scatter plot of observed and simulated cholera cases for Model M11 during calibration and validation periods

Table 7.1: Performance of ANN models and ensemble mean of all models (EMM) during the Calibration and Validation Periods.

ANN model	Calibration (1986-2005)				Validation (2006-2013)			
	R^2	nRMSE	Skill score	NSE	R^2	nRMSE	Skill score	NSE
M1	0.17	0.72	0.13	0.15	0.37	0.72	0.26	0.36
M2	0.22	0.76	0.10	0.08	0.20	0.84	0.21	0.12
M3	0.25	0.68	016	0.24	0.25	0.78	0.13	0.25
M4	0.18	0.72	0.11	0.16	0.38	0.72	0.20	0.35
M5	0.26	0.68	0.17	0.25	0.30	0.76	0.20	0.30
M6	0.20	0.73	0.07	0.13	0.20	0.82	0.15	0.18
M7	0.20	0.72	0.14	0.17	0.30	0.75	0.19	0.30
M8	0.23	0.69	0.17	0.22	0.24	0.79	0.17	0.23
M9	0.18	0.72	0.14	0.17	0.28	0.77	0.15	0.27
M10	0.22	0.70	0.16	0.21	0.21	0.80	0.15	0.21
M11	0.14	0.73	0.10	0.14	0.26	0.78	0.12	0.24
EMM	0.34	0.65	0.21	0.31	0.47	0.70	0.25	0.39

For simulating future cholera incidence of a particular projection, the ANN model was calibrated and validated and the calibrated period used as the baseline period of that climate projection to analyze.

7.4 Climate Change Impact

7.4.1 Climate projections

The annual cycle of the observed present-day rainfall, maximum temperature, and discharge in comparison with the RCP8.5 simulations for 2020-2039 (2030s), 2040-2059 (2050s), 2060-2079 (2070s) and 2080-2099 (2090s) has been shown in Figure 7.13. Maximum temperature increases of about 0.5°C – 3.2°C in the near future (2020-2039) which is statistically significant ($p < 0.01$) compared to 1986-2005 in 4 out of 12 months, including the months of February and March in which cholera incidence are greatest. In the far future (2080-2099), temperature increases of about 1°C – 6.8°C in all 12 months which are also significant ($p < 0.001$). Rainfall increases in pre-monsoon period (i.e. March, April and May) ranging between 28 and 118 mm which are significant. Rainfall decreases in post-monsoon period (Sept - Dec) which leads low river discharge.

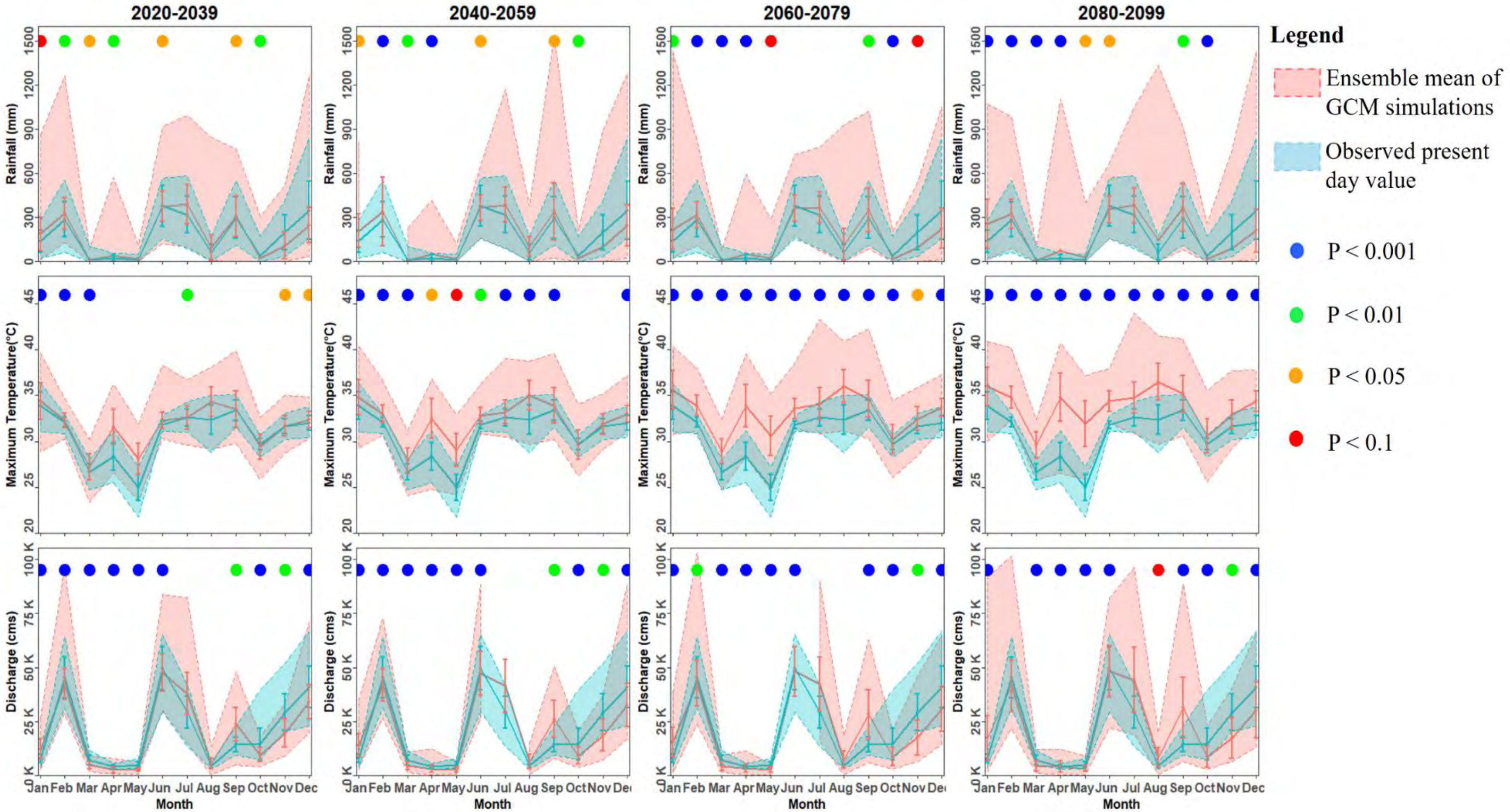

Figure 7.13: Annual cycle of the observed present-day (1986-2005) rainfall (mm), maximum temperature (°C), and discharge (m^3/sec) in comparison with the ensemble of downscaled RCP8.5 RCM projections in different time slices. The thick lines and shaded red and blue areas represent the mean and range of the RCM simulations and observed monthly values, respectively. The vertical lines represent ±1 standard deviation from the mean values. The colored dots on top represent the significance level (p<0.001, p<0.01, p<0.05, p<0.1) of the future changes vs. the observations, as indicated in the legend (top right).

