Hydrology, Remote Sensing and Water Related Diseases: Predicting Cholera Outbreaks in Bengal Delta

A dissertation

submitted by

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ABSTRACT

There is growing evidence that outbreaks of several water-related diseases are potentially predictable by using satellite derived macro-scale environmental variables. This research addresses cholera, which one of the most prevalent water-related infections in the tropical regions of the world. Since the macro-scale environment provides natural ecological niche for *Vibrio cholerae,* causative agent for disease outbreaks, and a powerful evidence of new biotypes is emerging, it is highly unlikely that cholera will ever be fully eradicated. Consequently, to develop effective intervention and mitigation strategies to reduce disease burden, it is necessary to develop cholera prediction mechanisms with several months' lead-time. Satellite data provides reliable estimates of plankton abundance, through chlorophyll, as well as reflectances which can form the basis of early warning models. Within this context, the overall goal of the proposed research is to develop a seasonal cholera prediction model with two to three months lead time, using primarily remote sensing data. Three closely related objectives of this research are to: (i) determine the space-time structure of chlorophyll in the Bay of Bengal, (ii) evaluate role of freshwater discharge in creating seasonality and relationships among phytoplankton and sea surface temperature, (iii) develop a cholera prediction modeling framework. This research shows, that seasonal cholera outbreaks in the Bengal Delta can be predicted two to three months in advance with an overall prediction accuracy of over 75% by using combinations of satellite-derived chlorophyll and air temperature. Such high prediction accuracy is achievable because the two seasonal peaks of cholera are predicted using two separate models representing distinctive macro-scale environmental processes. We have shown that interannual variability of pre-monsoon cholera outbreaks can be satisfactorily explained with coastal plankton blooms and a cascade of hydro-coastal processes. Thereafter, a new remote sensing reflectance based statistical index: Satellite Water Impurity Marker, or SWIM is developed to estimate impurity levels in the coastal waters and is based on the variability observed between blue and green reflectance (i.e., clear and impure water). The index can predict cholera outbreaks in the Bengal Delta with 78% accuracy with two months lead time. Our results clearly demonstrate that satellite data over a range of space and time scales can be very effective in developing a cholera prediction model for the disease endemic regions

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Introduction, Context and Motivation

1. Context, Motivation and Objectives

1.1 What do we know about cholera and remote sensing?

Cholera, an acute water-borne diarrheal disease, continues to be a significant global health threat. The ongoing seventh pandemic of cholera, which started in 1960s, has been reported in over 50 countries and has affected over 7 million people (Gleick, 2008). The disease remains a public health threat in many tropical regions of the world, specifically in coastal areas of South Asia, Africa, and Latin America. The life cycle of the bacterium *V. cholerae*, the causative agent for cholera outbreaks, is intricately linked to two different processes: *micro*- and *macro*-environmental processes, which have vastly different spatial and temporal scales of interacting variables. Here, we define *micro* as microbiological, genetic, and human intestinal processes and related variables, while *macro* refers to hydrological, ecological, climatic, and coastal processes and their related variables. A deep disciplinary focus on examining micro- and macro-environmental processes has produced an extensive body of information about cholera. Despite steady accumulation of knowledge of *V. cholerae* in respective research fields, we are not yet able to predict when and where the next cholera epidemic will strike. Since *V. cholerae* exists naturally in aquatic habitats with important ecological functions and there is powerful evidence of new biotypes emerging (Bhuiyan et al., 2009), it is highly unlikely that cholera will be eradicated.

The coastal regions of South Asia, for example Bangladesh, have a long history of cholera outbreaks and are collectively considered the native homeland of the cholera disease since the early 19th century (Bouma and Pascal, 2001). Cholera incidence data at the International Center for Diarrhoeal Disease Research in Bangladesh (ICDDR,B) is well documented and is perhaps one of the longest and most detailed cholera datasets in the world (Longini et al., 2002). Cholera incidence time series in Bengal delta is unique in a sense that it shows two cholera outbreaks in a given season (Akanda et al., 2009). Akanda et al (2009) hypothesized that spring outbreaks are the results of intrusion of coastal water in Bay of Bengal (BoB) aided through low river discharge while autumn cholera outbreaks are the result of flooding caused by high river discharge. Cholera incidence in this region have been historically linked to environmental and climate variables such as precipitation (Hashizume et al. 2008), floods (Koelle et al., 2005), river level (Emch et al., 2008), sea surface temperature (Lobitz et al., 2000), coastal salinity (Miller et al., 1982), dissolved organic material (Worden et al., 2005) and fecal contamination (Islam et al., 2006). The above studies on Bengal Delta cholera dynamics primarily focused on environmental and climatic variables with a single annual peak – and consequently were unable to identify the underlying seasonal processes or drivers behind the dual peaks.

Almost all major cholera epidemics start in the coastal regions, indicating a strong link between estuarine and riverine water systems and outbreaks of the disease (Jutla et al., 2010; Griffiths et al., 2006; Huq and Colwell 1996). From initial outbreaks in coastal regions, cholera then spreads to inland areas through river networks (Bertuzzo et al., 2008, 2009). Cholera bacteria attach to zooplankton, especially copepods, to form a thin biofilm (Colwell et al., 1996). Since copepods feed on phytoplankton, a high correlation is expected between copepods and phytoplankton (Huq and Colwell. 1996). Consequently, observed abundance in phytoplankton may correspond to an increase in the number of cholera bacteria (Colwell, 1996). The causative agent of cholera outbreaks, *V. cholerae*, cannot be measured from space. However, the bacteria show strong affinity with plankton blooms which can be estimated from satellites by measuring chlorophyll present in plankton. Chlorophyll, a key biochemical component that gives plants its green color, is responsible for facilitating absorption of sunlight for photosynthetic purposes. Currently, satellite measured chlorophyll is the only effective way to monitor space-time variations of plankton abundance over large coastal areas. Lobitz et al. (2000) is perhaps the first study that used limited remote sensing data to explore possible connection between Sea Surface Temperature (SST), chlorophyll and cholera incidence; using one 18km pixel and 16 month data from satellites. Potentials of using remote sensing data (such as chlorophyll, SST etc) for understanding cholera dynamics across a range of spatial and temporal scales has been highlighted in several studies (such as Emch et al, 2008; Magny et al., 2008), however, these studies did not elaborate on the precise role of remotely sensed variables for understanding cholera dynamics. These studies primarily attempted to relate single peak environmental and climatic variables with cholera incidence that show distinct double peak.

1.2. What do we not know about cholera and remote sensing?

A closer look at relationship between cholera and remote sensing reveals limited understanding of what remote sensing data can offer for establishing coastal and hydrological connections with cholera incidence. Satellite remote sensing provides estimate of chlorophyll, a surrogate for phytoplankton abundance. Phytoplankton concentrations are found to be considerably higher near the coastal zone (21^0 – 22.5^0 N and 86-93^0E) of the Bay of Bengal (BoB) (*Jutla et al., 2009*). The coastal zone of the BoB also shows high chlorophyll variability compared to relatively constant values away from the coast. There is limited understanding on the inter- and intra-annual variability of chlorophyll in coastal regions and its relationship with cholera incidence.

Satellite chlorophyll data is available at various scales such as daily, monthly, annual etc. There is incomplete understanding on how the space-time variability of phytoplankton affect cholera dynamics and what are the dominant time scales of phytoplankton and its controls on cholera outbreaks. Using chlorophyll and SST, several other studies from various ocean basins across the globe, suggest an inverse relationship between phytoplankton and SST (e.g., Solanki et al., 2001, Davenport et al., 2002; and several others). Phytoplankton blooms occur in cold ocean waters, however, in BoB, phytoplankton and SST are positively related (Jutla et al., 2009). However, such a positive relationship between SST and phytoplankton breaks down as we move away from the coastal areas. *Why do we observe positive association of SST and phytoplankton in BoB?*

How does the timing and location of phytoplankton bloom and SST variation affect the timing of cholera outbreak?

Prediction of cholera outbreaks remains an unresolved puzzle. *V. cholerae* exists naturally in brackish waters, and because of the growing evidence of new biotypes emerging, it is unlikely that cholera will ever be eradicated. Akanda et al (2009) proposed the role of rivers in two peaks of cholera outbreaks in Bengal delta. However, Akanda et al (2009) did not elaborate if large scale processes such as river discharge can predict cholera outbreaks. *What are the geophysical drivers which can be used for prediction of cholera outbreaks?* For example, Magny et al (2008) suggested that chlorophyll may be used as a predictor variable for cholera outbreaks in Bengal Delta, however, the study did not elaborate, if chlorophyll can predict seasonal double peak cholera outbreaks for this region. Identification of appropriate predictor variables is important to understand cholera dynamics for the region.

1.3 What is my motivation?

Four observations and empirical findings motivate me to explore the connections among coastal ecology, hydrology, and epidemiology of cholera and develop prediction model using recent advances in remote sensing: (a) cholera incidence in Bengal delta is unique with two seasonal peaks which are controlled by two separate hydrological processes (Akanda et al., 2009); (b) major cholera outbreaks have originated near coastal areas (Barua, 1992, Jutla et al., 2010); laboratory and field studies have shown significant positive correlation between zooplankton and cholera bacteria (Huq et al. 1990; Tamplin et al. 1990); (c) remote sensing provides unprecedented coverage of space-time measurements of phytoplankton variability in coastal regions (Uz and Yoder, 2005) and (d) most ocean basins show an inverse relationship between chlorophyll and SST, a positive relationship exists between SST and chlorophyll near the coastal areas of the BoB (Colwell 1996; Lobitz et al., 2000). Recent advances in remote sensing, via spatial and temporal coverage of satellites, can provide relevant data (such as chlorophyll, colored dissolved material, SST, sea surface height) to monitor environmental conditions favorable to cholera outbreaks. Therefore, it is important to establish relationships between environmental variables for comprehensive understanding of cholera dynamics.

1.3 What are my goals and objectives?

The overall goal of the proposed research is to develop a cholera prediction model with two to three months prediction lead time, using primarily remote sensing data. To achieve this goal, three closely related research objectives are outlined below:

(i) Determine the space-time variability of chlorophyll in the BoB

(ii) Role of freshwater discharge in creating seasonality and relationships among phytoplankton and SST

(iii) Develop a cholera prediction modeling framework

My approach starts with a simple premise: “data-rich” modeling driven by “adaptive-theory”. The data will dictate development of an adaptive theory and prediction model for cholera outbreaks. Such a premise will allow exploring a transformational approach to protect vulnerable and resource limited regions against cholera. This is a unique opportunity because now we have a decade long space-time oceanic (chlorophyll, organic matter, etc) data set over the global ocean for the first time which will allow us to examine their relationships with cholera incidence. Findings from these three research objectives are expected to provide comprehensive understanding of hydro-coastal controls on cholera dynamics and potentials for using remote sensing data for developing a cholera prediction model.

Figure 1.1 shows the schematic progression of this research as well as an outline of the thesis. Chapter 2 is an overview on what is known in literature about cholera and its relationship with hydrological processes. The chapter will also discuss how remote sensing derived chlorophyll has been related with cholera outbreaks in several parts of the globe. Since chlorophyll has been suggested as the primary variable of interest for understanding cholera dynamics, it is essential to understand the spatial and temporal scale variability in the Bay of Bengal. Chapter 3 addresses the issues of scales in chlorophyll and how such scales are related with cholera incidence in Bengal Delta. Chapter 4 provides explanation on the possible controls on production of plankton in the Bay of Bengal and addresses the paradox as to why a positive relationship between SST and cholera incidence in the Bay of Bengal should not be treated as causal. This chapter examines the hypothesis that the observed positive relationship between SST and cholera incidence is primarily controlled be the terrestrial nutrient outflows during high river discharge seasons. Chapter 5 presents a phenomenological prediction model primarily using satellite data for predicting cholera outbreaks in the Bengal delta with two to three months in advance. This chapter also introduces the idea that a cascade of hydro-coastal macro-scale processes may result in cholera outbreaks. Thereafter, a new satellite reflectance based index is developed in Chapter 6. Satellite Water Impurity Marker (SWIM) has shown existence of identifiable and robust statistical conditions in coastal waters which may lead to outbreaks of cholera in South Asia and Africa. The overall outcome of the research, major scientific contributions and scope of future work is mentioned in Chapter 7.

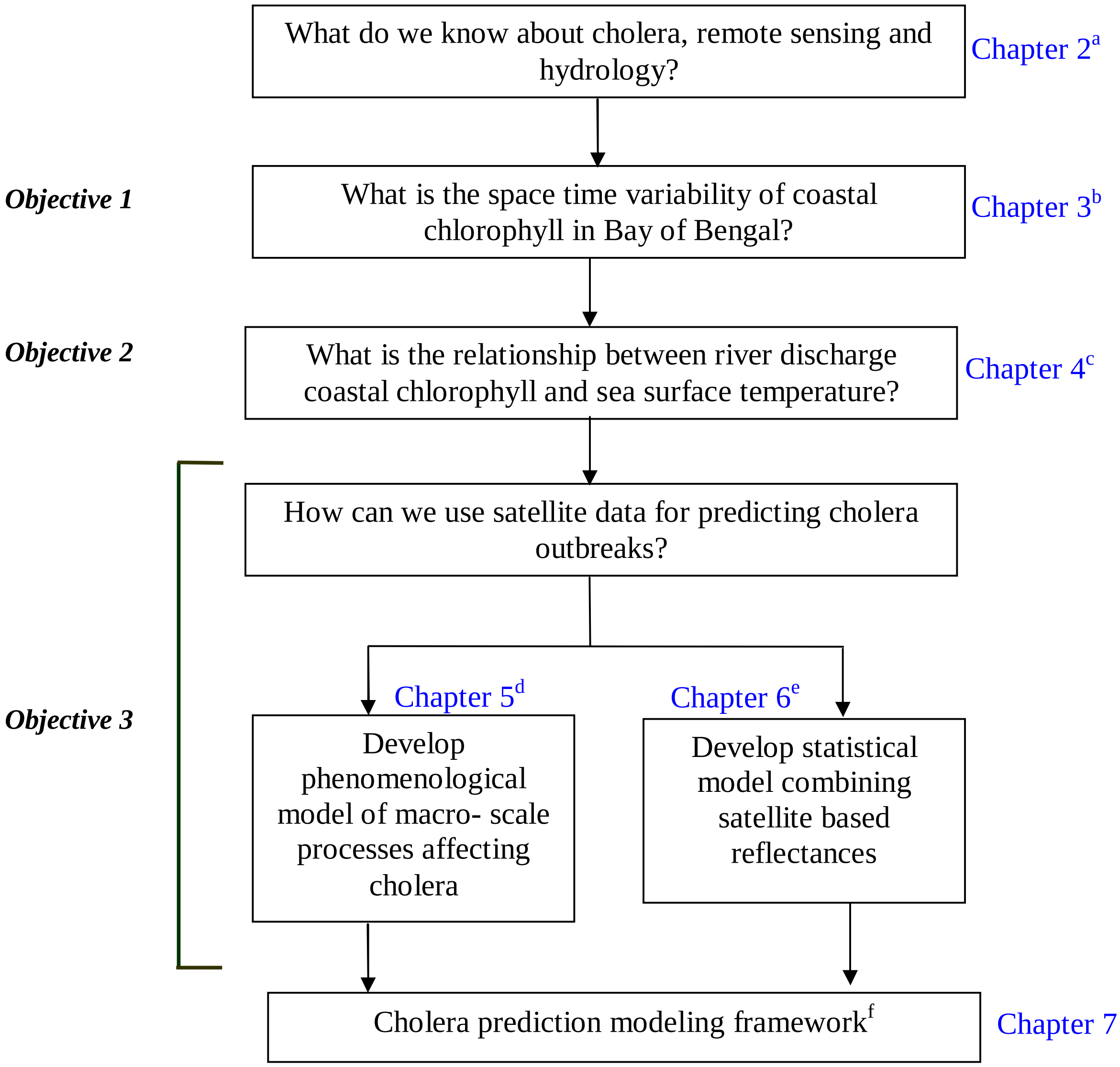

Figure 1.1: Research Pathway for Predicting Cholera Outbreaks

[a]**Jutla, A.S.,** Akanda, A.S. and Islam, S. 2010. Tracking Cholera in Coastal Regions using Satellite Observations. *Journal of American Water Resources Association.* 46(4):651-662. doi: 10.1111/j.1752-1688.2010.00448.x.

[b]**Jutla, A.S.,** Akanda, A.S. and Islam, S. 2011. Space-Time variation of chlorophyll in Northern Bay of Bengal. (minor revision, *Remote Sensing of Environment*).

[c]**Jutla, A.S.,** Akanda, A.S, Griffiths, J. Islam, S. and Colwell, R. 2011. Warming oceans, phytoplankton, and river discharge: Implications for cholera outbreaks. *American Journal of Tropical Medicine and Hygiene*. doi:10.4269/ajtmh.2011.11-0181

[d]**Jutla, A.S.,** Akanda, A.S. and Islam, S. 2011 Predicting seasonal cholera outbreaks from satellite data (submitted: Environmental Modelling and Software).

[e]**Jutla, A.S.,** Akanda, A.S. and Islam, S. 2011 Satellite Water Impurity Marker for cholera outbreaks (Preperation, *Geophysical Research Letters*).

[f]**Jutla, A.S.,** Akanda, A.S., Mazumdar, M., Colwell, R., and Islam, S. 2011. Predicting Cholera Outbreaks: Where is Next Haiti? (Submitted, Environmental Health)

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Chapter 2

Tracking Cholera in Coastal Regions using Satellite Observations[#]

Abstract

Cholera remains a significant health threat across the globe. The pattern and magnitude of the seven global pandemics suggest that cholera outbreaks primarily originate in coastal regions and then spread inland through secondary means. Cholera bacteria show strong association with plankton abundance in coastal ecosystems. This review study investigates relationship(s) between cholera incidence and coastal processes and explores utility of using remote sensing data to track coastal plankton blooms, using chlorophyll as a surrogate variable for plankton abundance, and subsequent cholera outbreaks. Most studies over the last several decades have primarily focused on the microbiological and epidemiological understanding of cholera outbreaks. Accurate identification and mechanistic understanding of large scale climatic, geophysical and oceanic processes governing cholera-chlorophyll relationship is important for developing cholera prediction models. Development of a holistic understanding of these processes requires long and reliable chlorophyll dataset(s), which are beginning to be available through satellites. We have presented a schematic pathway and a modeling framework that relate cholera with various hydroclimatic and oceanic variables for understanding disease dynamics using latest advances in remote sensing. Satellite data, with its unprecedented spatial and temporal coverage, have

potentials to monitor coastal processes and track cholera outbreaks in endemic regions.

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2.1 Introduction

Cholera, longest known water-borne epidemic disease in the history of mankind, was anecdotally reported as early as 400BC (Bishagratna, 1963). F. Pacini in 1854 was the first scientist to isolate Comma bacillius, now known as *V. cholerae* followed by a similar discovery by Robert Koch in 1884 (Bentivoglio and Pacini, 1995). John Snow, a British physician, was the first to discover that cholera spread through contaminated water. Ever since, cholera has been a subject of intense interest for a range of microbiological and epidemiological studies. The ongoing seventh pandemic of cholera, which started in 1960s, has been reported in over 50 countries and affected over 7 million people (Gleick, 2008). The disease remains a public health threat in many regions of the world, specifically in coastal areas of South Asia, Africa, and Latin America.

The causative agent of cholera, *V. cholerae,* is known to survive and multiply in favorable estuarine environments. Primary outbreaks of cholera over the last several decades in South Asia, Africa and South America have mostly originated in coastal areas (Gleick, 2008; Griffiths et al., 2006; Siddique et al., 1994; Huq and Colwell 1996). With the first correlative study relating cholera incidence and increased number of algae in water (Cockburn and Cassanos, 1960), several studies have postulated connection between initial cholera outbreak and oceanic plankton abundance (Siddique et al., 1994; Huq and Colwell 1996). Many of these microbiological and epidemiological studies have primarily focused on the annual and local scale variations of cholera with different ecological and climatic variables. Despite wide advances in the ecological and biological understanding of the cholera bacteria over the last half-century, our understanding of the influence of large scale climatic and geophysical processes on the global transmission of cholera remains limited.

Various environmental factors such as sunlight, precipitation, salinity, temperature, and nutrients are suggested for survival and growth of cholera bacteria in the aquatic environment (Singleton et al. 1982; Huq et al. 1984; Epstein, 1993). Cholera bacteria attach to zooplanktons by forming a thin pathogenic biofilm (Reidl and Klose, 2002). As copepods feed on phytoplankton, a high correlation is expected between the occurrence of copepods and phytoplankton bloom. Consequently, one may expect an observed abundance in phytoplankton to correspond to an increase in the number of cholera bacteria in the coastal waters. Recent advances in remote sensing may allow us to understand cholera outbreaks over large regions by observing chlorophyll concentration, as a surrogate measure of plankton abundance, from satellites.

Three empirical observations motivate the exploration of possible connections among the biology and ecology of the aquatic environment and large scale hydro-climatic processes: (a) almost all cholera outbreaks are originated near the coastal areas including reemergence of cholera in Latin America in 1991; (b) laboratory studies suggest a significant positive correlation between plankton abundance and pathogenic cholera bacteria; and (c) remote sensing provides unprecedented coverage of space-time measurements of chlorophyll variability in coastal regions around the world.