7.4.2 Cholera projections

Results indicate statistically significant increases in cholera incidence during February to March and June to July in the future, across all time periods in the projections (Figure 7.14). Changes are largest and have strongest statistical significance (p<0.001) towards the end of long dry season (February and March).

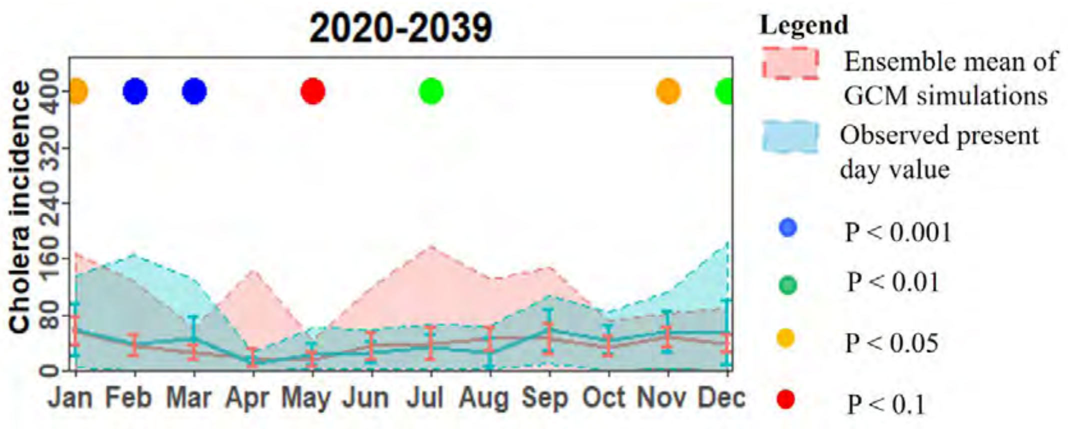

Figure 7.14: The annual cycle of cholera incidence for the present day (1986-2005) compared with projected incidence using the ensemble of 11 RCMs for RCP8.5 in 2020-2039

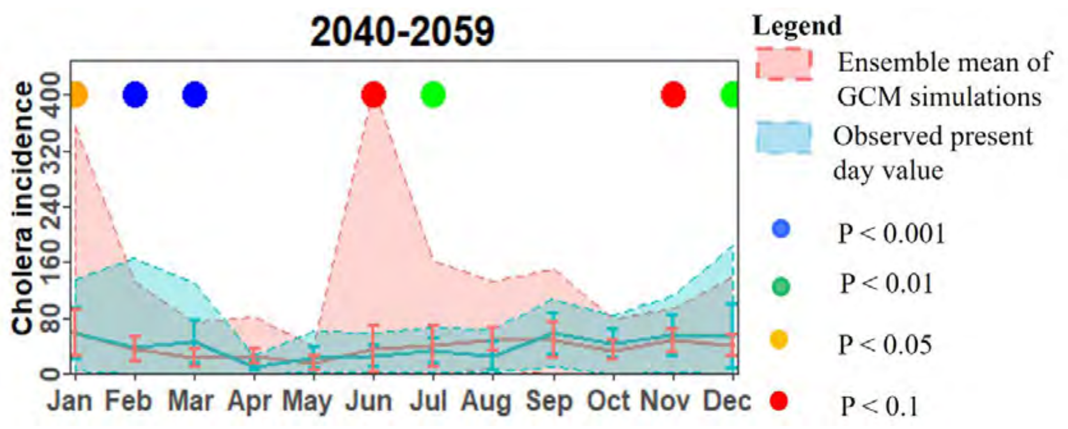

Figure 7.15: The annual cycle of cholera incidence for the present day (1986-2005) compared with projected incidence using the ensemble of 11 RCMs for RCP8.5 in 2040-2059

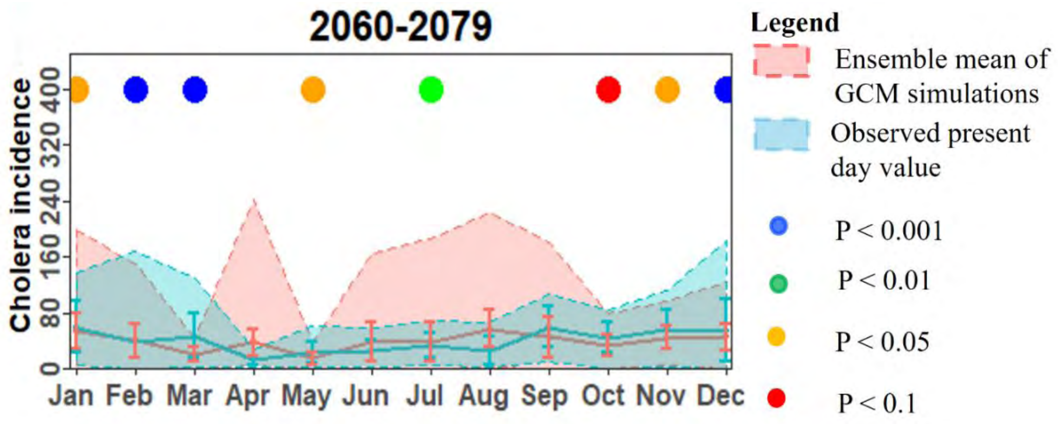

Figure 7.16: The annual cycle of cholera incidence for the present day (1986-2005) compared with projected incidence using the ensemble of 11 RCMs for RCP8.5 in 2060-2079

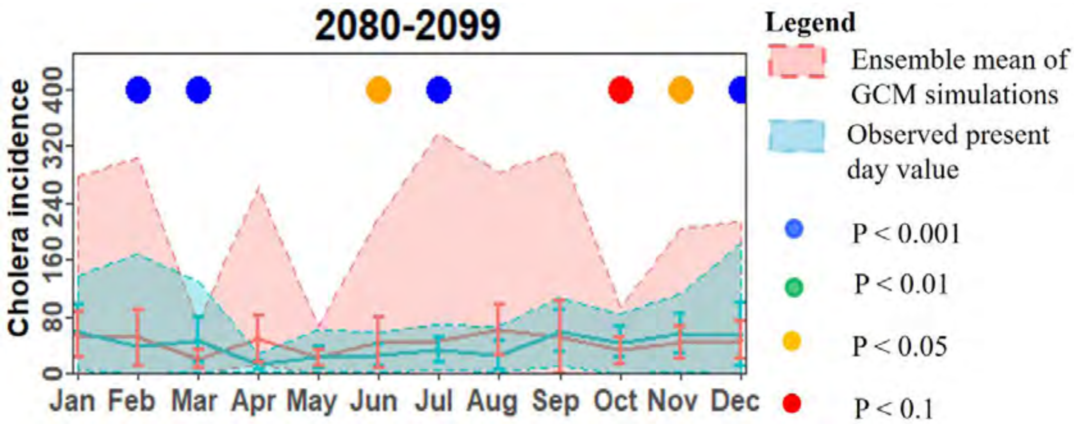

Figure 7.17: The annual cycle of cholera incidence for the present day (1986-2005) compared with projected incidence using the ensemble of 11 RCMs for RCP8.5 in 2080-2099

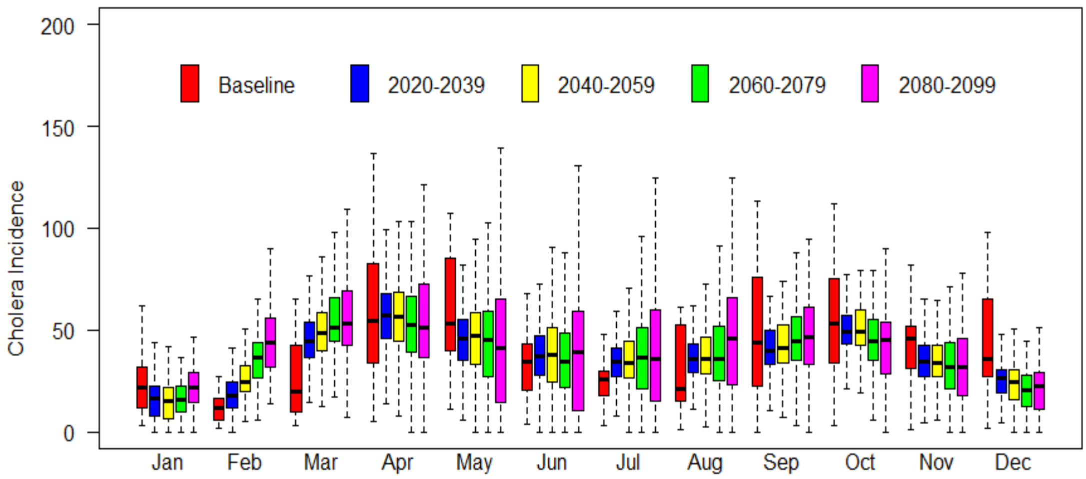

Figure 7.18: Boxplot of monthly mean of cholera cases in Dhaka, Bangladesh.

Table 7.2: Percentage change of mean monthly cholera incidence

Month	**Change compared to baseline period (%)**			
	2030s	**2050s**	**2070s**	**2090s**
January	-35	-37	-34	-6
February	58	119	208	308
March	80	96	124	137
April	-4	0	-10	-10
May	-21	-18	-24	-13
June	18	24	11	36
July	38	44	52	66
August	-6	-4	3	30
September	-26	-22	-16	-14
October	-13	-14	-22	-24
November	-22	-22	-27	-28
December	-45	-48	-57	-57

ANN simulated cholera cases were accumulated to mean monthly values, and results have been shown with a boxplot in Figure 7.18, which compares values for the five time slices. Each box includes data for the 11 climate projections used in this study. The median values of these boxes are tabulated in Table 7.2. It is observed from the predicted cholera anomaly that there will be large increases with a positive trend of increase of cholera cases in February – March and June – July in all time scale of near (2020 – 2039 and 2040 -2059) and far future (2060 – 2079 and 2080 - 2099) (Figure 7.18 and Table 7.2). This is because of large increase in temperature anomaly in February – March while large decrease of discharge for long-time (September - February) takes place due to low rainfall. This long-time decrease of rainfall and as a result of discharge, cumulative effect on increase in cholera anomaly increases in February – March (Figure 7.13). The largest increase for three time slices was found in February, with values of 119%, 208% and 308% for 2050s, 2070s, and 2090s, respectively.

7.5 Discussion

There is an urgent need to assess the potential impact of climate change on public health. Even though many promising developments may reduce the future risk for cholera transmission despite enhanced risk due to climate change, there may also be increased challenges for controlling disease outbreaks [118]. However, there are few studies looking at risk of future *V. cholerae* infection using projections from IPCC climate models [74, 119].

Climate change is likely to increase frequency and intensity of drought as well as extreme rainfall leading flood events in future [9]. Even if global warming is kept to 1.5°C, mountains of the Hindu Kush Himalaya region (upstream area of major rivers of Bangladesh) will likely be at least 0.3°C higher [65]. Fahad, et al. [66] found that at the end of this century the mean temperature increase over Bangladesh will vary from 3.2 – 5.8°C where spatially southwest and south central parts of Bangladesh will experience a greater temperature rise than other parts. Such large warming could trigger a multitude of biophysical and socio-economic impacts such as increased glacial melting which may affect the annual water budget i.e. less predictive water availability during pre-monsoon and increasing frequency and severity of floods, therefore, the endemic cholera outbreaks both at pre- and post-monsoon may increase largely. Mohammed, et al. [67] showed that due to climate change high-end scenario (RCP8.5), the average timing of both floods and hydrological droughts is projected to shift earlier compared to the present hydrological regime i.e., early onset of both flood and drought, therefore, this time change may also affect adversely on the dual peak cholera outbreaks annually that may prolong the cholera outbreaks.