Marine plankton exhibits wide variability in time and space. Previous studies have primarily used in-situ plankton data with limited daily measurements and attempted to establish chlorophyll-cholera connections. However, day-to-day variations of chlorophyll over a range of spatial scales can be as large as an order of magnitudes (Uz and Yoder, 2004). Thus, analysis of in-situ measurements of chlorophyll may provide limited and somewhat incomplete understanding of the space-time variations of phytoplankton and consequently cholera dynamics. With availability of continuous measurement of satellite-estimated chlorophyll, we are now able to examine chlorophyll variation at various temporal scales (~daily, weekly, etc.) with a range of pixel resolutions (~ kilometers) over very large regions for last ten years. The objectives for this chapter are to (1) establish possible relationship(s) between cholera incidence and coastal processes and (2) explore the utility of using remote sensing data to track coastal plankton blooms and subsequent cholera outbreaks in vulnerable regions. Cholera incidence in this manuscript is defined as the percent of new cholera infected patients from a total pool of patients visiting the hospital for treatment in a given region. Similarly primary cholera outbreak refers to the start of the cholera disease in a given season or area

2.2 Cholera and Coasts: A Geographical Overview

Cholera remains endemic in many countries of the developing world, mainly in coastal areas of South Asia and Africa (Colwell, 1996, Mouriño-Pérez, 1998) and has lately shown an unprecedented rise in infection and transmission in Africa (Griffith et al. 2006; Collins, 2003). The global awareness of cholera began in 1817 with the explosive epidemics breaking out in the lower Ganges River delta and spreading to the entire world in the form of pandemic (Sack et al, 2004). The seventh pandemic, still ongoing, started in Indonesia in 1961 and has already been reported in over 50 countries. Figure 2.1 shows the worldwide reach of the ongoing cholera pandemic. The global pattern and magnitude of the pandemics suggest that cholera outbreaks primarily originate in coastal environments, suggesting a link between changes in the near shore waters and outbreaks of the disease (e.g., Colwell and Huq, 2001; Mouriño-Pérez, 1998).

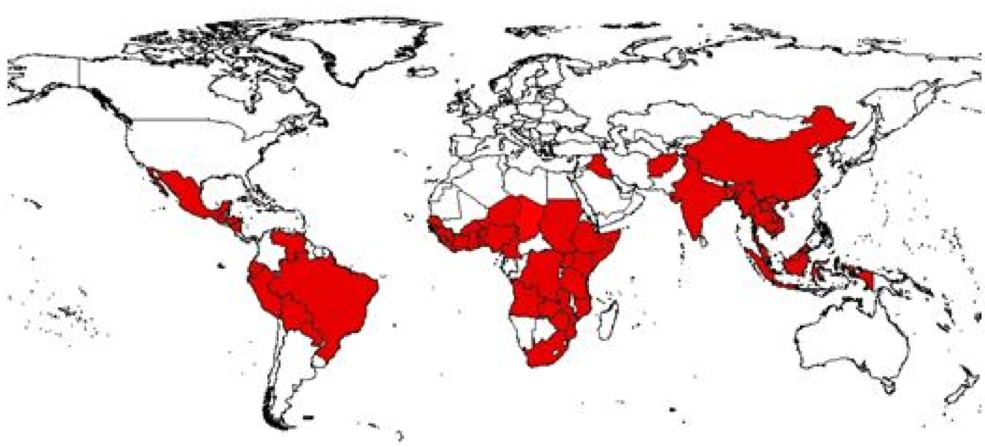

Figure 2.1: Countries affected by the Seventh Pandemic of Cholera (compiled from World Health Organization (WHO), Center for Disease Control and Prevention (CDC), and various news sources, Countries in the red shade have reported cholera outbreaks)

The coastal regions of South Asia, for example, have a long history of cholera incidence and are collectively considered the native homeland of the cholera disease since the early 19^{th} century (Bouma and Pascal, 2001). Recent studies focusing on this region (Lipp et al. 2002, Pascual et al. 2002) suggest significant seasonal patterns in cholera incidence with a primary outbreak occurring in the coastal districts. The historic cholera mortality rates in this region show significant correlation between sea surface temperature (SST) and spring cholera deaths in the coastal districts (Bouma and Pascual, 2001). Although cholera cases have been reported in inland districts of the Indian Subcontinent, the regions of endemicity are most frequently found near coastlines (Lipp et al. 2002). Huq and Colwell (1996) presented three case studies to qualitatively explain plausible mechanisms of transmission of the disease from coastal regions to inland. In Sub-Saharan Africa, initial cholera outbreaks were concentrated along coastal regions before spreading to other parts of the continent. In 1991, over five hundred thousand people were affected by cholera in 20 Latin American countries, with over 5000 deaths. The initial outbreak of this explosive transmission of cholera was identified to be in a coastal village near Lima, Peru. Similarly, December 1992 cholera outbreak originated in coastal Bangladesh that affected over 47 thousand people and killed 846 (Siddique et al. 1994). A detailed cholera epidemiological study from Bangladesh (Sack et al. 2003) showed that areas closer to the coast such as Bakerganj and Matlab experienced recurrent spring cholera outbreaks. The primary outbreaks of cholera in most regions thus show a strong link with the coastal areas, implying a role of the near shore marine environment. Table 2.1 shows the origin of major cholera outbreaks of the current pandemic and the proximity of these locations from the nearest ocean coast, confirming the coastal links to primary cholera outbreaks. Similar role of coastal ecosystems, working as environmental reservoirs of *V. cholerae*, has been suggested for South Africa (Mendelsohn and Dawson, 2008; Bertuzzo et al. 2008) and Peru (Gil et al. 2004; Martinez-Urtaza et al. 2008).

Table 2.1: Proximity to Coast for Major Seventh Pandemic Cholera Outbreaks

Year	Country	Area / City	Affected Population	Distance to Coast (km)
2006	Angola	Luanda	46,750	0
2005	Senegal	Touba	> 31,000	200
2002	Malawi	Lilongwe	32,618	50~100
2000	South Africa	Kwazulu-	86,107	0
2000	Madagascar	Antananarivo	15,173	0
1996	Peru	Lima	22,397	0
1992	Bangladesh	Dhaka	> 30,000	150
1991	Ecuador	Quito	46284	0~200
1974	Bangladesh	Dhaka	> 15,000	150

2.3 Cholera, Coastal Ecology, and Terrestrial Hydrology

A significant reservoir of *V. cholerae* is marine plankton, both phytoplankton and zooplankton (Colwell and Huq, 2001). Cholera bacteria attach themselves to the zooplankton, more specifically to crustacean copepods, to form a thin pathogenic biofilm, which provides protection from the external environment (Reidl and Klose, 2002). Phytoplankton serves as the primary food source for copepods and other zooplanktons, also releases nutrients into the water through disintegration. The bacteria then proliferate taking advantage of the nutrition conditions of the aquatic system (Lipp et al, 2002). Increase in phytoplankton has been associated with increased presence of copepods (Reidl and Klose, 2002). Phytoplankton and zooplankton, therefore, play vital role in facilitating the survival, growth, and transmission of *V. cholerae* in the natural aquatic environment (Lipp et al, 2002, Mouriño-Pérez, 1998). The role of sea surface temperature (SST) in creating and sustaining favorable environmental conditions for oceanic phytoplankton production is well documented (e.g., Timmermann and Jin, 2002; Legaard and Thomas, 2006; Garcia & Carr, 1999).

A closer look at cholera outbreaks and relevant oceanic and terrestrial variables, however, shows a lack of understanding of the seasonal and interannual variability and the processes governing cholera transmission. For example, cholera incidence data from Bangladesh shows bi-annual peaks while coastal phytoplankton primarily shows a single peak (Akanda et al, 2009; Jutla et al 2009 a,b). On the other hand, cholera incidence time series across most affected areas in Africa, such as Mozambique and Democratic Republic of Congo, show infection patterns with a single annual peak. Studies on historic mortality data and recent incidence data from Bangladesh show a coastal endemic pattern in the spring while a post-monsoon outbreak pattern in fall is usually observed further inland (Sack et al. 2003; Bouma and Pascual, 2001). However, other land locked regions such as inland districts of the Ganges-Brahmaputra-Meghna (GBM) basin and the East African lake region show epidemic cholera outbreaks in post-flood situation or after extreme precipitation events. In addition, global warming and an increasing number of natural disasters can contribute to an outbreak or occurrence of cholera in new places, or to the appearance of a new serotype of the causative agent (Koelle et al. 2005). For example, a new serogroup (O139 Bengal) caused epidemic cholera for the first time in history in 1992 in areas surrounding the Bay of Bengal (Siddique, 1994).

Cholera incidence data at the International Center for Diarrhoeal Disease Research in Bangladesh (ICDDR,B) is well documented and is perhaps one of the longest and most detailed cholera datasets in the world (Longini et al. 2002). The epidemic outbreaks in this region have been linked to a range of environmental and climate variables, such as, precipitation (Pascual et al. 2002; Hashizume et al. 2008), coastal phytoplankton abundance (Magny et al. 2008; Emch et al. 2008), floods (Koelle et al. 2005), peak river level (Schwartz et al. 2006), sea surface temperature (Cash et al. 2008; Lobitz et al. 2000), sea surface height (Lobitz et al. 2000), water temperature (Colwell 1996; Huq et al. 2005) and fecal contamination (Islam et al. 2006). Most recently, Akanda et al (2009) provided a preliminary explanation of the dual nature of the outbreaks through two distinctly different large scale hydroclimatic drivers. According to that study, intrusion of plankton and bacteria rich coastal water during the spring dry season is the primary mechanism of *V. cholerae* contamination of estuarine rivers and coastal cholera outbreaks; on the other hand, widespread monsoon flooding in the GBM Basin region and cross-contamination of water resources with bacteria already present in the ecosystem is primarily responsible for autumn outbreaks. Similar role of coastal rivers acting as conduits of cholera infection along the river have been proposed by Bertuzzo et al. (2008) for Southern Africa.

2.4 Cholera and Remote Sensing

Application of remote sensing to study cholera dynamics is an emerging research area with availability of longer datasets over the last decade (Harvell et al 2002). As mentioned in section 2, analysis of cholera incidence data from various regions of the world suggests transmission of cholera originate in coastal areas and then propagate to inland areas (Huq and Colwell, 1996). The causative agent of cholera outbreaks, *V. cholerae*, cannot be measured from space. However, the bacteria shows strong affinity with plankton blooms which can be estimated from satellites by measuring the green pigment (chlorophyll) present in plankton. Chlorophyll, a key biochemical component that gives plants its green color, is responsible for facilitating absorption of sunlight for photosynthetic purposes. Currently, satellite measured chlorophyll is the only effective way to monitor space-time variations of plankton abundance over large coastal areas.

Remote sensing of ocean color dates back to 1978 with successful launch of dedicated ocean satellite Coastal Zone Color Scanner (CZCS) on Nimbus7. CZCS was followed with **Sea**-viewing **Wi**de **F**ield-of-view **S**ensor (SeaWiFS) mission in 1997. Chlorophyll measured by SeaWiFS has been used in several studies ranging from detection of harmful algal blooms (Strumf et al., 2003; Tang et al., 2003), coastal pollution (Chen et al., 2007), oceanic processes (Tang et al., 2003; Yoder et al., 1987; Danling et al., 2002), land-ocean interaction (Lopez and Hidalgo, 2009; D'Sa and Miller, 2003; Jutla et al., 2009a) and marine fauna (Solanki et al., 2001; Polovina et al., 2003; Turley et al., 2000; Labiosa and Arrigo, 2003) . The SeaWiFS consists of eight channels at: 412, 443, 490, 510, 555, 670, 765, and 865 nm (nanometers: 1µm = 1,000 nm), each with bandwidths of 20 or 40 nm (O'Reilly et al., 2000). The orbital altitude of SeaWiFS is about 705 km (438 mi) with spatial resolution in the Local Area Coverage (LAC) of about 1.1 km (0.68 mi). The optimal resolution is 0.6 km at nadir. Currently, SeaWiFS data offer the longest available ocean color records for 10 years (1997 to till date) at various spatial (1.1km, 9km) and temporal scales (daily, monthly, annual). Current global SeaWiFS chlorophyll algorithm, OC4V4, is a fourth-order polynomial (Equation1) of the maximum band ratio of four bands (O'Reilly et al., 2000), and can be represented as:

$$Chl = 10^{0.366-3.067X+1.930X^2+0.649X^3-1.532X^4}$$
$$where X = \log_{10}(\max[R_{rs}(443)/(R_{rs}(555), R_{rs}(490)/(R_{rs}(555), R_{rs}(510)/(R_{rs}(555)])$$
[1]

where, *chl* is the chlorophyll in mg/m^3 and R_{rs}( ) is the wavelength in nm.

Chlorophyll variations on a daily scale appear to be a random process with very limited memory (Sumich, 1999, Uz and Yoder, 2004). Our preliminary analysis reaffirms above findings and suggests that chlorophyll signatures for the coastal Bay of Bengal region resemble white noise for a range of pixel sizes (10-100km); the signal exhibits a lag one autocorrelation value of 0.20 with no apparent temporal structure (Jutla et al., 2009b). Chlorophyll variations on a daily scale, irrespective of spatial averaging, thus may not be useful for understanding chlorophyll-cholera relationships. On the other hand, chlorophyll variations on monthly scales show distinct seasonality in coastal Bay of Bengal with highest chlorophyll levels observed in September and lowest levels in February (Jutla et al 2009b). Figure 2.2 shows the ten year (1998-2007) climatological mean (2.2a), lowest (2.2b) and highest (2.2c) chlorophyll months in coastal Bay of Bengal. Figure 2.2 has been calculated using monthly SeaWiFS data for latitudes between 20^0 to 22.5^0N and longitudes between 86^0 to 93^0E. Chlorophyll levels are high along the coasts and decreases as we move away from the coast. Climatological mean chlorophyll within this domain is about 3 mg/m^3 (Figure 2.2a), whereas the lowest and highest mean monthly chlorophyll values, 2.36 mg/m^3 and 4.15 mg/m^3, are observed during the months of February and September, respectively. Figures 2.2b and 2.2c shows the contrastingly different chlorophyll levels in these months.

Remote sensing measurements of other relevant climate variables (e.g., sea surface temperature) may also help in understanding the possible controls on chlorophyll production in the coastal regions and its links to terrestrial hydrology. For example, using satellite measured chlorophyll from various ocean basins across the globe several recent studies suggest an inverse relationship between chlorophyll (and hence phytoplankton) and SST (e.g., Solanki et al., 2001, Uz and Yoder, 2004, Legaard and Thomas, 2006, Smyth et al. 2001**).** In the Bay of Bengal (BoB), however, a positive relationship between phytoplankton and SST is observed (Lobitz et al., 2000; Chaturvedi, 2005; Emch et al, 2008; Magny et al., 2008). Preliminary analyses, using SeaWiFS data, suggest that terrestrial nutrient transport through fresh water discharge from the Ganges and the Brahmaputra rivers is the dominant process affecting phytoplankton production in the coastal BoB region (Jutla et al. 2009a), which alters the usually observed inverse relationship between SST and chlorophyll. Akanda et al (2009) explain further role of regional freshwater discharge, where they associate dry and wet season discharge volumes with spring and autumn cholera outbreaks in Bangladesh, respectively.

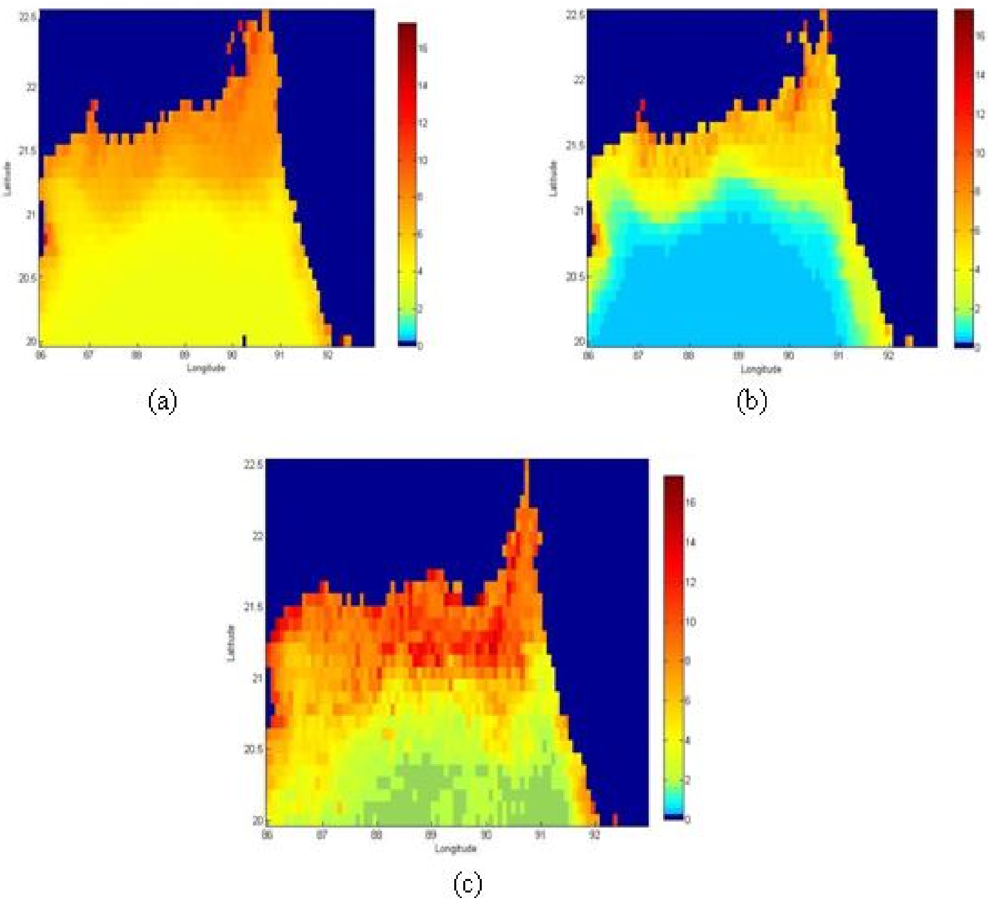

Figure 2.2: Space-time variations of chlorophyll (mg/m^3) in the Bay of Bengal (a) Mean chlorophyll; (b) Lowest chlorophyll month (February) and (c) Highest chlorophyll month (September). This figure is based on climatology of 10 years of SeaWiFS data at 9km spatial resolution.

Olsson (1996) was perhaps the first study to propose the potential of using satellite derived chlorophyll for studying cholera dynamics. Huq and Colwell (1996) suggested that remote sensing can be a helpful tool for tracking cholera outbreaks using ocean chlorophyll signatures. Lobitz et al (2000) used limited length SeaWiFS data (16 months) to stress the potential role of remotely sensed chlorophyll for understanding chlorophyll-cholera relationships. Since then there have been other studies that have qualitatively emphasized the use of remote sensing data for cholera (e.g., Colwell and Huq, 2001; Colwell et al., 2003; Koelle et al. 2005). There do not appear to be any quantitative analyses, however, that have used satellite based data to strengthen chlorophyll-cholera relationships. Recently, Magny et al (2008) developed a model for predicting cholera outbreaks based on several variables including coastal chlorophyll and other climatological data on a monthly time scale with approximately 100 km aggregated pixel scale. They concluded that there is approximately a month lag between plankton blooms in the Bay of Bengal and cholera incidence in Bangladesh. Magny et al (2008) also recommended that finer temporal and spatial scale chlorophyll data may be required for real-time tracking of cholera outbreaks. Emch *et al.*, (2008) have used satellite chlorophyll measurements from two coastal regions in South Asia (Bangladesh and Vietnam) and reported a two month lag between plankton blooms and cholera outbreaks in Bangladesh. They have also suggested that chlorophyll may not be a useful variable for understanding the sporadic cholera in Vietnam. These studies have suggested the role of chlorophyll as a key variable to understand cholera dynamics; however, they have not elaborated on how the seasonal and interannual variability of cholera incidence are linked with the variations of other coastal processes and chlorophyll variations.

Colwell and Huq (1996) and Lipp et al (2002) proposed qualitative cholera infection and transmission pathways from coastal to inland regions. Here, with ten years of monthly SeaWiFS data, we quantitatively investigate how cholera incidence are associated with chlorophyll in the Bengal delta region. Figure 2.3 shows the climatological monthly mean for chlorophyll, river discharge and cholera incidence in the Bay of Bengal region. Monthly chlorophyll in the coastal region of BoB and river discharge from the Ganges-Brahmaputra rivers show high positive correlation ($r = 0.75$; $p<0.05$), thereby suggesting that nutrients carried by river discharge is influencing chlorophyll production. In this region, cholera incidence exhibit(s) biannual peaks, however, chlorophyll and river discharge show single annual peaks. Akanda et al (2009) provide a tentative explanation of the roles of river discharge and coastal plankton intrusion on the dual peak cholera incidence pattern seen in this region. Cholera outbreaks in spring (March-April-May) show strong negative correlation with dry season (February-March) river discharge ($r = -0.65$; $p<0.05$), i.e., bigger spring cholera peaks are typically seen in water scarce years (Akanda et al 2009). However, a new transmission environment emerges in autumn, when water abundance contributes to elevated cholera outbreaks, i.e., bigger autumn peaks are seen in high flood years. Figure 2.4 shows the monthly river discharge, phytoplankton and cholera incidence patterns in Mozambique, plotted in a fashion similar to Figure 2.3. A peak in marine plankton blooms is observed in the coastal areas off southern Mozambique and the capital city of Maputo, during August which follows increased outbreaks of cholera from November. Increase in river discharge in March actually leads to decrease in cholera incidence, a very similar phenomenon observed in Bay of Bengal (Akanda et al, 2009). Mendelsohn and

Dawson (2008) also reported similar lags and mechanisms between chlorophyll peaks off South African coast and cholera outbreaks in the Kwazulu-Natal province. Figures 3 and 4 summarize the codependent relationships among chlorophyll, streamflow, and cholera outbreaks, and quantitatively reaffirm the potential use of remote sensing data for understanding cholera dynamics on large scales.

2.5 Cholera, Coast, Terrestrial Hydrology and Remote Sensing

Cholera is perhaps the only endemic disease interfacing oceans and human health for several centuries. Cholera has a strong coastal connection; a number of studies have associated coastal ecosystem processes with cholera outbreaks. We have compiled a list of studies and reports to show that majority of primary cholera outbreaks usually occurs along coastal areas and then spread inland through secondary means (Figure 2.1; Table 1). However, much of this information remained qualitative because of the lack of data over coastal areas on a range of space-time scales. With the availability of over ten years of remotely sensed data to examine space-time variations of chlorophyll (and hence plankton abundance), we are able to explore possible relationships between plankton abundance and cholera dynamics.