Our results suggest that cholera cases in Dhaka Bangladesh may increase in the future, across all time periods, primarily as a result of drier and warmer temperatures. During the peak of the season, cholera cases could potentially increase because of climate change by 18% - 80% for 2020-2039, by 24% - 119% for 2040-2059, by 11% - 208% for 2060-2079, and by 36% - 308% for 2080-2099. Model results are primarily a function of climate change and therefore represent the potential for increased cases if current treatment strategies, land use patterns, and lifestyles remain similar in the future. So, some or all of these factors will change, and therefore these results may encourage governments and public health workers to enhance efforts to control cholera incidence.

CHAPTER EIGHT
AN ADAPTATION GUIDELINE RELATED TO COMBATING CHOLERA

8.1 Introduction

This chapter describes an adaptation guideline through a systematic review on preparedness practices of combating cholera incidence related to securing public health, safe drinking water, sanitation, and hygiene in Bangladesh and other countries. There is strong relation among poverty, food security, nutrition, and health; thereafter low safe water supply, sanitation, and hygiene services make the cholera outbreak situation worse in an urban area with low living conditions. About 90% diarrheal diseases can be prevented by adequate sanitation, hygiene and safe water supply where sanitation interventions reduce diarrhea morbidity by one-third and hygiene interventions by half [120]. An adaptation guideline has been formulated for combating cholera incidence in future with the findings of this cholera study, and a careful review of existing strategy and plans e.g., National Adaptation Plan of Action [121], Bangladesh Climate Change Strategy and Action Plan [122], National Health Policy [123], Millennium Development Goals (MDGs) [124] which will be necessary for fulfilling the future goals of Bangladesh such as Sustainable Development Goals (SDGs) [125], Perspective Plan 2010-2021 of Government of Bangladesh [126], and Bangladesh Delta Plan (BDP) 2100 [127]. Related preparedness practices of other countries worldwide will also be tried to review for supporting the recommended adaptation guideline for combating cholera incidence in Bangladesh. The flow chart of fulfilling this objective has been shown in Figure 8.1.

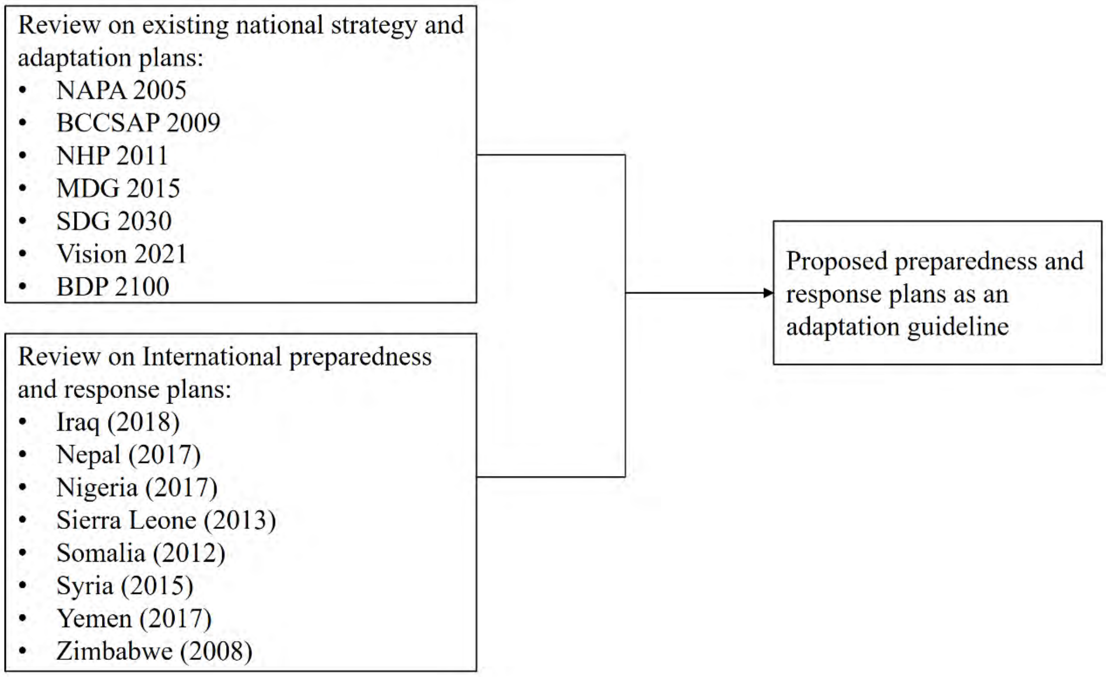

Figure 8.1: The flow chart which shows the steps to propose an adaptation guideline for cholera

8.2 Existing Strategy And Adaptation Plans for Bangladesh

8.2.1 NAPA 2005

In the NAPA 2005 [121], it is acknowledged that the combination of high temperature and potential increases in summer rainfall could create favorable conditions for greater intensity or spread of many infectious diseases like cholera. Still, the perceived risk to human health is low relative to those in other sectors (such as water resources) mainly because of the higher uncertainty about many of the possible health outcomes. Increased risk to human health from increased flooding and cyclones seems most likely. Changes in infectious disease are less certain as the causes of outbreaks of infectious disease are quite complex for combined effect of natural and human causes and often do not have a simple relationship with increasing temperature or change in rainfall. It is not clear if the magnitude of the change in health risks resulting from climate change will be apparent in the next few decades. However, in general climate change is expected to present increased risks to human health in Bangladesh, especially in light of the poor state of the country's public health infrastructure. In the Project No. 4, climate change and adaptation information dissemination to vulnerable community for emergency preparedness measures and awareness raising on enhanced climatic disaster, the objectives were mentioned as to improvement of human health facilities and to improve preparedness programme for sever communicable diseases in NAPA 2005.

8.2.2 BCCSAP 2009

BCCSAP 2009 [122] also acknowledged that climate change is likely to increase the incidence of water-borne diseases as bacteria, parasites and disease vectors breed faster in warmer and wetter conditions and where there is poor drainage and sanitation. In view of this, it will be important to implement public health measures (immunization, improved drainage, sanitation and hygiene) to reduce the spread of these diseases and to improve access to health services for those communities likely to be worst affected by climate change. Unless these steps are taken, the health of many of the poorest and most vulnerable people will deteriorate. Acute illness is known to be one of the main triggers driving people into extreme poverty and destitution in Bangladesh.

Population projection by BCCSAP 2009 shows that by 2050, Bangladesh’s population will have grown to more than 200 million with half of the people living in urban centers where Dhaka’s population will have become over 40 million. The impact of higher and more intense rainfall will be felt in urban areas where drainage is already a serious problem and sewers frequently back-up in the monsoon. The poor, who live in slums and informal settlements, often in low-lying parts of cities, will be worst affected. Rapid and unplanned urbanization in Bangladesh is going to become an even more urgent and pressing problem.

In this action plan of BCCSAP 2009, two new plans were incorporated to implement on health issues: one is to implement surveillance systems for existing and new disease risks and ensure health systems are geared up to meet future demands and another is to implement drinking water and sanitation programmes in areas at risk from climate change (e.g., coastal areas, flood- and drought-prone areas). In this adaptation programmes section, two directly cholera related programmes (out of 44 programmes) were incorporated which are summarized in Table 8.1.

Table 8.1: Details of two planned programmes and actions related to health

Programme number	Name of programme / Action number	Description	Timeline; Resposible institutions
T1P6	Theme 1 Programme 6 – Adaptation in health sector	The objective of T1P6 was to conduct research and monitoring on the impacts of climate change on disease patterns and the social and economic costs of disease and to develop adaptive measures. Under this programme, three actions were proposed for the implementation:	Medium to long term remediation of health risks; Ministry of Health and Family Welfare, in association with research centers (icddr,b) and others
	T1P6A1	Research on the impact of climate change on health (including the incidence of malaria and dengue, diarrhoeal diseases, heatstroke) and the cost of society of increased mortality, morbidity and consequent fall in productivity;	
	T1P6A2	Develop adaptive strategies against outbreaks of malaria, dengue and other vector borne diseases and invest in preventive and curative measures and facilities; and	
	T1P6A3	Develop adaptive strategies against diarrheal and other diseases, which may increase due to climate change, and invest in preventive and curative measures and facilities.	
T1P7	Water and sanitation programme in climate vulnerable areas	The objective of T1P7 was to ensure adequate water supplies and improved sanitation. Two actions were proposed to attain the objective of this programme:	Short, medium and long term; Ministry of Local Government, Rural Development and Cooperative and NGOs
	T1P7A1	Monitor changes in water quality and quantity available for drinking and forecast future changes due to climate change	
	T1P7A2	Plan for and invest in additional water supply and sanitation facilities	

8.2.3 NHP 2011

In the national health policy (NHP) of Bangladesh, the challenge of climate change induced increase of health hazard especially water-borne diseases is acknowledged. The NHP [123] has 19 goals and objectives, 16 policy principles, and 39 strategies. The cholera related goal, policy principle and strategy mentioned in NHP are summarized here. The goal-18 is to observe increase of burden of diseases and related health hazard due to climate change impact and to innovate the way of how to get rid of this hazard. The policy principle-15 stated that a health security belt has to be built by ensuring health service, medicine, equipment as emergency response to the affected people due to disasters and climate change. Strategy 34 of NHP stated that an integrated plan has to be formulated to adverse effect of climate change. Field studies have to be conducted to evaluate the short-, medium-, and long-term impact of climate change on health. A national action plan will be formulated to reduce the burden of disease due to climate change impacts.

8.2.4 MDG 2015

The Millennium Development Goals (MDGs) [124] were eight international development goals for the year 2015 that had been established following the Millennium Summit of the United Nations in 2000, following the adoption of the United Nations Millennium Declaration. The eight goals are: (1) to eradicate extreme poverty and hunger; (2) to achieve universal primary education; (3) to promote gender equality and empower women; (4) to reduce child mortality; (5) to improve maternal health; (6) to combat HIV/AIDS, malaria, and other diseases; (7) to ensure environmental sustainability; (8) to develop a global partnership for development. Each goal had specific targets and dates for achieving those targets. Goals 6 and 7 are directly related to combating cholera. Although in goal 6 it is not directly listed any target of combatting other diseases except malaria. While Target 7C was making half, by 2015, the proportion of the population without sustainable access to safe drinking water and basic sanitation in both urban and rural areas which is directly related to spread of cholera and other water-borne diseases. General criticisms of MDGs include a perceived lack of analytical power and justification behind the chosen objectives and indicators for within-country equality, despite significant disparities in many developing nations [128]. The sustainable development goals replaced the MDGs in 2016 that is elaborated in the next section.

8.2.5 SDG 2030

United Nations in its General Assembly in 2015 introduced the 2030 Agenda for Sustainable Development or SDG 2030 [125]. There are 17 sustainable development goals and 169 targets were included in the SDG 2030. These goals are followed by all the member countries of the United Nations including Bangladesh. Out of these 17 goals, Goal-3 is cholera related goal that incorporated target 3.3: Ensure healthy lives and promote well-being for all at all ages where by 2030, there will be end of epidemics of AIDS, tuberculosis, malaria and neglected diseases and combat hepatitis, water borne diseases and other communicable diseases; and Goal 6.1: Water and sanitation – better access to safe drinking water and improvement in hygienic practice prevalence of diarrheal diseases by 80%.