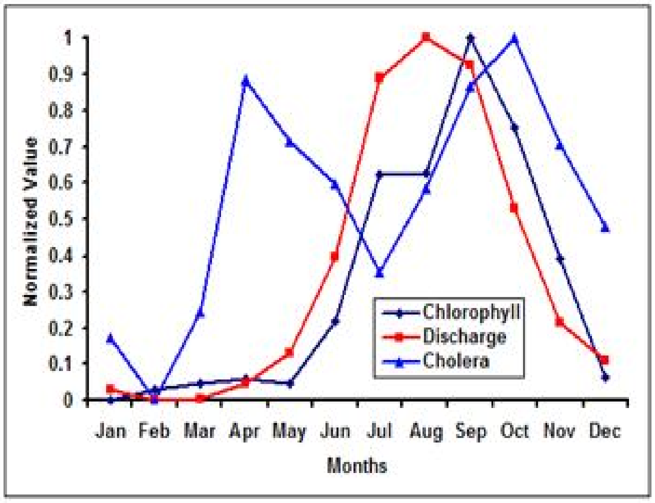

Figure 2.3: Cholera, River Discharge and Chlorophyll in Bay of Bengal. The climatology has been calculated using ten years of monthly (a) SeaWiFs data for chlorophyll, (b) incidence data of cholera incidence from ICDDR,B and (c) discharge data obtained from Bangladesh University of Engineering and Technology. The data has been normalized between 0 and 1.

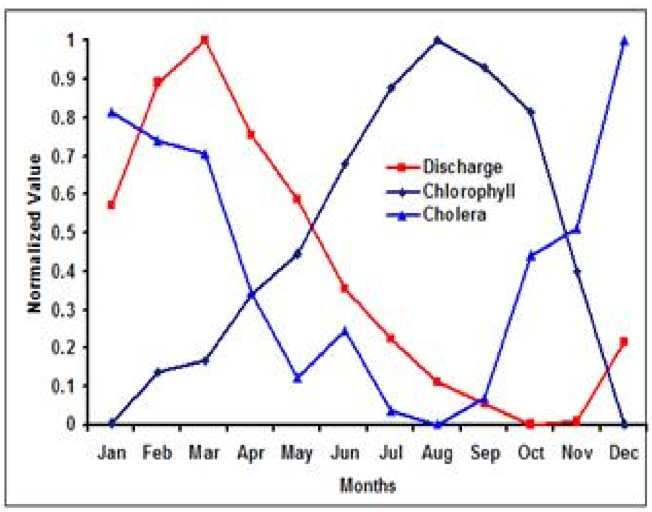

Figure 2.4: Cholera, River Discharge and Chlorophyll in Coastal Mozambique. The climatology has been calculated using ten years of monthly (a) SeaWiFs data for chlorophyll, (b) incidence data of cholera incidence from literature and (c) discharge data obtained from River Discharge Data (RIVDIS: www.rivdis.sr.unh.edu). The data has been normalized between 0 and 1.

Our quantitative analysis, Figures 2.3 and 2.4, supported by qualitative understanding in literature suggests that initial cholera outbreaks primarily occur in regions close to the coast, and may be related with coastal plankton. For example, in the Bay of Bengal region of South Asia, plankton intrusion through coastal waters in the dry season leads to early cholera outbreaks (Jutla et al. 2009b). Similarly, in Mozambique, there is strong evidence that coastal chlorophyll intrusion leads to cholera outbreaks, a phenomenon similar to observed processes in the BoB region. These results suggest that it may be feasible to develop predictive models of cholera using large scale oceanic and hydroclimatic signatures using remotely sensed observations.

Chlorophyll production in the coastal areas with freshwater discharge may be controlled by the river discharge (Arker et al., 2005; Jutla et al., 2009a). In other regions, coastal chlorophyll production is driven by upwelling and shows inverse association with SST (Legaard and Thomas, 2006, Smyth et al. 2001). For example, in the Bay of Bengal, plankton blooms immediately follow the peak monsoon discharge volumes carrying terrestrial nutrients, whereas in Mozambique, chlorophyll peak does not follow the discharge peaks immediately. Given the high relative differences between the discharge volumes (628 km^3/yr in the Bay of Bengal vs. 14 km^3/yr in Mozambique; Dai and Trenberth, 2003), it is likely that the production of chlorophyll in coastal regions of Mozambique may be governed by oceanic processes rather than terrestrial discharge. Identification of the appropriate drivers for chlorophyll production is thus important for understanding controls over cholera dynamics.

Significant heterogeneity observed in space-time variability of coastal chlorophyll cannot be captured with sporadic in-situ observations. For example, chlorophyll data resembles white noise on daily time scales irrespective of spatial averaging (Uz and Yoder, 2004). Consequently, use of satellite remote sensing to track phytoplankton abundance through chlorophyll measurement is the most efficient and cost-effective way to develop a large scale understanding of the cholera-plankton relationship. With ten years of available data and ongoing measurements of reliable chlorophyll data from SeaWiFS, remote sensing has a great potential to be used in a systematic development of the understanding of the relationship between coastal ecology and cholera dynamics in various endemic regions across the world.

As it has been discussed above, cholera is endemic in many regions and is affected by coastal processes. We now attempt to identify ocean-corridors from where plankton intrusion may be possible to inland waters using 10 years of SeaWiFS data (Figure 2.5). In regions 2, 3, 5, 6, cholera remains endemic and these regions are also active river discharge regions. The Senegal, Congo, Ganges and Brahmaputra, and Changjiang Rivers in the regions 2, 3, 5, 6, respectively, discharge into the ocean in areas where there is a high possibility of plankton laden coastal water intrusion and subsequent contamination of inland water bodies. Region 7 drains the Amazon River with the largest freshwater discharge volumes, but cholera has not been reported to be endemic in that region. This can be explained as river discharge in Amazon remains high throughout the year (Dai and Trenberth, 2001) and there is negligible coastal intrusion in this estuary along with the fact that the population in the Amazonia region is much scarcer compared to regions 5 or 6. In regions 1 and 4, cholera outbreaks are sporadic. There are no major rivers or coastal deltas in the region and the possible cause of disease outbreaks may be contaminated food from the coast and human interaction.

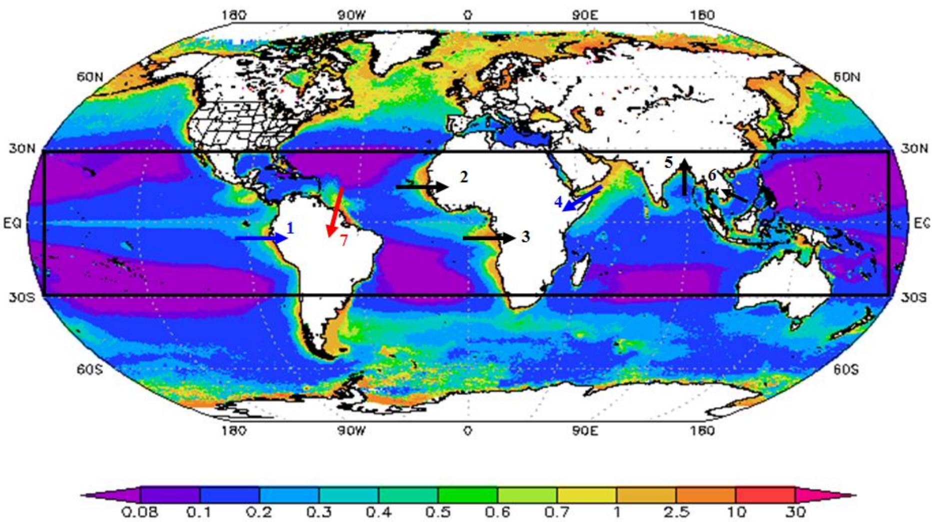

Figure 2.5: Possible ocean corridors for cholera outbreaks along tropical coastal regions (shown as the black box spanning between 22.5N to 22.5S) The figure has been constructed using ten years (1998-2007) of monthly SeaWiFs data projected onto Mercator projection.

This global overview of chlorophyll concentrations and possible vulnerable regions for cholera outbreaks is supported by other studies; Huq and Colwell (1996) presented an epidemiological global picture of cholera outbreaks in three continents (Africa, South Asia and South America) suggesting the role of coastal regions behind cholera outbreaks. This is perhaps one of the first attempts to quantify the chlorophyll-cholera relationships on a global scale using satellite remote sensing data. To summarize, section 6, we provide a schematic pathway integrating terrestrial hydrology, coastal ecology into existing microbiological framework for a holistic understanding of the cholera dynamics and associated large scale controls on cholera transmission using latest advances in remote sensing.

2.6 An Integrated Modeling Framework for Cholera Prediction

We propose a modeling framework to provide an adaptive understanding and prediction of cholera dynamics where “macro” (hydrological, ecological, climatic and coastal processes) and “micro” (microbiological, genetic, and human intestine scale processes) environmental conditions are integrated. . This distinction between “macro” and “micro” environmental controls on cholera dynamics is critical because the cholera bacterium can survive and proliferate in two distinctively different environments. We recognize the importance of micro-environmental (e. g.: microbiological, genetic, human intestines) understanding of cholera (Schoolnik and Yildiz 2000) to develop effective vaccines or treatment protocols. However, as *V. cholerae* exists naturally in aquatic habitats and there is strong evidence of new biotypes emerging, it is highly unlikely that cholera will be fully eradicated. Consequently, it is imperative that a broader perspective be taken to prevent cholera epidemics and minimize its impact by understanding the effects of macro-environmental conditions on cholera

One of the approaches to understand effects of macro environmental controls on cholera dynamics is by using the Susceptible-Infected-Recovered (SIR) based epidemiological models (*e.g., Codeco, 2001; Joh et al., 2009*). The basic idea of SIR models is to compute the theoretical number of people infected with a contagious illness over time and how the disease spread through a given population using various parameters. More details of SIR models can be found in Kermack and McKendrik (1972). Within the framework, we suggest a new class of SIR (Susceptible-Infected-Recovered) model, where macro-environmental factors inform traditional SIR model - will allow us to examine different facets of cholera dynamics. Our proposed model, **Macro-SIR**, will integrate macro-environmental and micro-environmental determinants of cholera occurrences and transmission. It will synthesize existing knowledge and new information from hydroclimatology, ecology, and remote sensing. Figure 2.6 provides a framework for the development and refinement of this modeling framework.

Cholera based SIR models usually start with the premise that cholera bacteria are transmitted via human to human interaction. Recently, role of indirect transmission via environmental reservoir has been introduced in SIR models (e.g., Codeco, 2001; Joh et al., 2009). Studies have highlighted the role of environmental conditions for creating seasonality in cholera (*Koelle et al., 2005; Pascual et al., 2008*) but did not elaborate on plausible physical mechanisms related to seasonality of outbreaks. Similarly, Bertuzzo et al. (2008; 2009) incorporated an SIR-type framework with a spatially distributed cholera transmission model, but the seasonality of transmission in that model was introduced with ***a-priori*** knowledge or assumption of the distribution of infections. Despite its ubiquitous nature and its importance in the timing of the outbreaks, the seasonality of cholera is not well understood (*Fisman 2007*). To our best knowledge, currently there are no models that can predict cholera outbreaks several months ahead.

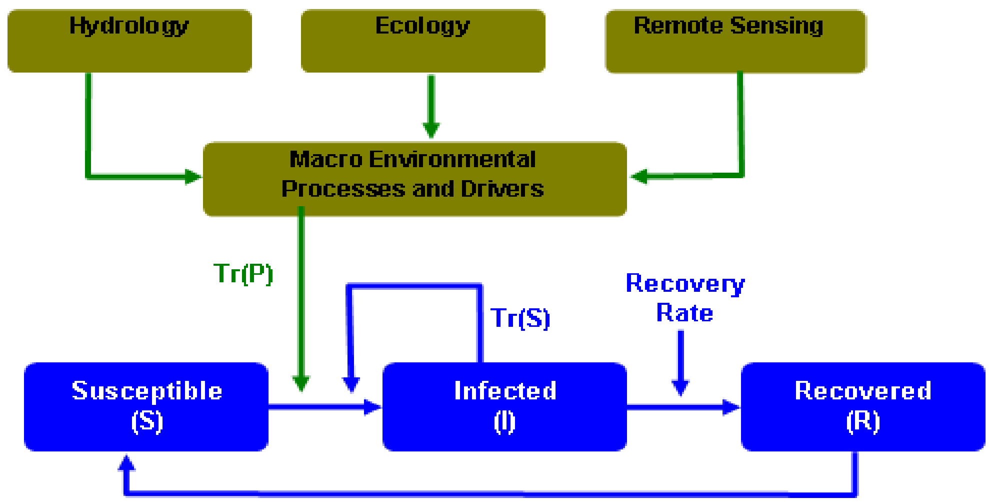

Figure 2.6: Plausible Flow Diagram for a Macro-SIR modeling framework

Issues of seasonality and prediction lead time for cholera are particularly important for the endemic areas of the Bengal Delta where cholera exhibits two peaks per year. To examine the origin of such seasonal patterns, one may focus on relative roles of two routes of transmission – primary or environmental transmission, **Tr (P)**, and secondary or person to person transmission, **Tr (S)**, - for cholera (*Miller et al., 1985*). Most SIR models focus on the secondary transmission mechanisms, Tr(S), as shown in Figure 2.6. Few studies included, Tr (P), as an environmental reservoir (e.g., *Codeco 2001; Jensen et al 2006*). Traditional SIR models presume exponential decay for bacteria in the reservoir even though this phenomenon is not frequently observed (*Joh et al., 2009*). The Macro-SIR modeling framework may be used to evaluate the roles of macro- and micro-environmental drivers in creating and sustaining primary and secondary transmission mechanisms for cholera outbreaks and promoting epidemic and endemic cholera.

The dynamics of direct disease transmission in humans have been studied using variants of SIR models. In these models, primarily micro-environmental conditions are emphasized and basic reproductive ratio (defined as "the number of secondary cases caused by a small number of infected individuals" Joh et al., 2009) is used as a central concept (*Joh et al., 2009; Dietz 1993*). But, these models cannot create seasonality unless some of the model parameters are ***a-priori*** chosen to vary seasonally. Such is the case for a recent study by *Pascual et al (2008)* where a complex SIR type model is used with susceptible fraction and transmission rate as ***a-priori*** chosen seasonally varying parameters. In the absence of plausible physical mechanisms to explain this choice of seasonally varying parameters, predictive capabilities of these models remain uncertain. For example, *Pascual et al (2008)* reported only 7% improvement in predictive capability when effects of El-Nino are included in their model. In a related study, *Koelle et al (2005)* reported low frequency variations in transmission rate to be negatively correlated with rainfall in Northeast India ($r = -0.797$, $p < 0.05$, lag = 14 months). There are no plausible hydroclimatological explanations for such a lagged relationship between rainfall and cholera transmission.

Instead of ***a-priori*** choosing transmission mechanisms (primary or secondary) that create and sustain seasonality in cholera, one can use an adaptive modeling framework (Figure 2.6). In a Macro-SIR framework, pathogen dynamics and within human transmission dynamics may be explicitly coupled. It recognizes that seasonality of cholera may be dependent on geography and climate (e.g., dual peak in the Bengal delta and single peak in Mozambique) and transmission rates must be estimated based on regional macro-environmental drivers. Such a regionalized approach will allow one to accurately estimate transmission that will result in better prediction.

Development of a holistic understanding off cholera dynamics and its relationship with coastal processes requires long and reliable chlorophyll data over a range of space and time scales, which is beginning to be available through satellite observations. Remote sensing observations, with its wide spatial coverage and continuous measurement capabilities, will thus play an important role in monitoring coastal processes and tracking potential cholera outbreaks in vulnerable regions of the world. We hope this study will provide the rationale and motivation for future research in this direction to explore how coastal processes, terrestrial hydrology, large scale climatic controls and remote sensing can be integrated into a combined environmental and epidemiological modeling framework to enhance the existing knowledge base to develop global and regional scale cholera tracking and prediction models.

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Chapter 3

Space Time Plankton Variability in the Bay of Bengal: Connections to Cholera Outbreaks[#]

Abstract

Characterization of space-time variability of chlorophyll, a surrogate for plankton abundance, in Northern Bay of Bengal is an essential first step to develop any methodology for predicting cholera outbreaks in the Bengal Delta region using remote sensing. This study quantifies the space-time distribution of chlorophyll in the Bay of Bengal region using ten years of satellite data. Variability of chlorophyll at daily scale, irrespective of spatial averaging, resembles white noise. At a monthly scale, chlorophyll shows distinct seasonality and chlorophyll values are significantly higher close to the coast than in the offshore regions. At pixel level (9 km) on monthly scale, on the other hand, chlorophyll does not exhibit much persistence in time. With increased spatial averaging, temporal persistence of chlorophyll increases and lag one autocorrelation stabilizes around 0.60 for 1296 km^2 or larger areal averages. In contrast to the offshore regions, spatial analyses of chlorophyll suggest that only coastal region has a stable correlation length of 100 km. Presence (absence) of correlation length in the coastal (offshore) regions, indicate that the two regions may have two separate processes controlling the production of phytoplankton This study puts a lower limit on space-time averaging of satellite measured plankton at 1296 km^2-monthly scale to establish relationships with cholera incidence in Bengal Delta.

[#] *Jutla, A.S., Akanda, A.S. and Islam, S. 2010. Space-time variability of chlorophyll in Bay of Bengal: Connections to cholera outbreaks. Remote Sensing of Environmental (in revision).*

3.1 Introduction

There is growing evidence that cholera, coastal waters, and marine plankton are strongly related. Cholera bacteria, a causative agent for cholera outbreak, are known to survive and thrive in brackish waters, particularly in the presence of abundant zooplankton and phytoplankton; suggesting a high correlation between plankton abundance and disease outbreaks (Huq et al., 1984; Reidl & Klose, 2002; Alam et al., 2006; Epstein, 1993). The disease remains endemic in many regions of the world, specifically in coastal areas of South Asia, Africa and Latin America (Jutla et al., 2010). Northern Bay of Bengal, adjacent to the Bengal Delta, the native homeland of cholera (Akanda et al., 2009), is the focus region of this study.

Laboratory studies from different regions of the world suggest a significant positive correlation between plankton abundance and pathogenic cholera bacteria (Tamplin et al., 1990). The complexity and costs involved in in-situ measurement of plankton abundance and cholera bacteria did not allow generalization of these laboratory findings over large spatial and temporal scales. Recently available satellite data provide space-time measurements of plankton abundance in terms of chlorophyll content (the greenness of ocean water) over large areas. As the availability and length of satellite data products increase, it is now possible to explore variability of plankton over large regions of the oceans and relate such variability with cholera outbreaks (Jutla et al., 2010). Satellite derived chlorophyll has been a subject of interest for several cholera-chlorophyll related studies. Olsson (1996) was perhaps the first study to document plankton-cholera connection using satellite data. Huq and Colwell (1996) suggested that remote sensing may be useful to study cholera outbreaks using ocean chlorophyll signatures. Lobitz et al., (2000) used Sea-viewing Wide Field-of-view Sensor (SeaWiFS) data and explored the potential role of remotely sensed chlorophyll for understanding plankton-cholera relationships. However, it was difficult to establish any conclusive relationship, given the limited availability of SeaWiFS data at the time of the study (16 months) and for one 18-km pixel. Recently, Magny et al., (2008) proposed a generalized linear regression model with embedded Poisson distribution for simulating monthly cholera outbreaks using previous season cholera incidences and chlorophyll estimated on a 100 km aggregated pixel scale. They concluded that there is approximately a month lag between cholera outbreaks in Bangladesh and plankton blooms in the Bay of Bengal. They recommended that finer temporal scale chlorophyll data would be required for developing models for simulation of cholera incidence, but did not elaborate on identifying the spatial zones or temporal scales of the required data. Emch et al., (2008) have used several environmental variables as well as chlorophyll measurements from the coastal region in South Asia and reported a two month lag between plankton blooms and cholera outbreaks in Bangladesh.

Given the range of space-time variability of coastal ecological processes related to cholera, it is important to examine at what scales this variability is linked with dynamics of cholera. More importantly, it is necessary to identify key variables that are related to cholera outbreaks and are measurable over large regions. From this perspective, two empirical observations encourage us to explore temporal and spatial variability of chlorophyll, a surrogate for phytoplankton, in the Bay of Bengal (a) cholera and plankton show strong association yet the temporal and spatial quantification of phytoplankton in northern Bay of Bengal remains elusive, and (b) satellite remote sensing is the most effective and efficient way to quantify large scale temporal and spatial variability of phytoplankton across coastal areas of cholera endemic regions. With increased availability of satellite derived chlorophyll data, several studies have analyzed data from different regions and suggested a wide scale of chlorophyll variability across time and space (e.g., Legaard and Thomas, 2006; Uz & Yoder, 2003). Recently, Abreu et al (2009) reported a possibility of two drivers for long and short term variability of chlorophyll in Patos Estuary in Brazil. They suggested that short term chlorophyll variability (daily or weekly scale) may be controlled by winds whereas the long term (monthly) variation in chlorophyll may mainly be due to influx of nutrients from terrestrial river discharges.

Our recent review study (Jutla et al., 2010), investigated relationship(s) between cholera incidence and coastal processes, and explored possible utility of using remote sensing data to track coastal plankton blooms, using chlorophyll as a surrogate variable for plankton abundance, and subsequent cholera outbreaks in vulnerable regions. The present study will quantitatively characterize the space-time variability of chlorophyll in northern Bay of Bengal over a range of space and time scales. In particular, we will examine the (1) temporal (daily to seasonal) and spatial (pixel to regional) variability of chlorophyll in Bay of Bengal; and (2) identify relevant spatial and temporal scales to be able to track cholera-chlorophyll relationships from satellites.