8.2.6 Perspective plan of 2010-2021

In the perspective plan of 2010-2021 by the Government of Bangladesh [126] also acknowledged the scarcity of healthcare facilities and services in urban centers in Bangladesh while poor nutrition represents a major health problem. Diarrheal diseases are still a major killer, though treatment is known and accessible. One of the objectives for human development in Bangladesh was to eliminating contagious diseases and ensuring primary healthcare and sanitation. Policies to deal with urban poverty focus on promoting equal access to and fair and equitable provision of services in urban areas. Emphasis will be given to urban policies and programs that ensure equal access to and maintenance of basic services, including those related to education, employment and livelihood; basic healthcare services; safe drinking water and sanitation.

8.2.7 BDP 2100

Bangladesh Delta Plan 2100 [127, 129](GoB, 2018a, 2018b) is the plan moving Bangladesh forward for the next 100 years which has been approved in September 2018 for achieving safe, climate resilient and prosperous delta. Whole Bangladesh has been divided into six climate impacted ‘hotspots’ namely: (i) coastal zone, (ii) Barind and drought prone areas, (iii) haor and flash flood areas, (iv) Chattogram hill tracts, (v) river system and estuaries, and (vi) urban areas; and one relatively less hazard prone (RLHP) areas in the BDP 2100. In the BDP 2100, it is acknowledged that health hazard will intensify due to climate change where water-borne diseases, such as diarrhea, dysentery, cholera, and vector-borne diseases, such as malaria and dengue are climate sensitive. Projections show growing morbidity could occur from dengue and malaria [129]. Long-term vision and strategies need specific targets for its implementation. This was done with a target of 80 large projects with capital investment of US$38 billion to implement by 2050 in BDP’s delta investment plan [130]. All the projects are divided under three themes: (i) preventing too much water, (ii) supplying sufficient quantity of water, and (iii) supplying sufficient quality of water. All three themes are related to cholera outbreaks as a whole so far documented by the literature. Therefore, all 80 projects would also be related to reducing cholera outbreak in future in Bangladesh. Although it is an over-ambitious plan to some critics, this investment plan will be reviewed/ updated in each five year like the five-year plans of Bangladesh to focus on the present conditions and current needs of the country. However, still there are huge challenges to implement this investment plan due to lack of adequate financial sources and possible environmental adverse impacts due to these development projects.

8.3 Cholera Preparedness and Response Plans for Different Countries

Table 8.2 illustrates the cholera preparedness and response plans in different countries of the world where cholera is mostly an epidemic character while Nepal is a country of endemic cholera with potential for large outbreaks. Here all the countries listed in the table made and follow their preparedness and response plan during cholera outbreaks which is also necessary for Bangladesh.

Table 8.2: Cholera preparedness and response plans in different countries of the world

Country; Major cholera outbreak information	**Preparedness plan**	**Response plan**	**Reference**
Iraq; 2015: case 2,868 2012: case 653 2008: case 926, death 11 2007: case 4,659, death 24	Preparedness for WASH cluster: develop a strategy and plan of action to WASH standards; improve sanitation (sewage, solid, and liquid waste management); monitor sanitation programme; chlorine ready including aquatabs at risk areas; instructions on aquatab use in local language; regular water testing; manage and share test results; develop an inventory of key water sources and update cholera endemic areas; disinfection of all drinking water sources (disinfection tablets, hygiene kits, jerry cans); agreement on common messages for cholera prevention; assess current WASH situation; disease prevention campaigns; better water management at community level Preparedness for health cluster: set a surveillance system; train a team of 3 persons per health facility at risk areas for data collection (interview) of cholera patients; share collected cholera epidemiologic data; estimate medical supply needs; make adequate stock of equipment at risk areas; prepare medical materials, human resources, and logistics ready to deploy at risk areas; train clinical staff, case managers and laboratory staff; set referral system and train on it; adequate stock of antiseptics; disinfectants and soap; set a vaccination plan;	Scenario-1 diarrhea rates unchanged: monitor water quality of all drinking water sources; monitor water quality of all drinking water sources; monitor water quality at HH (Household); monitor sanitation facility; monitor compliance for desludging; any suspected diarrhea or rumour case reported; continue preparedness actions; all diarrhea cases to be treated at PHC; cases requiring hospitalization to be referred; assess whether OCV is an option. Scenario-2 diarrhea rates escalate: continue response plan for scenario-1; assess water quality based on health surveillance data at high risk areas; deploy HH treatment if source chlorination is not feasible; sanitation improvement and repair; provide and maintain hand washing stations; establish 5-10 oral rehydration posts in a camp; establish referral mechanisms to Azadi hospital for adults and Hevi hospital for children; test for cholera cases Response plan for scenario-3 cholera confirmed: continue response for scenario-2; build emergency latrines and hand washing facilities at 1:20 ration at areas where coverage is not enough; spray chlorinated solution daily in public latrines and places; solid waste management; establish referral pathway of cases; develop discharge guidance	GovIraq [131]

Country; Major cholera outbreak information	Preparedness plan	Response plan	Reference
	plan for appropriate water supply, sanitation, bathroom and cloth washing facility at health centers; safe disposal of waste		
Nepal; 2016: case 169 in Kathmandu 2014: case 471 2013: case 703 2012: case 408 2011:case 345	prevent spread of cholera outbreaks; surveillance and early warning; hospital reporting; laboratory surveillance; improve WASH facility (especially community level water supply, sanitation); immunization with oral cholera vaccine; miking in high risk areas; active case finding, early detection and referral to health facilities.	chlorinate all piped drinking water system and tankers; regular monitor systems prior the season; food safety campaigns; hand washing with soap practice; proper waste management (solid, liquid and sewage); rebuild toilets and hand washing facilities; reduce morbidity of cholera by standardized case management; adequate supplies of services and logistics; coordination and collaboration surrounding cholera preparedness and response (steering committee, situation report); establish rapid response mechanism with rapid response teams; monitoring and evaluation of surveillance and response	GovNepal [132]
Nigeria; 2011: case 22,454, death 715 (CFR 3.2%) 2010: case 26,240, death 1,182 (CFR 4.5%)	Need estimation, risk mapping, risk estimation, capacity building	multi-sectoral coordination, disease surveillance and laboratory support, prompt access to treatment, provision of safe water and sanitation and hygiene, health education, and oral cholera vaccination	GovNigeria [133]
Sierra Leone; 2012: case 22,971, death 299 (CFR 1.3%) 2007: case 2,219, death 84 (CFR 3.8%) 2006: case 3,366, death 173 (CFR 5.1%)	disease surveillance and laboratory ready; case management to reduce cholera morbidity; improve WASH facility (access to safe water, sanitation awareness, coverage and use, waste management in urban, food hygiene); health promotion (information dissemination on cholera to policy makers, people, improve behaviors on safe disposal of faeces and hand washing, food safety, cholera awareness); identify operational needs for cholera cases;	activate emergency response plan; declaration of end of cholera epidemic; manage patients according to national guidelines; improve early case detection; establish referral system; reduce infection transmission in health facility and public places; provision of improved WASH facility at health centers; increase awareness and safe hygiene practices in community and public laces; establish coordination mechanism for logistical support;	GovSL [134]