3.2 Data

The Bay of Bengal is a semi enclosed tropical ocean basin, situated between 0° and 23°N and 80° and 100°E, occupying an area of 4.087 x 10^6 km^2 It has a unique system of coupled oceanographic and sedimentary processes which is caused by the seasonally reversing monsoon winds and an enormous supply of fresh water from several rivers (Shetye et al., 1996). The monsoon river discharge plays an important role in governing the surface as well as the coastal hydrology in the bay. During monsoons, large volumes of fresh water discharge from the Ganges-Brahmaputra-Meghna rivers lowers the salinity substantially and also reduces the intensity of upwelling at a distance up to ~40km from the coast (Shetye et al., 1996). We have used daily and monthly SeaWiFS chlorophyll pixel level (9x9km) data, which were obtained from NASA/Goddard Earth Sciences/Distributed Active Archive Center for 1998-2007. The selection of regions from Bay of Bengal is described in the following sections. Relevant details of the data are mentioned in the result section as well. We have divided our region of analysis (Figure 3.1a) into six latitudinal bands: LB1, from 21^0N to 22.5^0N and LB2 to LB6 are one-degree bands down to 16^0N. The longitudinal spread of each band is from 86^0E to 93^0E.

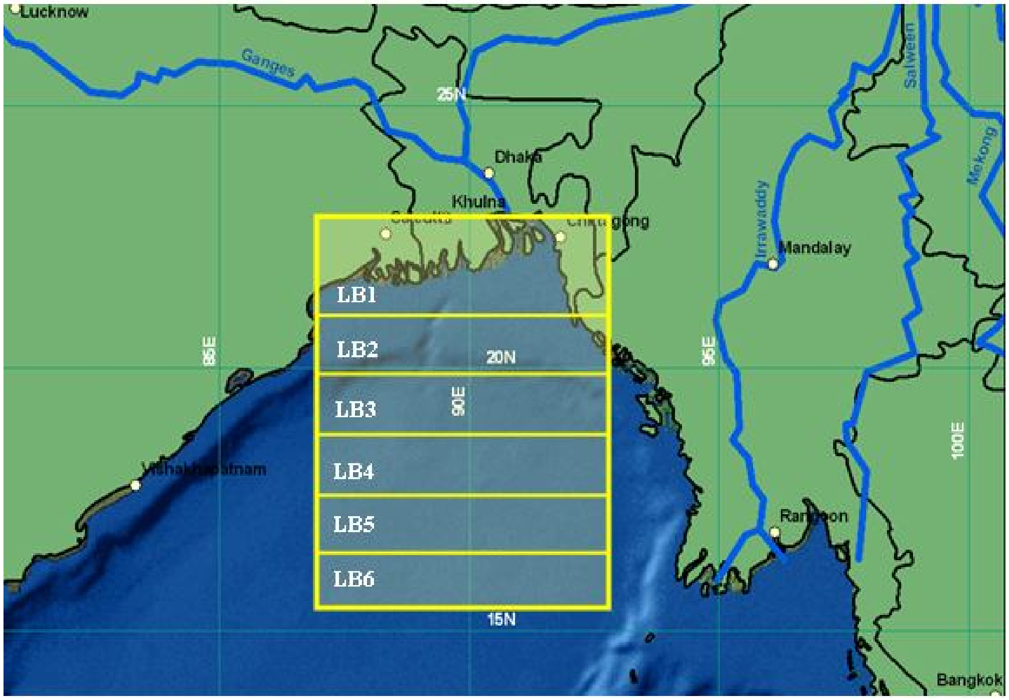
3.3 Remote Sensing of Plankton using Chlorophyll

Remote sensing of ocean started with the launch of the Coastal Zone Color Scanner on Nimbus7 in 1978, which was followed by the SeaWiFS mission in

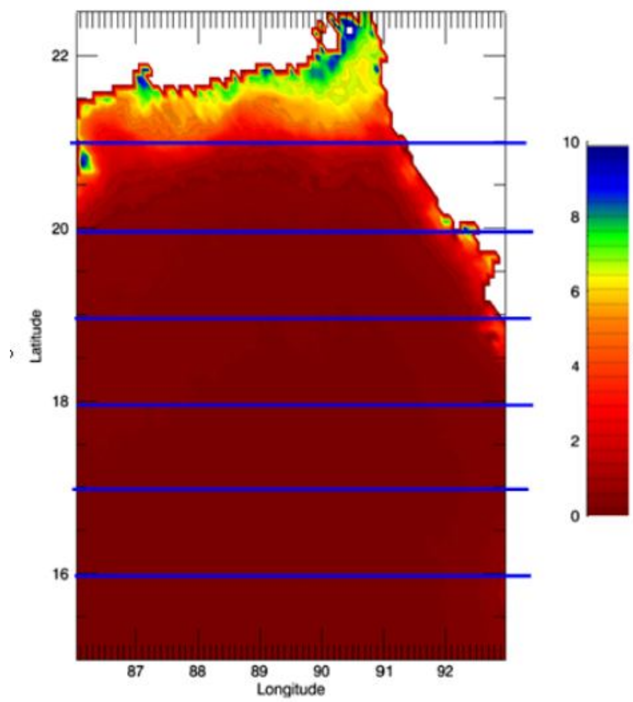
1997. Chlorophyll measured by SeaWiFS has been used in several studies ranging from detection of harmful algal blooms (Strumf et al., 2003; Tang et al., 2003), coastal pollution (Chen et al., 2007), oceanic processes (Tang et al., 2003; Yoder et al., 1987; Danling et al., 2002, Yuras et al 2005), to land-ocean interaction (Lopez and Hidalgo, 2009; D'Sa and Miller, 2003; Jutla et al., 2009a) and marine fauna (Solanki et al., 2001; Polovina et al., 2003; Turley et al., 2000; Labiosa and Arrigo, 2003). The SeaWiFS consists of eight channels at: 412, 443, 490, 510, 555, 670, 765, and 865 nm (nanometers: 1μm = 1,000 nm), each with bandwidths of 20 or 40 nm (O'Reilly et al., 2000). The orbital altitude of SeaWiFS is about 705 km (438 mi) with spatial resolution in the Local Area Coverage of about 1.1 km (0.68 mi). The optimal resolution is 0.6 km at the nadir. Currently, SeaWiFS data offer the longest available ocean color records for more than 10 years (1997 to till date) at various spatial (4km, 9km) and temporal scales (daily, monthly, annual). Current global SeaWiFS chlorophyll algorithm, OC4V4, is a fourth-order polynomial (equation1) of the maximum band ratio of four bands (O'Reilly et al., 2000), and can be represented as:

$$Chl = 10^{0.366 - 3.067X + 1.930X^2 + 0.649X^3 - 1.532X^4}$$
$$where X = \log_{10}(\max[R_{rs}(443)/(R_{rs}(555), R_{rs}(490)/(R_{rs}(555), R_{rs}(510)/(R_{rs}(555)]) \quad [1]$$

where, *Chl* is the chlorophyll in mg/m^3 and R_{rs}( ) is the wavelength in nm.



(a)



(b)

Figure 3.1: (a) Location of Bay of Bengal study region (Yellow demarcation); LB1 to LB6 are the six latitudinal bands used in this study. (LB1: 21^{0}N, 89.5^{0}E; LB2: 20.25^{0}N, 89.0^{0}E; LB3: 19.25^{0}N, 90.10^{0}E; LB4: 18.75^{0}N, 91.25^{0}E; LB5: 17.45^{0}N, 91.25^{0}E; LB6: 16.25^{0}N, 89.0^{0}E); (b) Annual Climatology of Chlorophyll in Bay of Bengal

Satellite remote sensing is perhaps the best way to study and quantify large scale monitoring and variability of phytoplankton in absence of in-situ plankton data, which is prohibitively expensive to obtain. A recent study by Gregg and Casey (2004) observed a correlation of 0.78 between in-situ chlorophyll and SeaWiFS derived chlorophyll using over 2400 coastal region stations. Our study region experiences discharge from the large the Ganges, the Brahmaputra and the Meghna (GBM) ,river system, which bring huge amounts of freshwater containing terrestrial nutrients to the coastal waters during the summer monsoon months. There is no in-situ plankton data in the GBM coastal region; consequently we have used a proxy region for comparing applicability of SeaWiFS algorithm for the Bay of Bengal. Using subset of the chlorophyll data from SeaWiFS, Gregg and Casey (2004) reported a correlation of 0.61 between observed and measured chlorophyll close to mouth where Amazon River discharges into Atlantic Ocean. Amazon is one of the largest rivers discharging freshwater into ocean, a feature similar to the GBM river systems.

Remote sensing measurements of other relevant variables (e.g., sea surface temperature; sea surface height) may also help in understanding the possible controls on chlorophyll production in the coastal regions and its links to terrestrial hydrology. For example, using satellite measured chlorophyll from various ocean basins across the globe several recent studies suggest an inverse relationship between chlorophyll (and hence phytoplankton) and SST (e.g., Solanki et al., 2001, Uz and Yoder, 2004, Legaard and Thomas, 2006, Smyth et al. 2001**).** In Bay of Bengal, however, a positive relationship between phytoplankton and SST is observed (Lobitz et al., 2000; Chaturvedi, 2005; Emch et al, 2008; Magny et al., 2008). Our preliminary analyses, using SeaWiFS data, suggest that terrestrial nutrient transport through fresh water discharge from the Ganges and the Brahmaputra rivers may affect phytoplankton production in the coastal Bay of Bengal region (Jutla et al. 2009a), which may also alter the usually observed inverse relationship between SST and chlorophyll. Increase in phytoplankton through freshwater discharge has been observed in several basins such as Chesapeake Bay (Acker et al., 2005), and the Delaware (Pennock and Sharp, 1985), Po (Revenlante and Gilmartim, 1976], Orinoco (Bidigare et al., 1993) and Mississippi rivers (Lohrenz et al., 1990). To summarize, space time characterization and relationship between SST and chlorophyll in Bay of Bengal is not well understood and is beyond the scope of the present study.

There are very few remote sensing related studies available for the Bay of Bengal region. Islam et al (2002) studied distribution of suspended sediments in the coastal regions of GBM region using Landsat data. According to Islam et al (2002), suspended solids play role in the estuarine regions, which are very close to the mouth of the GBM rivers draining to the Indian ocean. According to their analysis, suspended solids increase during the high flow seasons after monsoonal river discharge. However, the extent of the suspended solids in the region is limited to the estuarine region (refer to figure 1a and figure 6 of Islam et al 2002) does not appear to impact the zones specified for chlorophyll measurements in this study. Mishra et al (2008) reported a sudden increase in chlorophyll at the river mouths of the Ganges and the Brahmaputra and attributed such increase to an increased terrestrial organic load carried by volume of discharge during the monsoon season. More recently, Prasad and Singh (2010) showed a peak in chlorophyll in coastal region of Bay of Bengal after 1-2 months of peak river discharge. Our preliminary results suggest a strong relationship between terrestrial discharge and phytoplankton variability for the Bay of Bengal and three other high discharge regions of the world (Jutla et al., 2009a). Taken together, findings from these studies suggest that it is reasonable to expect that the SeaWiFS algorithms capture the spatio-temporal variability of chlorophyll in the region despite suspended solid loads during monsoonal discharge.

Our analysis suggests that the average cloud cover is high (70%) during the months of May through July, while it is much lower (25%) from August through April in each of the latitudinal bands in the Bay of Bengal region. The focus of our current manuscript is to understand the implications of chlorophyll variability on two seasonal cholera outbreaks: one in the spring (defined as the average of March-April-May months) and the other in autumn (defined as the average of September-October-November months) season in Bengal Delta. Our recent study (Akanda et al., 2009) suggested that low river discharge conditions during the dry season and associated coastal intrusion of plankton water are responsible for spring cholera outbreaks in Bangladesh. Jutla et al (2010) also reported a strong correlation ($r=0.81$; $p<0.05$) between preceding autumn chlorophyll in coastal regions and spring cholera outbreaks in Bangladesh. On the other hand, autumn cholera outbreaks are strongly associated with the widespread breakdown of sanitary conditions due to flooding in the Bengal delta (Akanda et al., 2011). As streamflow direction is predominantly seaward during the high discharge season (average discharge during July-August-September months), it is highly unlikely that coastal chlorophyll is associated with autumn season cholera outbreaks since water intrusion cannot occur during this season. Therefore, the high cloud cover during summer months (Chaturvedi., 2005) in this region is not likely to significantly affect the analysis in our study.

3.4 Temporal Characterization of chlorophyll

3.4.1 Climatological chlorophyll distribution in the Bay of Bengal

We start our analysis with the annual climatological distribution of the chlorophyll in northern Bay of Bengal (Figure 3.1b). The climatology has been calculated by averaging monthly chlorophyll pixel values available for 10 years (1998-2007). Mean annual chlorophyll is 5.54, 1.34, 0.52, 0.33, 0.23 and 0.23 mg/m^3 in LB1 through LB6, respectively. From Figure 3.1b it is evident that chlorophyll values are significantly higher along the coast of Bay of Bengal than in the offshore regions. As an example, chlorophyll decreases by 96% from LB1 to LB6 . Chlorophyll is likely to be more along the coastal areas of Bay of Bengal because of two reasons: (a) it is the freshwater outlet region with high discharge from the GBM system (Jutla et al., 2009a); and (b) coastal regions experience more upwelling compared to offshore regions (Yarus et al., 2005) .

3.4.2 Chlorophyll variation at daily scale

With the availability of daily measurement of chlorophyll from remote sensing data, it is now possible to determine synoptic scale variability of chlorophyll in northern Bay of Bengal. Figure 3.2a and 3.2b show daily time series of chlorophyll for LB1 and LB6. On an average, the day to day variation between chlorophyll in LB1 and LB6 can vary up to 72%. A similar observation was made

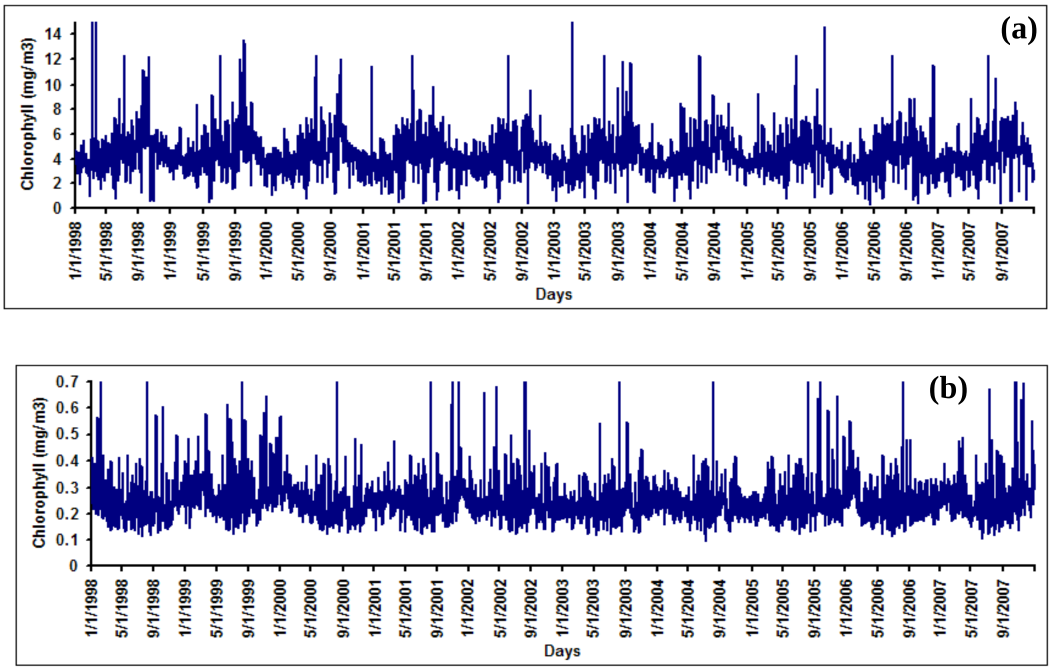


Figure 3.2: Chlorophyll time series for (a) LB1 and (b) LB6 from 1998-2007.

by Abreu et al. (2009) where they have used in-situ data along Patos Lagoon Estuary in Brazil and reported that day to day variation in chlorophyll can be as large as 60%. Figure 3.3 show the autocorrelation function for daily chlorophyll time series at the pixel scale (Figure 3.3a) and for six latitudinal bands (Figure 3.3b). Autocorrelation is the measure of the linear dependence of the data or the correlation in the time series with itself at different lag periods, which is used to check periodicity as well as randomness in the data (Box and Jenkins, 1991). A sharp decay in the autocorrelation structure for pixel scale (9 km) and band scale (1 degree) suggests that, at the daily scale irrespective of spatial averaging, chlorophyll time series does not have any temporal memory and resembles more like a white noise (random signal with no defined structure) signal (Figure 3.3). Such large variability from pixel to band levels suggests that it is not feasible to develop a predictive understanding of cholera-chlorophyll relationships at these scales.

3.4.3 Chlorophyll variation at monthly scale

As daily chlorophyll time series does not show much temporal structure, irrespective of spatial averaging from 9 km pixel scale to 1-degree band (approximately 100 km) scale, we now proceed to examine the variability of chlorophyll at a monthly time scale. Figure 3.4a shows monthly time series of chlorophyll in LB1. The red line is three month average chlorophyll, plotted to visualize presence of any regular variability in the time series. A seasonal maximum is usually observed in the fall season (September or October) and seasonal minima usually occur in early spring (February or March) in LB1 A closer examination of Figures 3.4 suggests that the underlying governing processes for LB1 and LB2 are different than those of the offshore bands. For example, chlorophyll variability for LB1 and LB2 shows distinct seasonality as evident from their autocorrelation function (Figure 3.5) with very high lag 1 autocorrelation suggesting strong month to month persistence.

For the offshore bands (LB3 through LB6), on the other hand, there is no discernable periodicity and lag 1 autocorrelation is low. There are no statistically significant peaks (greater than 1/e: 0.37) at any lag for all the bands except for LB1 and LB2. Thus, from here on, we will focus our analysis on the coastal bands (defined as LB1 and LB2 combined) and the offshore bands (LB5 and LB6 combined) only. For the coastal bands, monthly chlorophyll time series shows significant memory (Figure 3.5); yet at the pixel scale (9 km) it does not exhibit much persistence in time ; for all pixels in coastal bands show very low lag one autocorrelation (0.12±0.24). With increased spatial averaging, temporal persistence of monthly chlorophyll increases and lag one autocorrelation stabilizes at around 0.60 for 1296 km^2 or larger areal averages (Table 2). These results suggest that to have a reasonable prediction lead time, one needs to aggregate chlorophyll time series to monthly scales along with a spatial averaging scale of 1296 km^2 or larger.

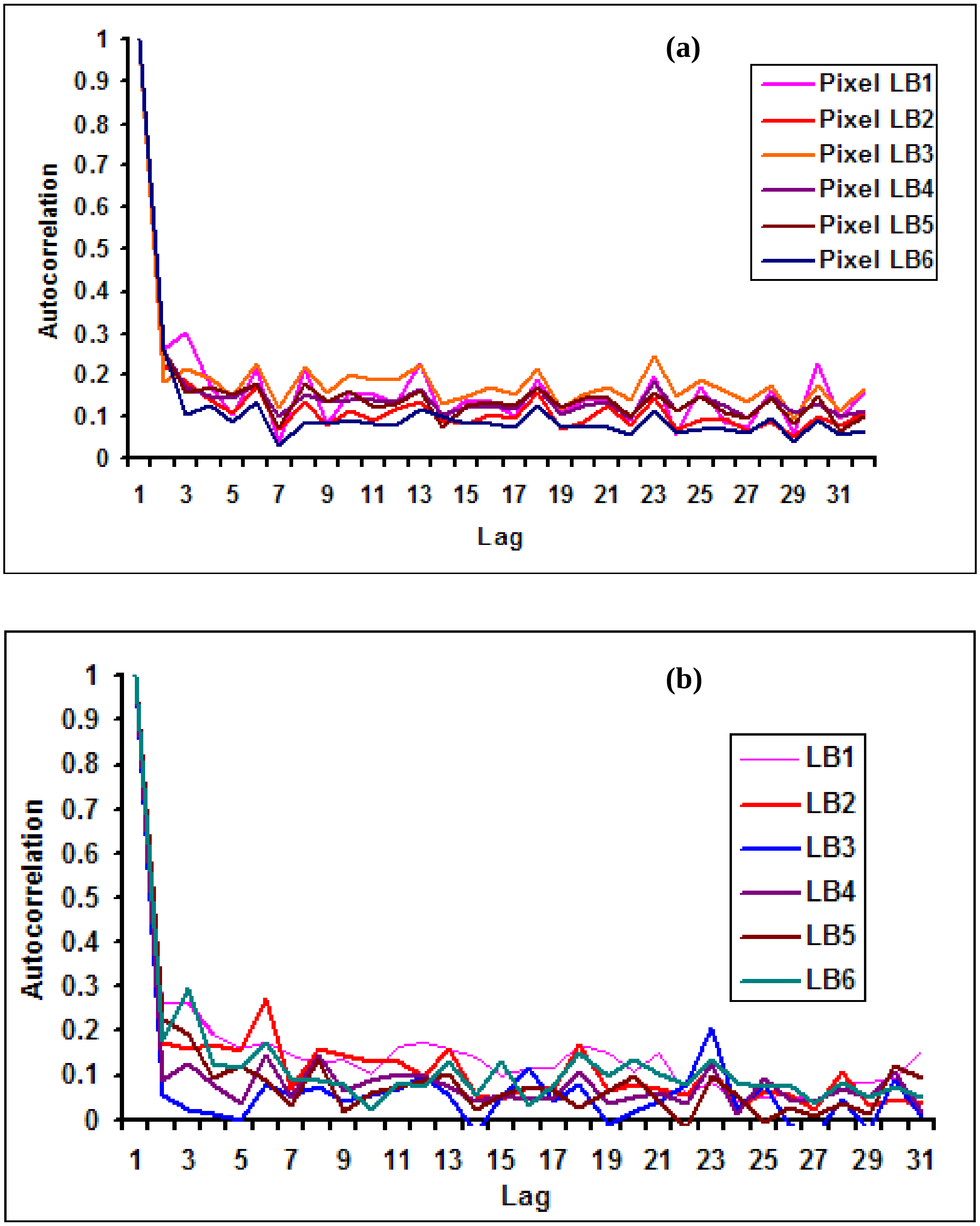


Figure 3.3: Autocorrelation function for daily chlorophyll at (a) pixel scale (LB1: 21^{0}N, 89.5^{0}E; LB2: 20.25^{0}N, 89.0^{0}E; LB3: 19.25^{0}N, 90.10^{0}E; LB4: 18.75^{0}N, 91.25^{0}E; LB5: 17.45^{0}N, 91.25^{0}E; LB6: 16.25^{0}N, 89.0^{0}E) and (b) at band scale.

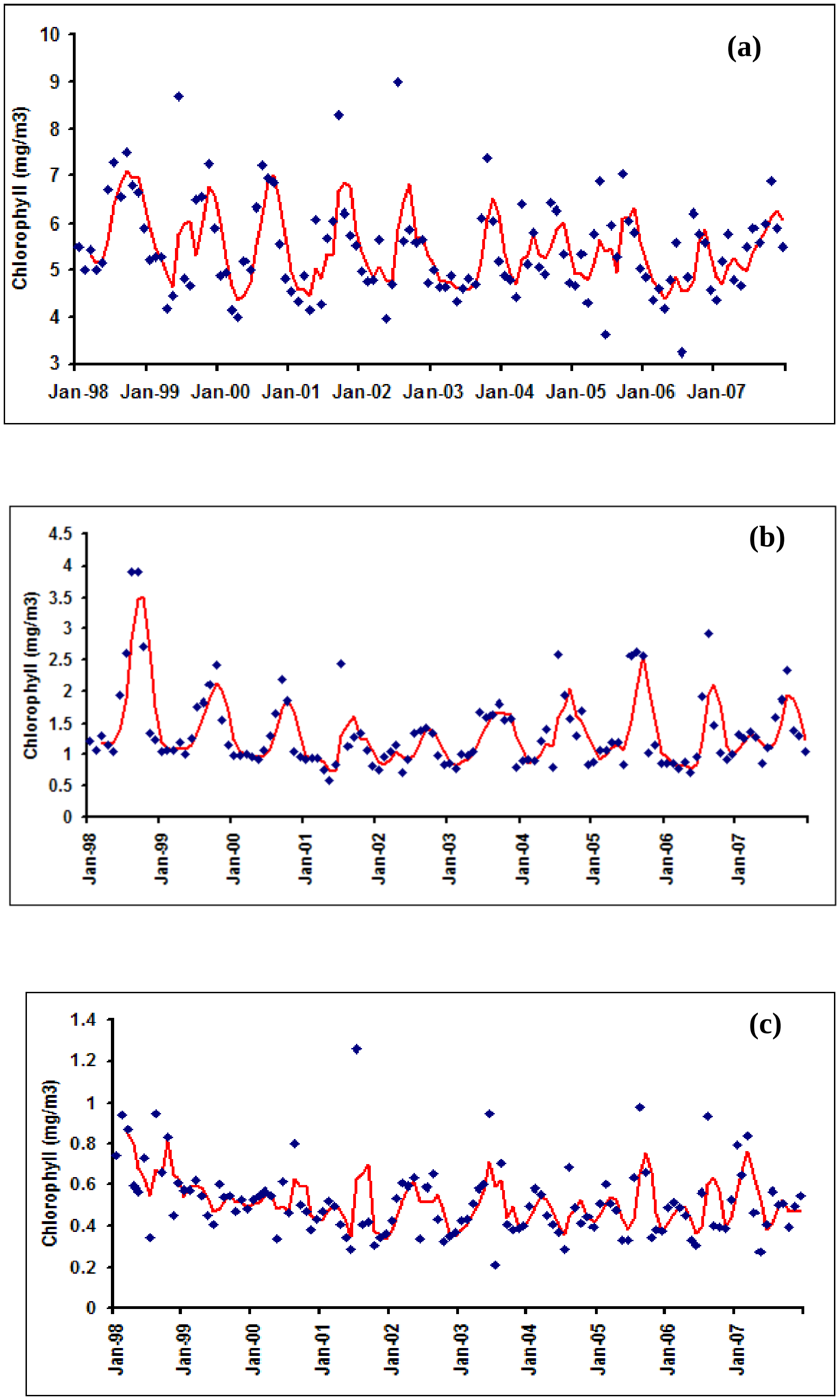
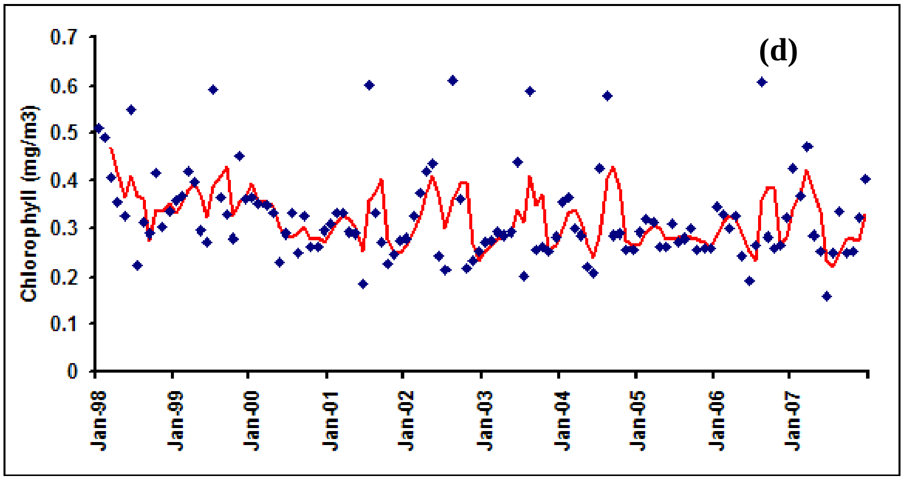
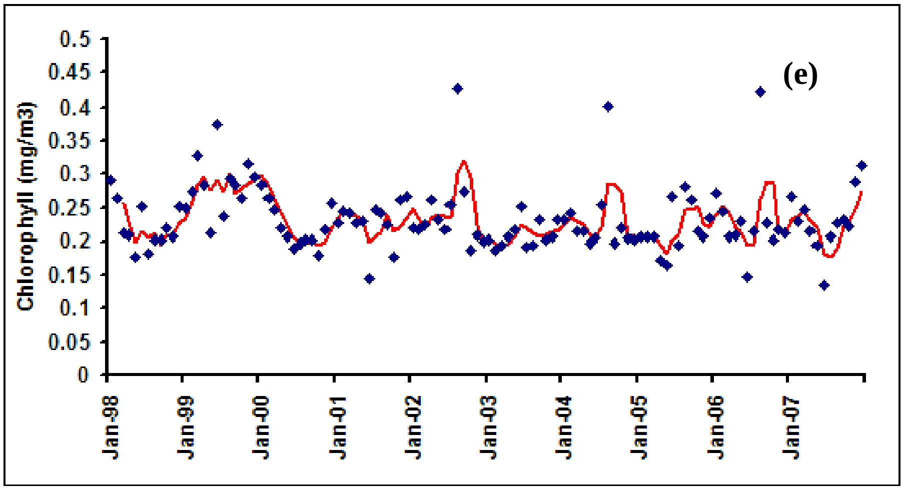


Figure 3.4: Monthly chlorophyll in six latitudinal bands (a) LB1; (b) LB2; (c) LB3





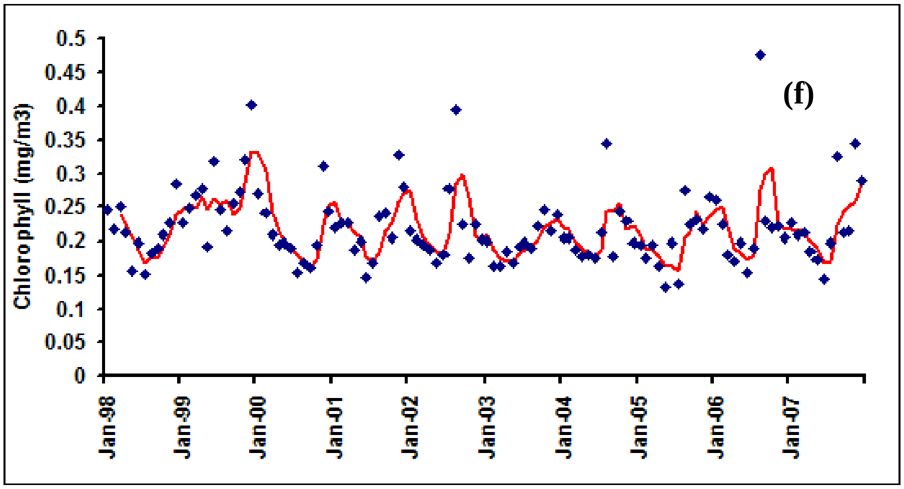


Figure 3.4: Monthly chlorophyll in six latitudinal bands (d)LB4; (e) LB5 and (f) LB6

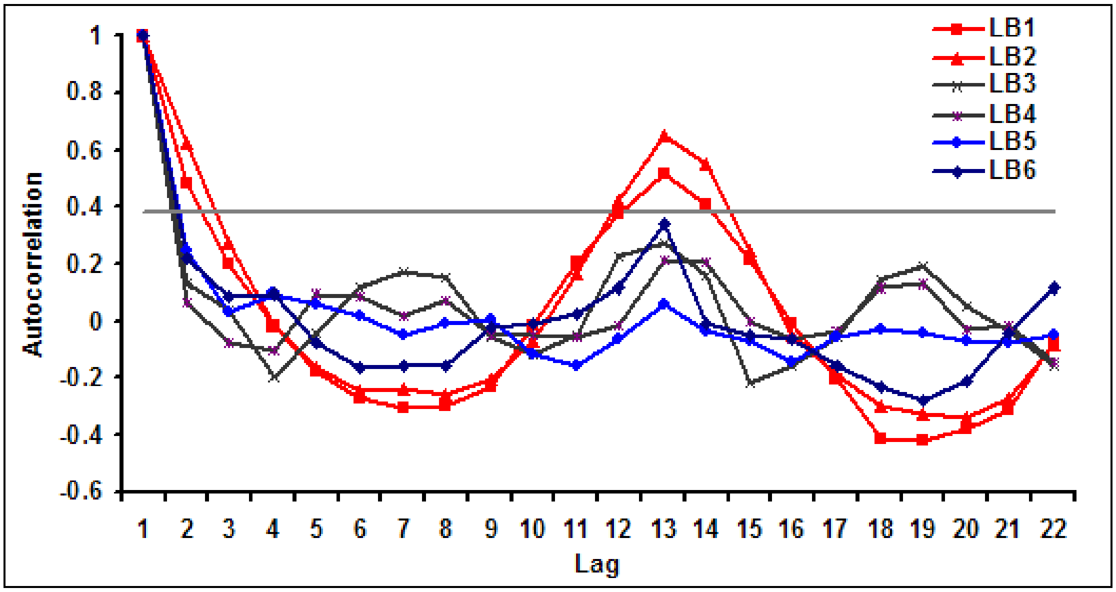


Figure 3.5: Autocorrelation function for monthly chlorophyll for six latitudinal bands

Table 2: Lag 1 autocorrelation as a function of spatial averaging for LB1 and LB2

Pixel size (km)	Sample (P1) Centered 21^0N, 88^0E	Sample (P2) Centered 21.5^0N, 90^0E
1x1	0.10	0.55
2x2	0.34	0.56
3x3	0.45	0.60
4x4	0.58	0.64
5x5	0.63	0.61
6x6	0.61	0.63

3.5 Spatial Characterization of Chlorophyll in the Bay of Bengal

Understanding spatial variability of phytoplankton is important since such variability at different scales may indicate growth, distribution and survival of planktonic species, plan for efficient use of instrumentation but most importantly, identify possible controls on plankton production (Steele 1976; Walsh 1978; Valiela 1984; Mackas 1984; Campbell and Esaias 1985). Within this context, the goal of spatial analysis is to compare and contrast the variability of chlorophyll in the coastal and offshore regions. Geostatistical technique, such as the semivariogram analysis, is often used to characterize and understand spatial patterns geophysical variables, such as soil moisture (Entin et al., 2000; Mohanty et al., 2000; Western et al., 2002), precipitation (Hevesi et al., 1992; Bachhi & Kottegoda, 1995). A key concept in geostatistics, the variogram, describes the variance between the points in a spatial field as a function of their separation distances (Western et al., 2004). Three main structural parameters of the variogram are the sill, the range or the correlation length and the nugget. The sill is the point where the semi-variogram flattens out. The range or the correlation length determines the spatial continuity of the variable of interest. The range is the distance beyond which the correlation between points is minimal. If there exists a sill in the semivariogram, the spatial distribution of the variable is stationary upto the range or correlation length. The nugget determines the variance between pairs of points separated by very small distances, which are a combination of measurement error and small-scale variability that cannot be distinguished from the spatial dataset (Western et al., 2004).

3.5.1 Spatial Structure of Chlorophyll at Monthly Scale

Spatial geostatistical analysis was conducted on ten years of chlorophyll data using geostatistical software GSLIB (Deutsch & Journel, 1992). Figure 3.6 shows monthly semivariograms for six months (October to March) for the coastal band. The choice of these six months is motivated by the dynamics of cholera outbreaks in the Bengal delta as well as accuracy of satellite data. As mentioned before, the autumn (~October) peak of cholera outbreaks has been associated with the hydrology of the region (such as floods), the spring (~March) peak is associated with the coastal processes in Bay of Bengal, such as intrusion of coastal waters into inland water bodies (*Akanda et al., 2009*). These six months (October through March) are also relatively cloud free for the Bay of Bengal region (*Chaturvedi, 2005)* and hence provide better accuracy for chlorophyll measurements from satellites. Figure 3.6 shows the semivariogram for coastal bands; the solid line shows the average semivariogram for ten years of data. To define the sill in the semi-variogram, we followed a procedure similar to Yoder et al (1987): a decrease in the slope to 10% or less of the mean slope before it decreases; constant (±10%) or decreasing semivariance after the break in the slope; and sill value is at least twice as that of the nugget variance. Based on this criterion, for the coastal band, we observe a range or a correlation length of 102, 92, 104, 105, 108, 106 km for October, November, December, January, February and March months respectively. Average observed correlation length for these six months in the coastal band is about 100km. The offshore band (Figure 3.7), on the other hand, does not have a defined correlation length except for the month of January (correlation length ~200km). This, presence (absence) of correlation length in the coastal (offshore) bands, indicates that the two regions have two separate processes controlling the production and space-time variability of phytoplankton. Such a regional demarcation of chlorophyll in Bay of Bengal has significant implications for understanding and modeling cholera-plankton relationships.

Using variogram analysis along the continental southeastern United States, Yoder et al (1987) indicated that the correlation length in the coastal regions is smaller than the offshore waters. Two major reasons for shorter correlation lengths in coastal regions than those for the offshore regions were given as: (a) mesoscale ocean current variability caused by eddies (Gower et al., 1980; Karhu et al., 1982; Yoder et al., 1987) and (or) (b) addition of terrestrial nutrient and consequent increase in phytoplankton (Mackas, 1984; Campbell & Esaias, 1985). In coastal region of Bay of Bengal, freshwater discharge from the two major rivers, the Ganges and the Brahmaputra, substantially increase terrestrial nutrient fluxes (Sheyte, 1996) and thereby may affect the correlation length for the coastal band. Absence of a defined correlation length in the offshore region indicates that chlorophyll variability is perhaps controlled by large-scale oceanic processes, such as frontal eddies (Yoder et al., 1987; McClain et al., 1984).

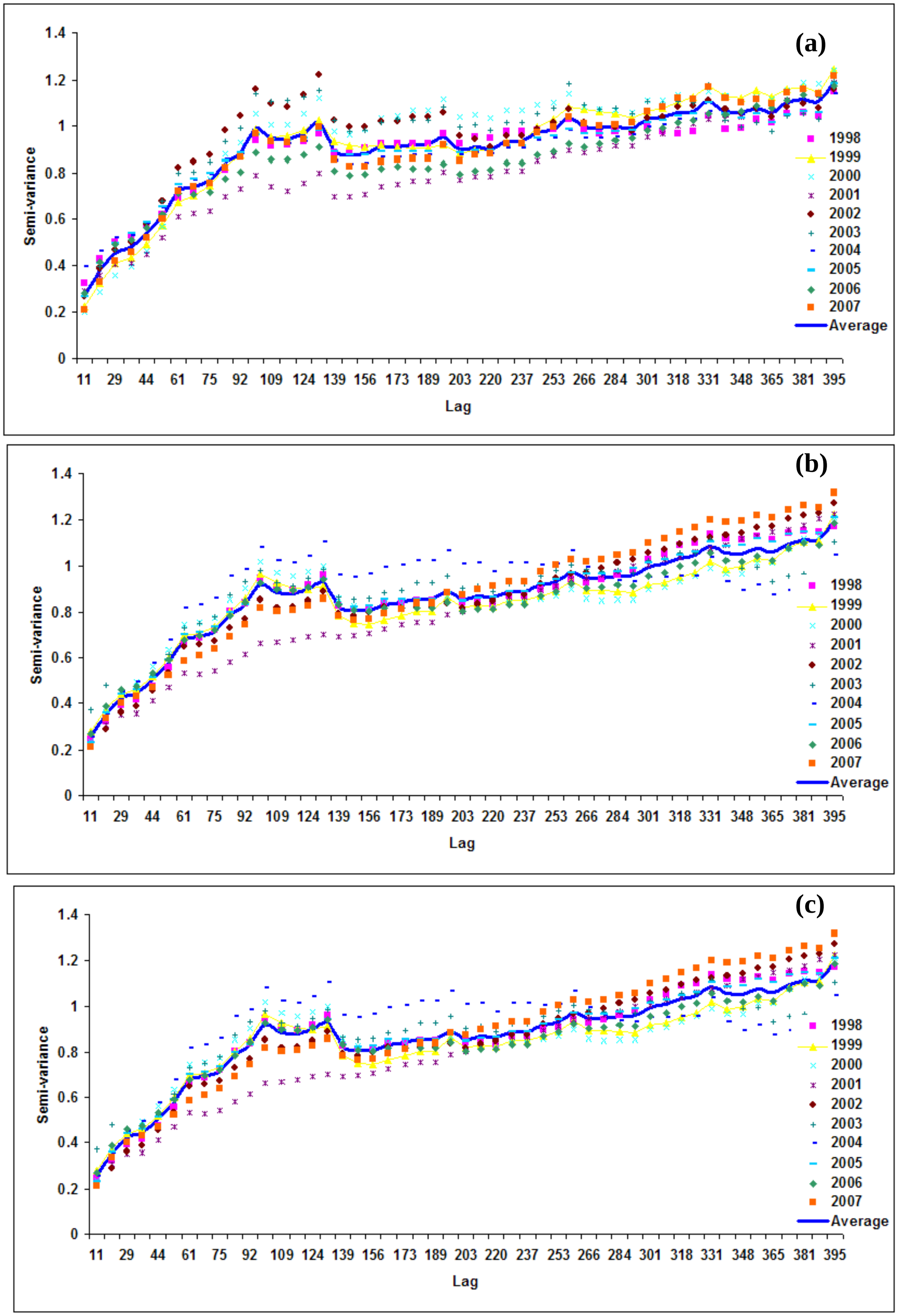


Figure 3.6: Semivariograms for LB1+LB2 for (a) October, (b) November, (c) December

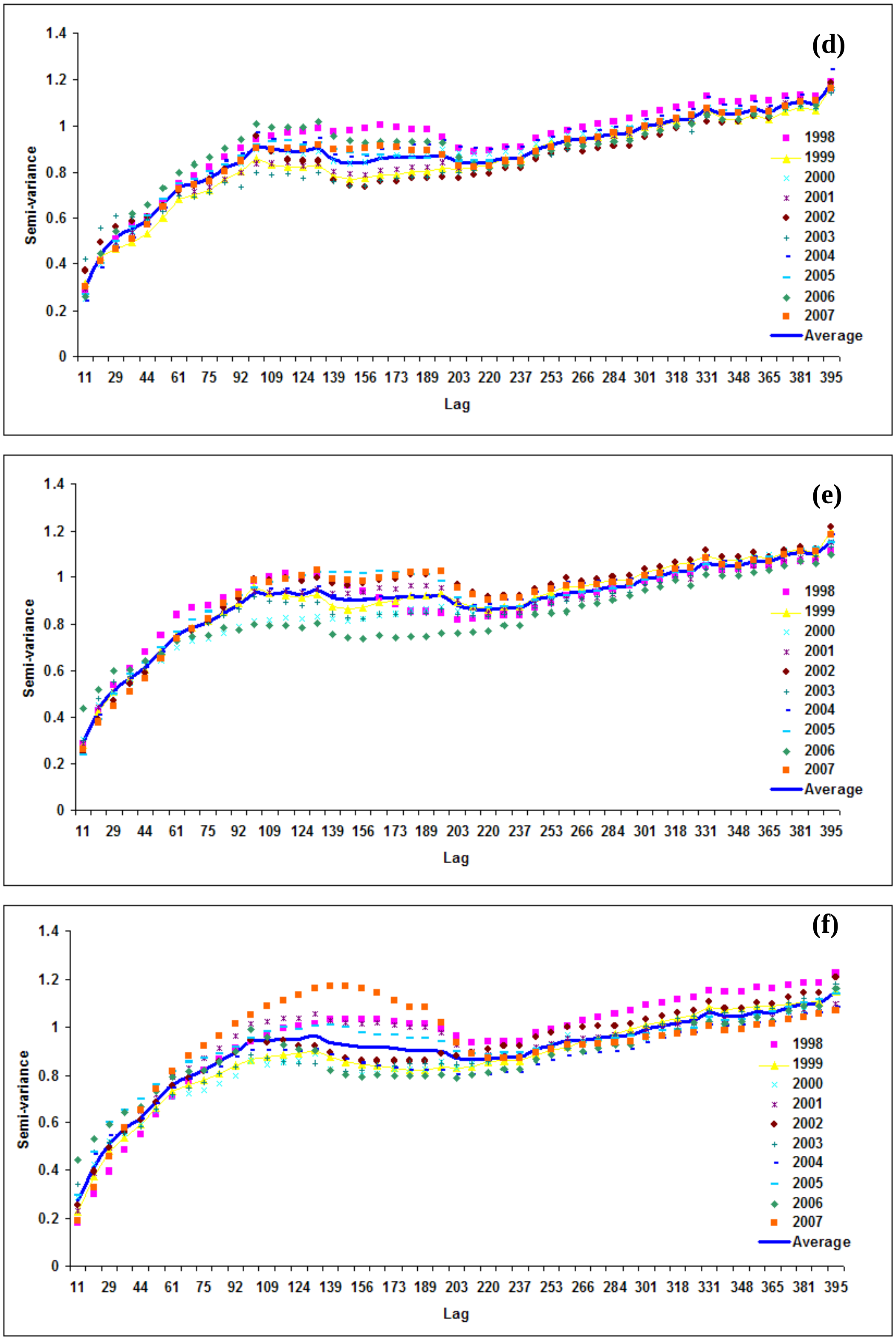


Figure 3.6: Semivariograms for LB1+LB2 for (d) January (e) February and (f) March