Country; Major cholera outbreak information	Preparedness plan	Response plan	Reference
1995: case 36,326 death 839 (CFR 2%) 1985-87: case 14,000, death 1,200 (CFR 9%)	a proper implementation plan for preparedness	establish efficient storage and distribution mechanism at all levels; monitoring and evaluation framework on achievement of specific thematic indicators and end evaluation of the plan which will inform the next plan	
Somalia 2011: case 77,636	Chlorine and WASH hygiene kit, coordination by reviewing prevention measures, access to safe drinking water, testing water sources, map unprotected water sources, chlorinate unprotected sources, service ready with treatment, distributing WASH hygiene kit, handwashing with soap/ash, water treatment tablets, water filters, monitor surveillance, detailed instructions in local language, 40% women community mobilizer, hygiene promotion project for 6-month	Disinfect affected households by patient relatives and caretakers, provide soap, disinfectant and hygiene education, training on disinfection of toilet, cooking and bedding, provide toilets and hand washing facilities at cholera treatment centers, safe excreta disposal in high risk areas, ensure solid waste disposal, provide all facilities in schools and child friendly spaces	GovSomalia [135]
Syria 1993: case 10,917 1977: case 8,523 1970: case 2,816 1993: case 10,917 1977: case 8,523 1970: case 2,816	cholera risk assessment; mapping high risk or hotspot areas; mapping cholera response capacity; mapping human and financial resources; setting up coordination committee; securing stock of strategic reserves; building local capacity; setting standards of managing all activities; readiness of rapid response teams at high risk areas; identify cholera treatment centers and rehydration corners; provide laboratory supplies; enhance surveillance;	enhance surveillance at health facility at community levels; active case findings; reinforce infection control practice; identify potential partners to be assigned different roles; analyze and disseminate data and weekly trends; control over environmental risk elements; evaluation of cholera response	GovSyria [136]

Country; Major cholera outbreak information	Preparedness plan	Response plan	Reference
	strengthen information management; regular monitoring on preparedness.		
Yemen 2017 March: case 24,504, death 143 (CFR 0.44%) Projected outbreak: additional > 84,000 in 2017 (July - December)	increase surveillance, expedite laboratory testing facility, understand root of contamination, reactivate and sustain an integrated cholera operational room at national and affected sub-national level, cholera task force, strengthen community based surveillance, water testing, support rapid response team, improve data management and information dissemination	establish/ reactivate/ sustain diarrhea treatment centers, establish ORS corners and diarrhea treatment unit at community level for moderate cases, establish referral system for cases failing to recover, training health workers and laboratory staff, distribution of treatment guidelines, diarrheal kits, promote safe burial practices, ensure infection prevention, joint monitoring to ensure quality of services, provide household chlorination tablets and hygiene kits (soap)	GovYemen [137]
Zimbabwe 2008: case 9,000, death 400	Functional early warning system; form inter-agency rapid assessment team (IARAT); humanitarian information system for operational purpose; database of alerts; assessments and feedback;	mapping laboratory capacity; make ready portable laboratory kits; identify laboratory operators; establish national and provincial emergency stocks; emergency reserve fund to facilitate deployment of personnel; establish information flow, feedback and dissemination mechanisms; inter-cluster monitoring and evaluation; establish cholera treatment centers; make cholera treatment kits available within 24 hours; mobilize required number of personnel to run the centers; train at least 90% of all personnel; make treatment protocols; enforce rational use of antibiotics for cholera patients; monitor daily admissions; cure death in centers; monitor case fatality and address potential risk factors identified	GovZimbabwe [138]

Note: CFR = Case fatality rate; ORS = Oral Rehydration Solution

8.4 Adaptation Guidelines for Cholera Preparedness and Response

Although most of the countries' cholera outbreaks are reported as epidemic except in Nepal, where it is of endemic character (Table 8.1). However, Nepal has already formulated the preparedness and response plan in 2017 [132]. Nepal is advanced comparing to Bangladesh in respect of coverage of safe drinking water (93% in Nepal vs. 87% in Bangladesh in access to improved water supply), sanitation (72% in Nepal vs. 70% in Bangladesh sanitation through pit latrines), but regressed in open defacation of 26% while it is only 1% in Bangladesh in 2013 although was 39% in 1990 [139, 140].

8.4.1 Emergency Guideline adopted from WASH

There is yet no 'Cholera preparedness and response plan' in Bangladesh. Instead Bangladesh developed an operational guideline for WASH activities in emergency situations in 2017 [141]. In the WASH emergency guidelines, six guidelines were adopted:

- (i) Water guidelines;
- (ii) Excreta disposal guidelines;
- (iii) Inclusiveness guidelines;
- (iv) Hygiene promotion guidelines;
- (v) WASH non-food item guidelines; and
- (vi) Waste, drainage and vector control guidelines for emergency relief and early recovery.

These six guidelines illustrate only the WASH activities during emergency situation of disasters e.g., floods, cyclone, and different disease outbreaks in Bangladesh. However, a need of a preparedness and response plan of actions is necessary for preventing regular endemic cholera outbreaks in Bangladesh.