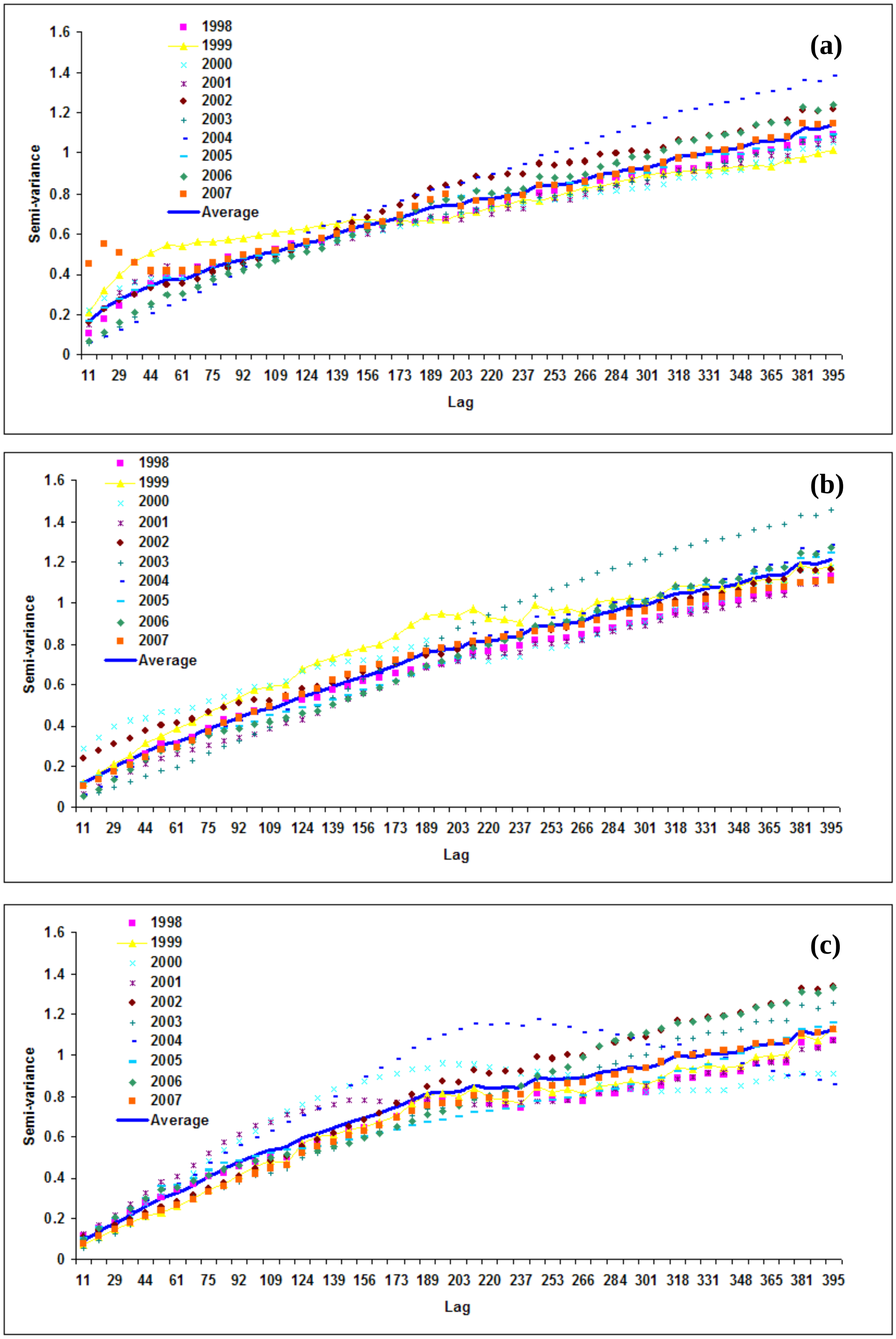


Figure 3.7: Semivariograms for LB5+LB6 for (a) October, (b) November, (c) December)

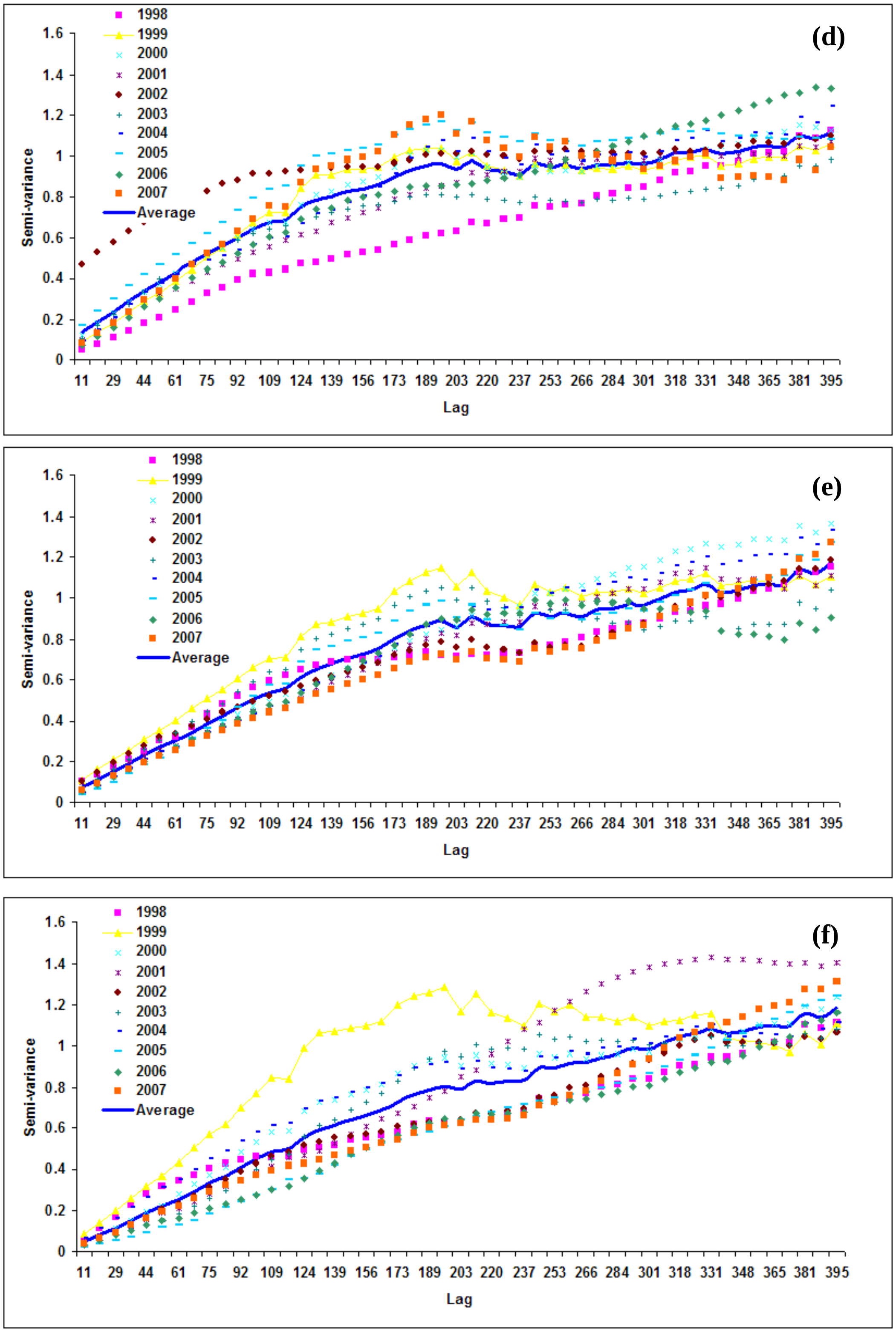


Figure 3.7: Semivariograms for LB5+LB6 for (d) January, (e) February and (f) March

3.6 Cholera and Space-Time variability of Chlorophyll

The findings from sections 4 and section 5 have direct implications on understanding plankton-cholera relationships in the Northern Bay of Bengal. We have established that chlorophyll in the coastal band (LB1+LB2) shows a distinct annual cycle. Cholera incidence data were acquired from a surveillance system maintained by the International Centre for Diarrheal Disease Research, Bangladesh (ICDDR,B), where incidence is recorded as the percent of new cholera infected patients among a statistical subset of patients selected from a

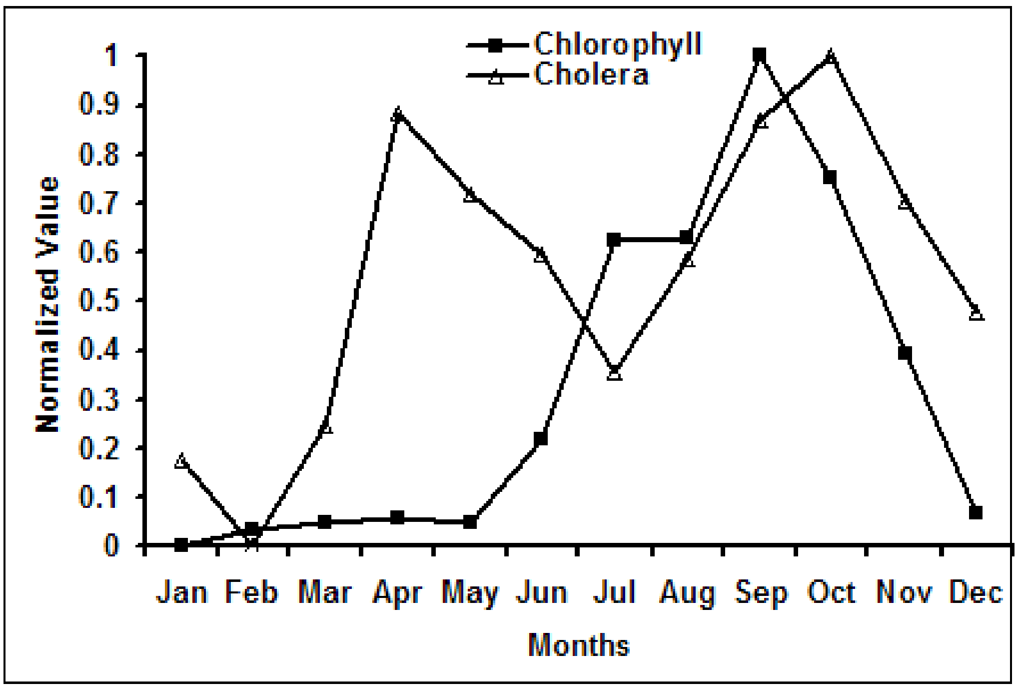


Figure 3.8: Annual Cholera and Coastal Chlorophyll in Bay of Bengal. Monthly cholera time series were obtained from International Center for Diarrhoeal Disease Research in Bangladesh (ICDDR,B).

total pool of patients visiting the hospital for treatment during a given week (Longini, 2002). Figure 3.8 shows climatological monthly cholera and coastal chlorophyll for ten years (1998-2007). Cholera incidence in the Bay of Bengal region exhibit bi-annual peaks; one in autumn season and the other in spring seasons (Figure 3.8). However, coastal chlorophyll shows only one seasonal peak in autumn season. The presence of a single peak in chlorophyll and double peak in cholera suggests that chlorophyll variability may not be the only variable affecting cholera outbreaks.

Based on our current understanding (Akanda et al.. 2009) high river discharge from the GBM rivers are responsible for the autumn peak in cholera outbreaks, whereas the spring peak is related to low flow discharges and subsequent intrusion of coastal plankton laden seawater. The high levels of chlorophyll during autumn is unlikely to be responsible for the simultaneous outbreaks in autumn since the river discharge is high in this season; making it impossible for plankton to get into inland water systems. On the other hand, plankton abundance in autumn may lead to cholera in the spring season through various mechanisms, such as the one suggested by Seeligmann et al. (2008) and Binsztein et al. (2004). Historically, it is observed that cholera bacteria activity subsides with the onset of winter (Cliff et al., 2004). Binsztein et al. (2004) suggested that cholera bacteria may enter the dormant non-culturable state with the onset of winter, and under favorable condition(s), the bacteria can become viable and cause epidemic. During low discharge months, intrusion of chlorophyll through river networks, under favorable conditions, may lead to cholera outbreaks in spring seasons. Also, Huq and Colwell (1995) suggested that cholera bacteria require zooplankton for survival that in turn feed on the phytoplankton in the coastal waters, therefore the presence of lagged relationship between spring cholera outbreaks and autumn chlorophyll may be justified. Sack et al. (2003) have indicated that the spring outbreaks of cholera are primarily observed in the coastal region of Bay of Bengal. Correlation between autumn chlorophyll and spring cholera is about 0.81, suggesting that spring cholera outbreaks may be related to previous autumn chlorophyll (Jutla et al., 2009b). Such high correlation between chlorophyll and cholera makes coastal chlorophyll a likely variable to be used in development of any predictive models for spring cholera outbreaks.

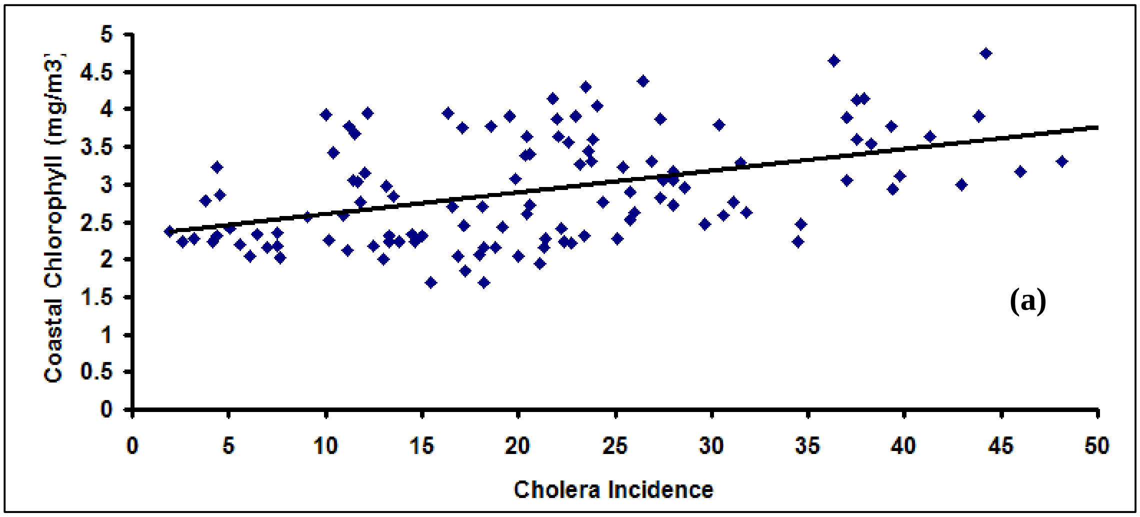
Concurrent correlation between monthly cholera and coastal band chlorophyll time series (Figure 3.9a) is about 0.45. For the offshore region, this correlation between cholera and chlorophyll (Figure 3.9b) drops to about 0.10. This is another indication that chlorophyll measurements in the coastal band are likely to play an important role in understanding plankton-cholera relationships. Plausible lead-lag relationships between chlorophyll and cholera need to be explored in future studies.

3.7 Discussion

Endimicity of cholera in the Bengal Delta and a strong laboratory based relationship between cholera and plankton abundance motivated this study to explore the spatial and temporal variability of chlorophyll in northern Bay of Bengal. Space-time characterization of chlorophyll is an essential first step to establish relationship between cholera and plankton abundance over a range of scales. Using ten years of daily SeaWiFS chlorophyll data, we have established that chlorophyll time series is a white noise process for pixel (~10km) to band

(~100 km) scales. We also note that the large temporal variations of pixel level chlorophyll concentration put a practical constraint on the design and implementation of in-situ plankton measurements for coastal areas. Such large temporal variations of pixel level chlorophyll concentration put a practical constraint on the design and implementation of in-situ plankton measurements for coastal areas. These results are similar to those of Uz & Yoder (2004) who also suggested that variability of chlorophyll, along Southeastern US Continental shelf, on daily time scale resembles a white noise process with significant day to day variability in coastal as well as in open ocean waters.

Results of chlorophyll variability at the monthly time scale are more encouraging. We have established that chlorophyll in the coastal band shows a distinct annual cycle while such a cycle is not apparent for offshore regions. For the coastal bands, monthly chlorophyll time series shows significant memory; yet at the pixel scale (9 km) it does not exhibit much persistence in time. With increased spatial averaging, temporal persistence of monthly chlorophyll increases. An aggregated monthly chlorophyll concentration for the coastal band - with a spatial averaging scale of 1296 km^2 or larger -is likely to provide a lower limit on spatial scale of plankton measurements for a useful prediction lead time for a potential cholera outbreak model.



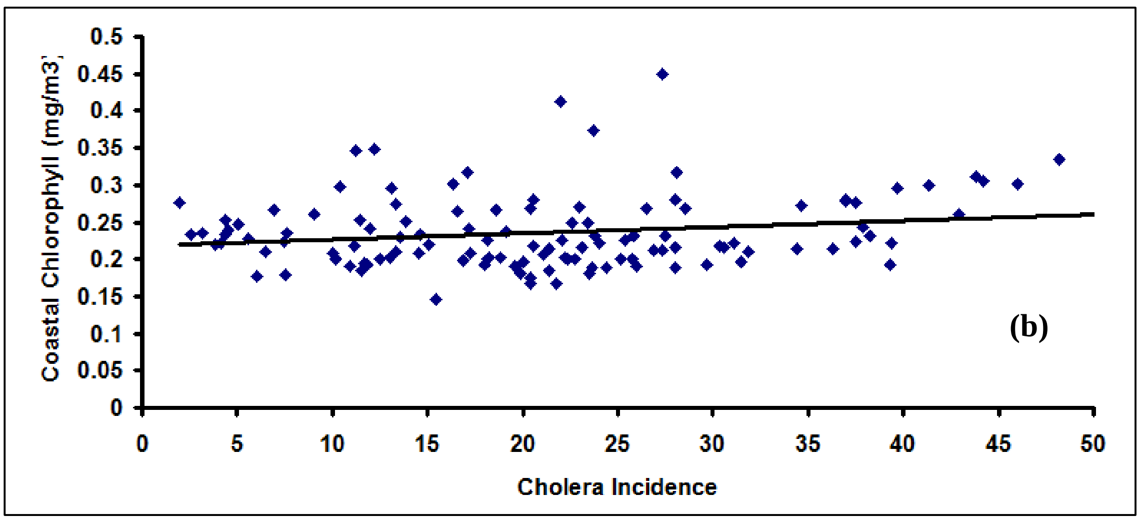


Figure 3.9: Correlation plot between monthly cholera incidence and (a) Coastal, (b) Offshore chlorophyll in the Bay of Bengal region.

Peak chlorophyll levels in the coastal band tend to occur in the autumn season, whereas lowest chlorophyll is observed in early spring season. On the other hand, chlorophyll in offshore regions of Bay of Bengal does not exhibit any preferential seasonal maxima or minima. A plausible reason for the presence of an annual cycle in chlorophyll variability for the coastal band may be attributed to large freshwater discharge and associated terrestrial nutrient influx from two rivers, the Ganges and the Brahmputra, into the northern Bay of Bengal. A peak discharge for these two rivers is observed in August (Dai & Trenberth, 2001) while peak chlorophyll is observed in September. River discharges have been associated with the increase of phytoplankton from other coastal regions as well (Arker et al., 2005; Smith & Demaster, 1996; Lopez & Hidalgo, 2009). Spatial analysis indicates that chlorophyll in the coastal band has a correlation length of approximately 100km whereas offshore bands have no well-defined correlation length. The dominance of different space-time variations for coastal and offshore chlorophyll suggests that physical processes and drivers for chlorophyll are indeed different in the two regions. These results suggest that physical processes and drivers for chlorophyll may be different in the coastal and offshore regions.

To our knowledge, this is perhaps one of the first studies to examine cholera-chlorophyll relationship over such a large range of spatial and temporal scales in northern Bay of Bengal using satellite data. We recognize that the SeaWiFS chlorophyll data is likely to be noisy due to sediments, organic and inorganic matter particularly close to the coastal areas (Martin, 2004). However, NASA's latest OC4v4 chlorophyll algorithm has correction already applied to the data. In the presence of sediments, the correction algorithm shifts to a higher wavelength to maintain high signal to noise ratio (Martin, 2004). Several recent studies (e.g., Legaard & Thomas (2006), Uz & Yoder (2004), Doney et al., (2003), Chaturvedi (2005)) demonstrate that the SeaWiFS sensor has been reasonably stable over the years of operation and calibration approach provided consistent global water-leaving radiances, and the products meet the accuracy goals over a diverse set of open ocean validation sites (McClain et al 1998; Gregg and Casey, 2004). A key strength of the SeaWiFS dataset is that, despite the inherent measurement accuracy and noise level, it captures the seasonal dynamics of chlorophyll in coastal regions. Although pixel level chlorophyll values have uncertainty and noise, it is the "contextual information" of neighboring pixels that make this data set a useful tool for our analysis.