8.4.2 Preparedness and Response Plan for Bangladesh

Implementation of cholera preparedness and response plan is for mitigation of cholera outbreaks and reduction of case fatality. Prevention of cholera in a country will have a large impact on general wellbeing of the society by reducing disease burden especially among high risk communities in a cholera prone area. To establish the profile of cholera beyond the health sector, a well-publicized launch of the plan would help to mitigate or control cholera outbreak in a country. Despite the emergency situations, there are a few potential preparedness and response plan to be prepared and followed every year.

Preparedness plan

(i) Household water treatment and safe storage of drinking water;
(ii) Access to clean drinking water in urban slums;
(iii) Water security in drought-prone areas;
(iv) Regular monitor the water supply systems prior the season;
(v) Improve WASH facility (access to safe water, sanitation awareness, coverage and use, waste management in urban, food hygiene);
(vi) health promotion (information dissemination on cholera to policy makers, people, improve behaviors on safe disposal of faeces and hand washing, food safety, cholera awareness)
(vii) Proper waste management for individually solid, liquid and sewage waste; sewerage and storm-water drainage systems should be separate where sewage especially fecal sludge should not be mixed with regular drainage lines which should be separately treated/managed;
(viii) Water quality monitoring regularly;
(ix) Improve data management and information dissemination;
(x) Functional early warning system;
(xi) Enhance surveillance at health facility at community levels;
(xii) Train clinical staff, case managers and laboratory staff

Response plan

i) Multi-sectoral coordination; a high level steering committee led by health minister; regular situation reporting and need assessment
ii) Establish a rapid response mechanism with rapid response teams at upazila level;
iii) Cholera surveillance and laboratory support at upazila level in cholera prone district;
iv) Emergency supply of safe drinking water in cholera outbreak areas;
v) Adequate supplies of logistics and health services;
vi) All diarrheal diseases to be treated at public hospitals at district and upazila levels where icddr,b response actions may be followed with special beds.

Due to creating access to safe drinking water and improvement in hygienic practice of people, deaths due to diarrheal diseases in Bangladesh has been dropped by 60% in the past decade due to mainly improved safe water supply (97.9%, 5.7% piped water into dwelling), sanitation (56% in an average, 26% poorest, 80% richest) and hygiene (hand washing 59% in an average, 70% urban, 56% rural, 39% poorest, 84% richest) [140]. Moreover, 79% children under 5 with diarrheal diseases received ORT i.e., oral saline or recommended homemade fluid. These indicate improvement of the adaptation strategies for the cholera outbreak preparedness, however, still a lot of measures to be taken for improving the outbreak scenario of cholera in Dhaka as well as in Bangladesh. The plans mentioned in this chapter especially for achieving SDGs and BDP 2100 would be helpful for future preparedness for cholera outbreaks in Dhaka megacity as well as for whole Bangladesh.

CHAPTER NINE
CONCLUSIONS, RECOMMENDATIONS AND LIMITATIONS

9.1 Conclusions

- The relationship between cholera incidence and hydro-climatic variables was investigated
- A significant relationship of rainfall and temperature with cholera incidence was found
- These results helped further to use for developing a forecast model and also to simulate future projections
- The relationship between cholera incidence and climatic variables varies with locations and climatic variables
- A single variable model showed for 1°C monthly maximum temperature increase, cholera incidence increases by 7% ($p < 0.001$) at 1-month lag
- Multi-variable model with 1-month lag showed the best result with the lowest errors of AIC and BIC
- From the predictions it was summarized that cholera incidence in Dhaka, Bangladesh may increase in the future, especially in February, March, June and July
- These results also revealed that changes in climate extremes may have more adverse impact on the cholera dynamics than that of the mean climate.
- For example, increase in the intensity and occurrence of heat events may increase the risk of disease transmission.
- Similarly, occurrence of extreme rainfall may increase the risk of flooding which might assist the risk of cholera.
- A systematic review was done on preparedness practices of combating cholera to recommend adaptation guideline for Bangladesh.
- The government of Bangladesh is eager to improve preparedness against waterborne diseases by ensuring safe drinking, which will also be helped by knowledge from this study.
- This study proposed some preparedness and response plans as adaptation guidelines for Bangladesh.

- An effective guideline can be formulated through use of new technologies and finalize a communication strategy for health emergencies for whole Bangladesh.

9.2 Recommendations

This study has been conducted with many limitations as well as could not include many related things that would be further investigated. Here, such items have been listed that may be considered for further research or actions for reducing the cholera devastation for Dhaka as well as for Bangladesh.

- This study has been considered for only the cholera incidence recorded in icddr,b that is the only available authentic cholera incidence data. The improved detailed surveillance in community based study can be considered further for more accurate information on cholera incidence and reasons behind this. Further, all data collected for different purposes should be open for all to make available for further investigation on cholera.
- This study has been conducted using only one IPCC scenario i.e., the high emission scenario RCP8.5. For detail insight of climate change impact on cholera outbreaks, the other IPCC scenarios may also be investigated e.g., RCP scenarios – RCP2.6, RCP4.5 and RCP6.0 may provide additional information on future cholera scenario under climate change.
- This study took into account of only climatic factors, considering socioeconomic factors e.g., poverty/income, literacy rate; and water and sanitation infrastructure information that means the Shared Socioeconomic Pathways (SSPs) in the further study may improve the results.
- Further, for a detail adaptation guideline and preparedness and response plan for reducing cholera incidence and fatality, more detail study would require consultations with different stakeholders, concern authorities and experts working in Bangladesh.

9.3 Limitations of the Study

There are a few limitations of this study;

- The cholera incidence of icddr,b data is assumed to be representative of the entire spatial extent of Dhaka megacity. This is due to the fact that detailed lab tested cholera incidence data is only available at icddr,b, where cholera cases are diagnosed by the laboratory testing of stool.
- icddr,b receives most of cholera patients for Dhaka and surrounding as it is renowned as the only cholera hospital in Dhaka, where special response program is taken every year during the endemic outbreaks.
- The cholera data availability of only 14 years (January 2000 – December 2013) for forecasting model may also be considered as a limitation.
- This study only took account of climatic variables on existing socioeconomic conditions.

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APPENDIX 1

THE OVERALL FLOW CHART OF FOUR OBJECTIVES