An important implication from this study is likely to be on the design of *in-situ* sampling strategies of coastal chlorophyll in northern Bay of Bengal to establish plankton-cholera relationships. Given the day to day variability of chlorophyll for a range of spatial scales, findings from this study suggest that continuous measurements of plankton will be necessary for an extended period of time to develop any meaningful time series for analysis and model development. Although chlorophyll measurement from satellites eliminates detailed field sampling needs over large regions; yet, to establish limits of accuracy of satellite measurements as well as to relate chlorophyll measurements with phytoplankton types, *in-situ* measurements will be needed. Findings from this study further suggest that daily chlorophyll concentration may not be particularly useful to develop any cholera predictive model. We do recognize that comprehensive monthly and seasonal scale analyses are needed, in future, to explore synchronous as well as lead-lag relationships between chlorophyll variability and cholera outbreaks.

3.8 References

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Chapter 4

Warming oceans, phytoplankton, and river discharge: Implications for cholera outbreaks[#]

Abstract

Phytoplankton abundance is inversely related to sea surface temperature (SST). However, positive relationship is observed between SST and phytoplankton abundance in coastal waters of Bay of Bengal. This has led to an assertion that in a warming climate, rise in SST may increase phytoplankton blooms and, therefore, cholera outbreaks. Here, we explain why a positive SST-phytoplankton relationship exists in the Bay of Bengal and the implications of such a relationship on cholera dynamics. We found clear evidence of two independent physical drivers for phytoplankton abundance. The first one is the widely accepted phytoplankton blooming produced by the upwelling of cold, nutrient-rich deep ocean waters. The second, which explains the Bay of Bengal findings, is coastal phytoplankton blooming during high river discharges with terrestrial nutrients. Causal mechanisms should be understood when associating SST with phytoplankton and subsequent cholera outbreaks in regions where freshwater discharge are predominant mechanism for phytoplankton production.

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4.1 Background

The causative agent of cholera, *Vibrio cholerae*, is endemic to brackish riverine, estuarine, and coastal waters. It is commensal with copepods, which feed on phytoplankton (Colwell and Huq, 2001; Richardson and Schoeman, 2004). Therefore, it has been hypothesized that high levels of phytoplankton may lead to high numbers of cholera-containing copepods, increasing the likelihood of cholera epidemics in coastal human populations. There is an intense interest in the use of remote sensing satellite data for cholera outbreak prediction (Lobitz et al., 2000, Jutla et al., 2010) since satellite remote sensing is an efficient and effective way to track the spatial and temporal concentrations of chlorophyll, a surrogate for phytoplankton, over large areas. Using chlorophyll, many rigorous studies demonstrate an inverse relationship between phytoplankton and sea surface temperature (SST) (Solanki et al., 2001; Davenport et al., 2002; Acha et al., 2004; Legaard and Thomas, 2006; Perez et al., 2005; Joliff et al., 2008; Smyth et al., 2008; Shen et al., 2008)**.** Puzzlingly, in the Bay of Bengal (Bay of Bengal) region (Figure 4.1), a positive relationship has been observed between phytoplankton and SST (Lobitz et al., 2000; Emch et al., 2008; Magny et al., 2008; Colwell, 1996; Chaturvedi., 2005; Kumari and Babu., 2009). This apparently contradictory relationship between Bay of Bengal SST and phytoplankton has led to the assertion that, in a warming climate scenario, increasing SST will lead to increasing phytoplankton and thus more cholera outbreaks globally (Lobitz et al., 2000). To address these contradictory viewpoints, we undertook an analysis of the role of nutrients carried by freshwater river discharge into the ocean in several major freshwater discharge ocean basins across the globe. This paper seeks (i) to explain why a positive SST-phytoplankton relationship exists in the Bay of Bengal and (ii) to understand the implications of such a relationship on cholera dynamics.

Figure 4.1: Location of four major river basins: Ganges and Brahmaputra rivers discharge into the Bay of Bengal, Orinoco river drains into Atlantic Ocean, Congo River drains into the Atlantic Ocean and Amazon River drains into the Atlantic Ocean.

4.2 Methods

4.2.1 Study Design and Dominant Hypothesis

We examined the role terrestrial nutrients - through fresh water discharge (Smith and Demaster, 1996) into the Bay of Bengal from the Ganges, Brahmaputra, and Meghna (GBM) rivers - might play in causing phytoplankton and zooplankton blooms and their subsequent relationships with SST. The GBM river system in the Indian Subcontinent discharges approximately 628 km^3/ year of freshwater into the Bay of Bengal (Dai and Trenberth, 2002), the third largest freshwater flow in the world behind the Amazon and the Congo. Increases in phytoplankton through freshwater nutrient discharge have been observed in the Chesapeake Bay (Acker et al., 2005), and the Delaware (Pennock and Sharp, 1985), Po (Revelante and Gilmartin, 1976), Orinoco (Bidigare et al., 1993) and Mississippi rivers (Lohrenz et al., 1990), implying that high discharge brings nutrients with it, that further aid in phytoplankton blooming. However, the effect of river discharge on the relationship between SST and satellite-derived phytoplankton abundance, through chlorophyll estimates, remains unexplored. We hypothesize that large amount of terrestrial nutrients carried by the GBM rivers lead to a positive relationship between SST and phytoplankton abundance in the Bay of Bengal. We used correlation and wavelet analysis of appropriate time series to explore our hypothesis. We then validated the Bay of Bengal results by analyzing the SST and chlorophyll, a surrogate for phytoplankton abundance, relationships in three other major discharge regions around the globe (Figure 4.1: Amazon, Orinoco, and Congo), which are hydrologically similar to the GBM riverine system. Lastly, we directly assessed the concurrent relationship between cholera incidence and coastal Bay of Bengal SST.

4.2.2 Data sources

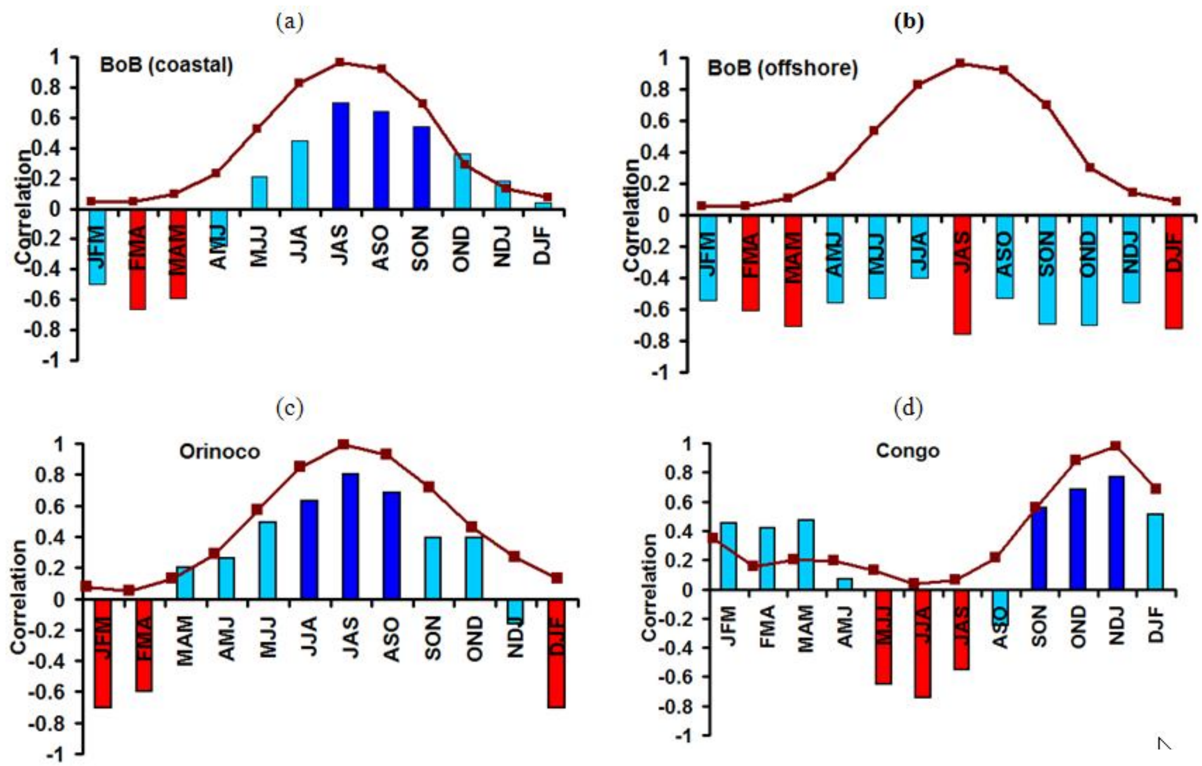
The coastal water zone of the Bay of Bengal is defined as the region between 21-22.5^{0}N and 86-93^{0}E based on bathymetry of the region (Barua et al., 1994). Our data products were Sea-viewing Wide Field-of-view Sensor (SeaWiFS) monthly chlorophyll data at 9-km resolution, obtained from the NASA/Goddard Earth Sciences/Distributed Active Archive Center, for a 12 year period (1997-2009. More detailed descriptions about these products, sensors, estimation algorithms, and accuracy are available elsewhere (Martin., 2004; Uz and Yoder, 2004). Prior work has demonstrated that the SeaWiFS sensor has been reasonably stable over the years of operation, the calibration approach provided consistent global water-leaving radiances, and the products meet the accuracy goals over a diverse set of open ocean validation sites (McClain et al., 1998; O'Reilly et al., 2000; Gregg and Casey, 2004). Monthly interpolated data (Reynolds and Smith, 1994) for the concurrent time period were used for SST analysis. Daily Ganges and Brahmaputra river discharge data were obtained from the Bangladesh Water Development Board, and aggregated into a monthly time series for the analysis. The two river gauge stations are located in Bahadurabad and Paksey, where the Brahmaputra and the Ganges rivers enter Bangladesh from India, respectively. To determine total discharge into the Bay of Bengal, monthly river discharge data for the two rivers were added to obtain combined monthly discharge. Cholera incidence data from 1997 through 2009 were acquired from surveillance bulletins maintained by the International Centre for Diarrheal Disease Research, Bangladesh. Cholera epidemiologic data from Bangladesh, perhaps one of the longest cholera datasets available (Longini et al., 2002), were averaged over sequential three month periods to obtain seasonal cholera outbreak estimates.

4.3 Results

4.3.1 Relationship between SST, Phytoplankton and River Discharge

We calculated the correlation between SST and chlorophyll as a function of mean of three consecutive months for the entire year (e.g., January-February-March (JFM), February-March-April (FMA), March-April-March (MAM), etc.). A positive correlation in Figure 4.2 indicates the correlation coefficient between SST and chlorophyll is positive for a simultaneous 3-month seasonal period, and vice versa. Deep blue and red bars in Figure 4.2 are the statistically significant correlations (Kendall Tau test $p<0.05$).

In the coastal Bay of Bengal region, Figure 4.2a, eight positive and four negative seasonal correlations were observed. Negative correlations were found for the following seasons: JFM, FMA, MAM, AMJ; and positive correlation for the rest of the seasons. A seasonal discharge curve, the brown line in Figure 4.2a, is superimposed on the correlation plot. As shown in Figure 4.2a, when the seasonal river discharge is high (JAS, ASO, and SON), the correlation between SST and chlorophyll is positive. In contrast, when river discharge is low (JFM, FMA, and MAM), the correlation between SST and chlorophyll is negative. There are two interesting observations in Figure 4.2a in coastal Bay of Bengal: (i) the highest statistically significant correlation value lies in the region of high (JAS: correlation between SST and chlorophyll = 0.70) and low (FMA: correlation between SST and chlorophyll = -0.66) discharge season and (ii) the correlation value decreases outside two marked zone of interest (high and low discharge seasons). Correlation values decrease after the SON period and gradually become negative as flow decreases. Figure 4.3 provides seasonal values for coastal chlorophyll, SST, and river discharge for the Ganges and the Brahmaputra rivers. It shows that coastal Bay of Bengal SST has an annual bimodal peak, the first in spring (MAM) season and the second in fall (SON) season.



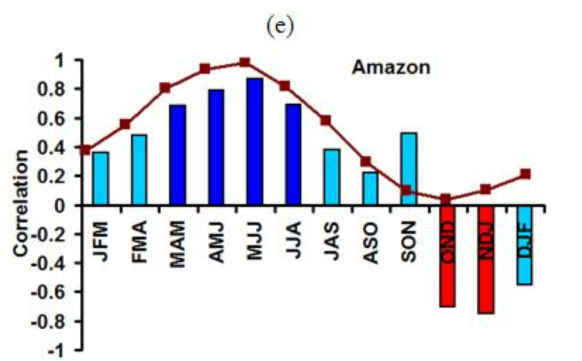


Figure 4.2: Seasonal correlation between SST and chlorophyll from 1997-2010 (a) Bay of Bengal (coastal); (b) Bay of Bengal (offshore); (c) Orinoco, (d) Congo and (e) Amazon. Deep blue and red bars represents statistically significant correlation (using Kendall Tau test $p<0.05$). Brown line, superimposed on the correlation plots, is the seasonal river discharge, scaled between 0 and 1, from respective river basins. J, F, M …D represents January, February, March… December respectively. JFM, FMA is the mean of three consecutive months.

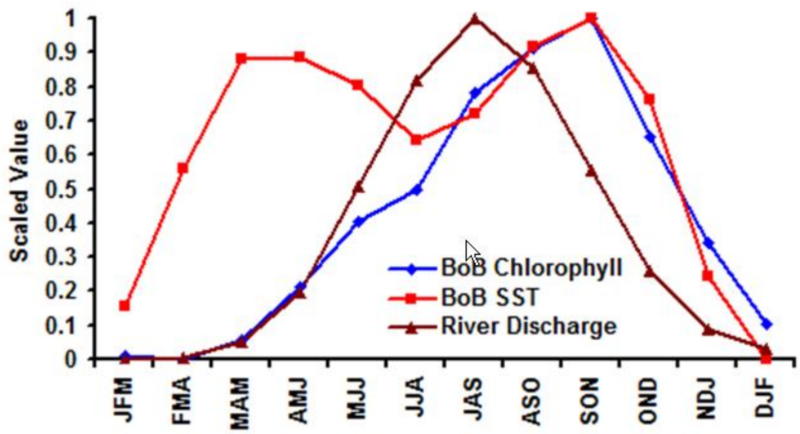


Figure 4.3 Three month chlorophyll, SST and river discharge at the mouth of the river for coastal Bay of Bengal. All values have been scaled from 0 to 1.

If an increase in SST is related to the increase in phytoplankton and, subsequently, zooplankton, then a similar bimodal peak in coastal chlorophyll should be detected. However, seasonal chlorophyll shows only one peak similar to the peak observed in seasonal river discharge. As a supporting evidence, correlation between highest river discharge season (JAS: July-August-September) highest phytoplankton abundance (SON: September-October-November) season in coastal Bay of Bengal is 0.81 ($p<0.05$). These relationships suggest that during time of high discharge, terrestrial nutrients are washed from land and deposited in the coastal Bay of Bengal, consequently increasing the concentration of chlorophyll (phytoplankton abundance). During low river discharge seasons, in contrast, the flow of terrestrial nutrients is limited and the correlation between SST and chlorophyll is negative, suggesting that the production of chlorophyll in the Bay of Bengal at these times of the year is controlled by processes other than river flow.

We then determined the statistical relationships between SST and chlorophyll in the offshore region of the Bay of Bengal. If high river discharge is the dominant mechanism for producing positive relationship between SST and chlorophyll then we would detect an inverse relationship between the two variables (SST, chlorophyll) in all the seasonal correlations. If such an inverse relationship is observed, it would imply that river discharge has little or no impact for offshore phytoplankton. The seasonal correlation between SST and chlorophyll, for the offshore region (17-18^{0}N and 86-93^{0}E), is indeed negative throughout the year (Figure 4.2b). Thus, river discharge appears to affect phytoplankton production only in the coastal zone of the Bay of Bengal during high discharge season, and the expected inverse relationship between SST and chlorophyll re-emerged away from the coast.

As an aggregate metric, correlation can be deceptive as the only measure to ascertain causal relationships. In order to verify these results obtained using correlation analyses, we used wavelet analysis (Najafi et al., 2003) to decompose the coastal and offshore daily chlorophyll time series to determine if there are any discernable time period differences between the two time series. Daily chlorophyll time series shows that coastal chlorophyll has a statistically significant 30-90 day peak, (Figure 4.4a) whereas offshore chlorophyll has a peak at 3 years, which is absent in coastal waters (figure 4.4b). This distinctive variation of time scales for coastal, and offshore chlorophyll suggests that the physical processes and drivers for chlorophyll variability are indeed different in these two regions.

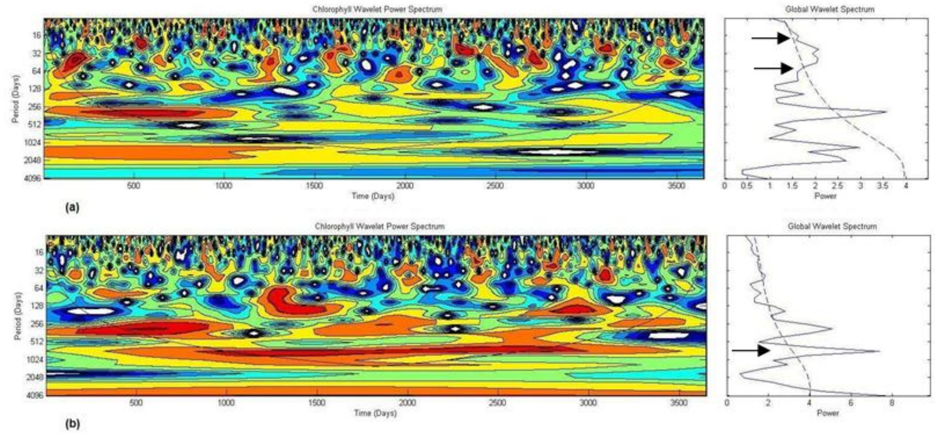


Figure 4.4: Wavelet power spectrum analysis for (a) daily coastal chlorophyll and (b) Offshore chlorophyll time series. A five day running mean was applied to the daily time series to remove missing values. Climatological daily values were inserted for missing chlorophyll values after a five day running mean was applied.

4.3.2 Relationship between SST and Phytoplankton in Amazon, Orinico and Congo regions

We conjectured that if high freshwater discharge in the coastal Bay of Bengal alters the more generally observed inverse relationship between chlorophyll and SST, then this phenomenon should occur elsewhere. Thus, we should expect to see a positive association between SST and chlorophyll during high discharge, and a negative relationship during low discharge months in other major freshwater basins globally. To explore this hypothesis, we calculated the correlation between SST and chlorophyll in three of the largest freshwater basins in the world (Figure 4.1) – the Amazon (discharge of 6640 km^3/year), Congo (1308 km^3/year) and Orinoco (1129 km^3/year). The results of these analyses are displayed adjacent to the Bay of Bengal data for ease of comparison. The Orinoco (Figure 4.2c) showed positive correlations (JJA: 0.63, JAS: 0.80, ASO: 0.68) during high discharge seasons and negative correlations (JFM: -0.70, FMA: -0.63

and DJF:-0.71) during low flow seasons. Similarly, high discharge seasons in Congo (Figure 4.2c OND: 0.68; NDJ: 0.77; DJF: 0.51) and Amazon (Figure 4.2d MAM: 0.68; AMJ: 0.79: MJJ: 0.87: JJA: 0.69) river show positive correlations between SST and chlorophyll. During low discharge seasons, a negative correlation is observed in Congo (Figure 4.2d) and Amazon (Figure 4.2e) rivers. The SST and chlorophyll relationships for the three large freshwater discharge regions are very similar to that for the Bay of Bengal, which is consistent with the hypothesis that river flow is a dominant driver for phytoplankton growth during high river discharge season. For these three rivers, similar to coastal Bay of Bengal, we note that the highest statistically significant correlation values lie in the region of high (Orinoco JAS: 0.80; Congo NDJ: 0.77; Amazon MJJ: 0.87) and low (Orinoco JFM: -0.70; Congo JJA: -0.73; Amazon NDJ: -0.75) discharge seasons. This high degree of physical consistency between SST and chlorophyll variations in three other major freshwater discharge basins suggests that the positive correlation between SST and chlorophyll in major coastal zones around the world may result from similar dominant processes, such as terrestrial nutrients with high volume river discharge. The negative correlation pattern for these basins during low discharge seasons is also consistent with the hypothesis that during low flow, with limited terrestrial nutrient availability, non-riverine oceanic processes drive chlorophyll production.

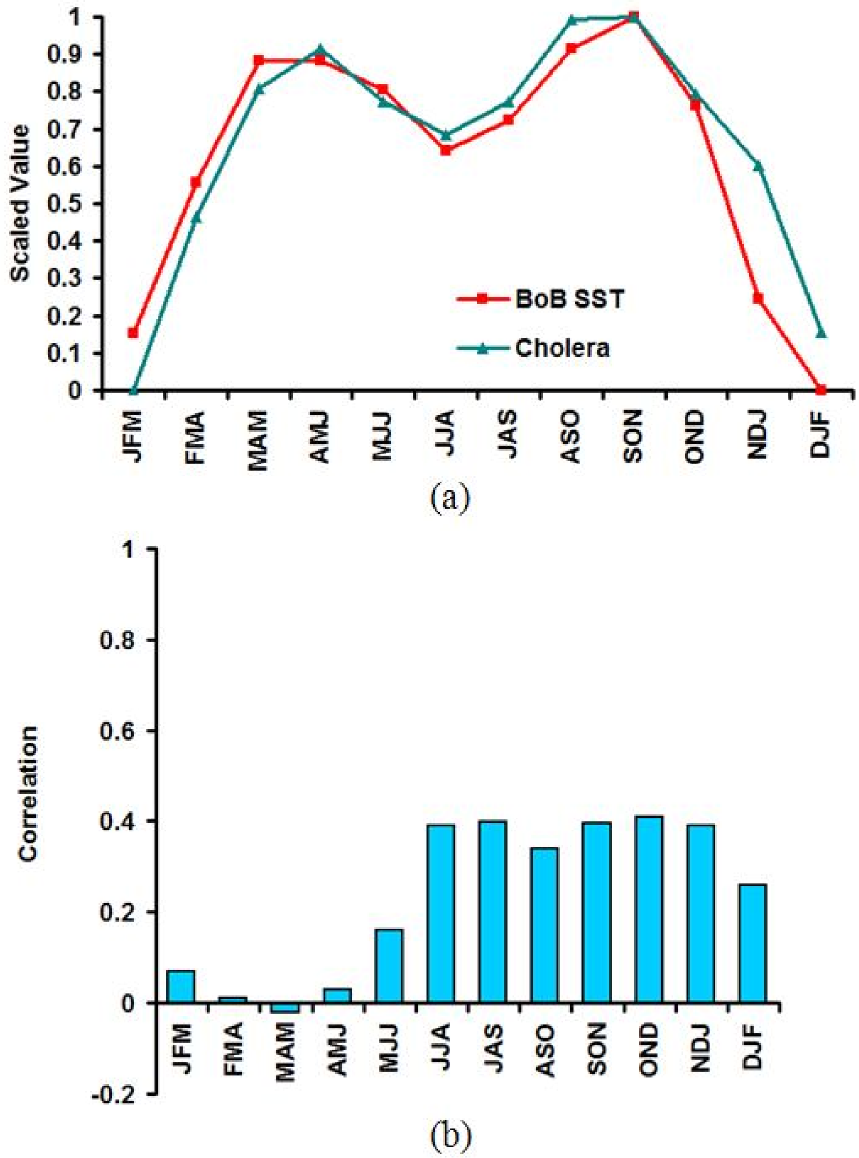


Figure 4.5: (a) Climatology of cholera and coastal Bay of Bengal SST; (b) Seasonal correlation of coastal Bay of Bengal SSTs with concurrent seasonal cholera outbreaks

4.3.3 Lack of a significant relationship between 3-month seasonal SST and cholera incidence

Cholera remains endemic in the Bengal delta with typically two seasonal, spring (March-April-May) and autumn (September-October-November), outbreaks in a given year (Figure 4.5a). The majority of existing studies have suggested a positive association between these cholera outbreaks in Bangladesh and coastal Bay of Bengal SST (Emch et al., 2008; Magny et al., 2008; Colwell, 1996; Bouma and Pascual, 2001). This observation is primarily based on a climatological understanding of SST and cholera incidence (Figure 4.5a), which shows that coastal SST and cholera incidence data both have concurrent bimodal peaks with high climatological correlation ($r=0.88$; $p<0.01$). If cholera outbreaks were causally associated with coastal SST, then we should expect to see a similar strong correlation between the two time series. However, we found the relationship to be weak (Figure 4.5b) with no statistically significant concurrent relationships between the two time series, nor with any evidence of a bimodal distribution among correlation values.

4.4 Discussion and Implications for Cholera Prediction Models

Our results suggest that it is the presence and dominance of high river discharge - not SST -, which may account for the prior reports of a positive association between cholera and SST in the Bay of Bengal. If so, this may have important implications for the understanding of cholera transmission dynamics. If cholera outbreaks were associated with SST then we should observe strong correlations between the time series of cholera incidence and SST in coastal Bay of Bengal; however, no such relationship was found. The absence of a strong correlation is also an indication that cholera is not related with SST for concurrent seasons.

Consistent with our results, an asymmetric role for river discharge as a predictor of cholera outbreaks in the Bengal Delta has recently been reported (Akanda et al., 2009). High and low river discharge conditions may differentially contribute to cholera transmission and outbreaks; for example, during low discharge periods, the population may be forced to ingest water already contaminated with cholera bacteria (Akanda et al., 2009). Our analysis points to a similarly asymmetric influence of SST and chlorophyll for high and low discharge seasons (Figure 4.2). Consequently, any cholera prediction models needs to carefully analyze and account for concurrent as will as lagged relationships among SST, chlorophyll, river discharge and cholera incidences.

The relationship between coastal phytoplankton, SST, and river discharge may be critical to understanding the environmental conditions which lead to cholera epidemics in coastal regions of the Bay of Bengal. Here we show that river discharge in major freshwater basins around the world affect the relationship between ocean temperature and coastal phytoplankton, both temporally and spatially. Using seasonal cross-correlation between SST and chlorophyll time series in the Bay of Bengal, these variables have been shown to be correlated positively during high discharge and negatively during low discharge. Furthermore, the SST and chlorophyll time series for coastal and offshore regions have been compared and shown that the usually observed inverse relationship between SST and chlorophyll, which exists for offshore regions does not hold true for coastal regions of major river basins (Figures 4.2). A plausible explanation for this is that the SST-chlorophyll relationship can be affected by nutrient influx during high river discharge into coastal regions. Our finding of a positive association between chlorophyll and SST during high flow months supports our hypothesis that chlorophyll productions in the coastal regions are dominated by river discharge through the influx of terrestrial nutrients (Acker et al., 2005; Revelante and Gilmartin, 1976; Lohrenz et al., 1990).

Our results are also supported by the data from coastal regions which do not have high freshwater input. Logically, if river discharge were indeed the dominant mechanism of phytoplankton production in the four major freshwater basins we examined; and if the positive SST-chlorophyll relationship during high discharge seasons were to be true; then, it is likely that a negative SST-chlorophyll relationship would be observed in coastal basins without significant terrestrial freshwater input. Indeed, several coastal regions without significant freshwater discharge show a consistently negative correlation between SST and chlorophyll, notably, the California coast (Legaard and Thomas, 2006; Nezlin and Li, 2003), the Arabian Sea (Chaturvedi, 2005) and the Gulf of Cadiz along coastal Spain (Navarro and Ruiz, 2006).

In sum, we believe the observed positive correlation between SST and chlorophyll in the Bay of Bengal and other major freshwater basins globally are primarily caused by terrestrial nutrient inputs from river discharge. An important aspect of our study is that it provides a new and physically meaningful explanation as to why despite higher SST, more phytoplankton are found in the coastal areas where freshwater discharge is high. Our results suggest that the observed positive correlation between SST and chlorophyll in the Bay of Bengal is in fact not causal, and should not form the basis to infer or construct prediction models for cholera outbreaks. Cholera prediction models may benefit from including data on terrestrial nutrient influx and subsequent phytoplankton and zooplankton blooms. These results will provide a mechanistic insight for constructing cholera prediction models based on environmental processes that influence the coastal regions of cholera endemic countries.

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Chapter 5

A framework for predicting cholera outbreaks using satellite derived macro-scale environmental determinants

Abstract

There is growing evidence that outbreaks of several water-related diseases are potentially predictable by using satellite derived macro-scale environmental variables. Cholera remains one of the most prevalent water-related infections in many tropical regions of the world. Macro-environmental processes provide a natural ecological niche for *Vibrio cholerae* and because powerful evidence of new biotypes is emerging, it is highly unlikely that cholera will be fully eradicated. Consequently, to develop effective intervention and mitigation strategies, it is necessary to develop cholera prediction models with several months' lead time. Three observations motivate us to explore the use of satellite data derived macro-scale environmental variables to develop a cholera prediction model: (a) almost all cholera outbreaks originate near the coastal areas; (b) cholera bacteria exhibit a strong relationship with coastal plankton; and (c) cholera bacteria cannot be measured easily and regularly over large areas. Using chlorophyll as a surrogate for plankton bloom in coastal areas, recent studies have postulated a relationship between chlorophyll and cholera incidence. Here, we show that seasonal cholera outbreaks in the Bengal Delta can be predicted two to three months in advance with an overall prediction accuracy of over 75% by using satellite-derived chlorophyll and air temperature data. Such high prediction accuracy is achievable because the two seasonal peaks of cholera are predicted

using two separate models representing distinctive macro-scale environmental processes. We have shown that interannual variability of pre-monsoon cholera outbreaks can be satisfactorily explained with coastal plankton blooms and a cascade of hydro-coastal processes. Post-monsoon cholera outbreaks, on the other hand, are related to macro-scale monsoon processes and subsequent breakdown of sanitary conditions. Our results demonstrate that satellite data over a range of space and time scales are effective in developing a cholera prediction model for the Bengal Delta with several months' lead time. We anticipate our modeling framework and findings will provide the impetus to explore the utility of satellite derived macro-scale variables for cholera prediction in other cholera prone regions.

Jutla, A.S., Akanda, A.S. and Islam, S. 2011 Predicting cholera outbreaks using satellite derived macro-scale environmental determinants. (Submitted, *Environmental Modeling and Software*).

5.1 Context, motivation for, and objectives of this study

Cholera, an acute water-borne diarrheal disease, continues to be a significant global health threat. The ongoing seventh pandemic of cholera, which started in 1960s, has been reported in over 50 countries and has affected more than 7 million people (Gleick, 2008). The disease remains one of most prevalent water-borne infections in many tropical regions of the world, specifically in coastal areas of South Asia, Africa, and Latin America. The life cycle of the bacterium *V. cholerae*, the causative agent for cholera outbreaks, is intricately linked to two different processes: *micro*- and *macro*-environmental processes, which have vastly different spatial and temporal scales of interacting variables. Here, we define *micro* as microbiological, genetic, and human intestinal processes and related variables, while *macro* refers to hydrological, ecological, climatic, and coastal processes and their related variables. Despite steady accumulation of detailed knowledge of *V. cholerae* in these two environments, our ability to adequately predict when and where the next cholera epidemic will strike remains limited. We recognize the importance of micro-environmental processes in understanding cholera dynamics in order to develop effective vaccines and treatment protocols. However, since *V. cholerae* may thrive in a wide range of natural environmental conditions, and since evidence of new biotypes is emerging (Siddique et al., 1994**)**, it is unlikely that this disease will be defeated by medicine alone. Rather, we need a new approach—an early cholera warning system with several months' lead time—to minimize the impact of this devastating disease by predicting where and when it will occur and then initiating effective intervention strategies. Thus, our approach attempts to identify appropriate macro-environmental processes and variables that are expected to have sufficient temporal and spatial “memory” to allow the development of an early cholera warning system.

Cholera outbreaks in the Bengal Delta show two seasonal peaks: one in spring (defined as the average cholera incidence in March-April-May months) and another in autumn (defined as the average cholera incidence in September-October-November months) (Jutla et al., 2010). Cholera outbreaks have been associated with a wide range of environmental variables, such as sea surface temperature (SST) (Lobitz et al. 2000; Cash et al. 2008), sea surface height (Lobitz et al., 2000), monsoon precipitation (Hashizume et al. 2008), coastal plankton (Magny et al. 2008; Emch et al. 2008; Lobitz et al., 2000; Tamplin et al., 1990), air and water temperature (Islam et al. 2009; Huq et al. 2005), and coastal salinity (Miller et al., 1982). Because of the presence and survival of cholera bacteria in marine environments, relationship between coastal plankton and cholera has also been explored (Griffiths et al. 1994; Huq and Colwell, 1996; Colwell, 1996, Lobitz et al., 2000; Tamplin et al., 1990; Islam et al 1999; Worden et al., 2006; Alam et al 2006; Emch et al., 2008; Jutla et al. 2010).

Our recent studies have established that biannual peaks of cholera incidence in Bengal Delta are influenced by two separate macro-environmental processes (Akanda et al., 2009, 2011). Existence of such processes for cholera and three other complementary observations motivate us to explore utility of a satellite derived macro-environmental variables to develop a cholera prediction model: (i) almost all cholera outbreaks originate near the coastal areas, including the reemergence of cholera in Latin America in 1991 (Jutla et al., 2010, Magny et al. 2008; Emch et al. 2008; Lobitz et al., 2000; Tamplin et al., 1990); (ii) laboratory studies suggest a significant positive correlation between plankton abundance and pathogenic cholera bacteria (Colwell and Spira, 1992; Huq et al. 1990; Tamplin et al. 1990); and (iii) remote sensing provides unprecedented coverage of space-time measurements of plankton in coastal regions around the world (Uz and Yoder, 2004; Jutla et al. 2011). The overall objective of the present study is to develop a cholera prediction model using remote sensing information and limited ancillary data with two to three months' prediction lead time; and suggest a plausible pathway through which the variables used for development of the cholera prediction model may provide an explanation for an environment conducive to cholera outbreak and transmission. This chapter is organized as follows: Section 5.2 provides examples of the utility of satellite derived macro-environmental determinants in predicting several water related diseases. Section 5.3 provides an overview of existing cholera prediction models, and Section 5.4 describes major data sources used in this study. Section 5.5 provides rationale for chosen macro-environmental variables to develop cholera prediction models, whereas Section 5.6 presents key findings. Discussion of the results and concluding remarks are provided in Section 5.7.

5.2 Satellite derived variables for prediction of water-related diseases

With increased availability of newer types of sensors and remote sensing data, the opportunity to employ satellite derived data to predict water related diseases has enhanced significantly. Outbreaks of several water related diseases such as Malaria (Hay et al., 1998; Adimi et al., 2010; Elipe et al., 2007), Rift Valley Fever (Linthicum et al 1999), Cholera (Magny et al., 2008), Cryptosporidium (Jagai et al., 2009) and Schistosomiasis (Malone et al., 2001) has been predicted through macro-environmental determinants using latest advances in satellite remote sensing. Appropriate spatial and temporal scale variability in the natural habitats, responsible for outbreaks of several water-related diseases, can be detected using satellite remote sensing data. Hay et al (1998) developed a remote sensing based regression model to predict malaria outbreaks in Kenya using Normalized Density Vegetation Index (NDVI) from AVHRR at 8 km resolution as a surrogate for mosquito habitat and larvae growth. The authors reported an adjusted r^2 of 0.71 (range 0.61-0.79) between one month lagged NDVI and mean monthly annual malaria admissions for three study sites in Kenya. Recently, Elipe et al (2007) predicted malaria outbreaks in the Burundi highlands, also using NDVI (8km resolution). Using an autoregressive integrated moving average method, their model predicted malaria outbreaks with a predicted r^2 of 93%. A more recent study by Adimi et al (2010) involving twenty three provinces in Afghanistan suggested that precipitation, air temperature and NDVI can be used to predict malaria outbreaks atleast a month in advance with overall predicted accuracy of as high as 95% for some provinces. Also, using satellite derived NDVI and SST, Linthicum et al (1999) predicted Rift Valley Fever in Kenya for two to five months in advance. Using 16 years of NDVI (8 km resolution) data from Kenya, Linthicum et al (1999) developed an auto-regressive model incorporating SSTs and two month lagged NDVI and reported very high accuracy for predicting Rift valley fever outbreaks in Kenya.

5.3 Current state of knowledge for predicting cholera outbreaks

Efforts to develop prediction models for cholera outbreaks probably started with Roger (1958), who suggested that absolute humidity (quantity of water in a particular volume of air) might be used to demarcate regions of epidemic and endemic cholera outbreaks. Lobitz et al. (2000) were perhaps the first to use remote sensing data to explore a possible connection between SST, phytoplankton, and cholera incidence by using 16 months' of satellite data from one pixel in the Bay of Bengal. Table 3 shows three key studies that have attempted to develop cholera incidence models using micro- and macro-environmental variables.

Table 3: Available cholera prediction models

S. No	Author	Model Type	Variables	Scale (spatial , temporal)
1	Magny et al. (2008)	Regression-based	Previous season cholera incidence, chlorophyll, precipitation, SST	Monthly, regional (two cities)
2	Pascual et al. (2008)	Semi-mechanistic	Population, biological variables (immunity levels, susceptibility rates), ENSO	District level, monthly
3	Matsuda et al. (2008)	Regression-based	rainfall, air temperature	Monthly, prediction of cholera for children, district level

Magny et al. (2008) and Emch et al. (2008) used the plankton data from the coastal Bay of Bengal region to explore the relationship between plankton and cholera outbreaks. Magny et al. (2008) associated cholera incidence time series with coastal chlorophyll data and reported that one month's lag existed between cholera incidence and coastal plankton, but they did not elaborate on the strength of the relationship or the plausible physical mechanism for such an association. A closer look at the regressive structure of Magny et al (2008) reveals that the persistent effects of the previous season's cholera incidence is far more important than the environmental variables used to construct the model. In other words, their model essentially resembles a moving average model (Table 1 in Magny et al., 2008). Using the same data, Emch et al. (2008) reported that there is a strong two-month lag between coastal chlorophyll and cholera incidence in Bangladesh. Part of the reason for disparity in the results of Magny et al. (2008) and Emch et al. (2008) can be attributed to the choice of spatial and temporal scales of plankton data. Our study indicates that there is significant spatial variability of plankton in the Bay of Bengal; consequently, substantial spatial averaging is required before plankton data can be used to establish a cholera-chlorophyll relationship (Jutla et al., 2010). Magny et al. (2008) and Emch et al. (2008) also did not elaborate on the lag in the relationship between coastal chlorophyll and cholera incidence as well as assumed that chlorophyll, SST, and rainfall affect the disease outbreaks throughout a given year

Pascual et al. (2008) presented a semi-mechanistic model for simulating endemic cholera in the Bengal Delta. Their complex model structure involves biological variables such as disease rates and immunity levels, which are not easy to measure. In addition, Pascual et al. (2008) reported a strong correlation between cholera incidence and ENSO for three summer months only—June, July, and August —which are the three lowest cholera incidence months. While predicting the cholera outbreaks using ENSO, Pascual et al. (2008) suggested that the model failed to predict cholera outbreaks in two of five strong El Niño events. Matsuda et al. (2008) developed a regression model based on the cholera incidence time series in children who were less than 10 years old using precipitation and air temperature in Bangladesh. The authors indicated that their model cannot be generalized to the entire population; they also did not elaborate as to why precipitation and air temperature should be used as predictor variables for outbreaks of cholera.

Our analysis of existing cholera models (*Emch et al., 2008; Pascual et al., 2008; Magny et al., 2008*) thus suggest that they are not adequate to predict cholera outbreaks in the Bengal Delta with several months lead time partly because they (i) do not capture the asymmetric hydro-climatic influence on two distinctive cholera outbreaks since all three studies were performed in a controlled population (cholera incidences from a small coastal town in Bangladesh); (ii) include variables, such as immunity levels of population, which are not easily quantifiable over regional scales; and (iii) have not paid particular attention to significant space-time variability of plankton. With the availability of longer datasets, such as over 10 years of chlorophyll data from ocean satellites, as well as growing evidence of macro-environmental controls on cholera transmission, it is now possible to closely study the relationships of cholera outbreaks with satellite derived macro-environmental variables. This study will identify a set of macro-environmental variables with appropriate space-time resolution that will provide adequate lead-time for predicting the two seasonal cholera outbreaks in the Bengal Delta.

5.4 Data

Figure 5.1a shows the study region in South Asia (Bangladesh) vulnerable to cholera outbreaks. Daily discharge data from the Ganges and Brahmaputra rivers were obtained from the Bangladesh University of Engineering and Technology. To determine the total discharge into the Bay of Bengal, discharge data for the two rivers were added to obtain a combined monthly discharge time series. Cholera incidence data from Bangladesh are perhaps one of the longest datasets available (Longini et al. 2002). Cholera incidence data were acquired from surveillance bulletins maintained by the International Centre for Diarrheal Disease Research, Bangladesh. Incidence is recorded as the percent of new cholera infected patients among a statistical subset of patients selected from a total pool of patients visiting the hospital for treatment during a given week (Longini et al. 2002).

For this study, the coastal water zone of the Bay of Bengal is defined as the region between 20-22.5°N and 89-93°E, based on bathymetry data (Jutla et al., 2009). We have used Sea-viewing Wide Field-of-view Sensor (SeaWiFS) monthly chlorophyll data at 9-km resolution, obtained from NASA/Goddard Earth Sciences/Distributed Active Archive Center for an eleven-year period (1997-2008). More-detailed description about these products, sensors, estimation algorithms, and accuracy are available elsewhere (Martin, 2004; Uz and Yoder, 2004). The initial validation results demonstrate that the SeaWiFS sensor has been reasonably stable over the years of operation, the calibration approach provided consistent global water-leaving radiances, and the products met the accuracy goals over a diverse set of open-ocean validation sites (McClain et al., 1998; O'Reilly et al., 2000; Gregg and Casey, 2004). The accuracy of SeaWiFS chlorophyll data is likely to be affected by turbidity, sediments, and organic and inorganic matter from river discharges in coastal regions (Martin, 2004). NASA's OC4v4 chlorophyll algorithm is designed to account for these errors (Martin, 2004; O'Reilly et al., 2000). Gregg and Casey (2004) validated the SeaWiFS data, both for open-ocean and coastal waters and have reported correlation values to be 0.71 and 0.60, respectively, when compared with *in situ* data. Laboratory studies indicate a strong association of cholera bacteria with plankton (Huq et al. 1990; Tamplin et al. 1990*)*; consequently, we have chosen to use chlorophyll, a surrogate for plankton abundance, as a primary remotely sensed variable to develop cholera-prediction models.

5.5 Selection of macro-environmental variables

Our working hypothesis, supported by several recent studies, is that spring cholera outbreaks in the Bengal delta are primarily coastal in nature and are caused by the intrusion of coastal plankton and saltwater from the Bay of Bengal aided by low river discharge during the dry season (Akanda et al., 2011; Magny et al. 2008; Emch et al. 2008; Lobitz et al., 2000; Tamplin et al., 1990; Sack et al., 2003) We thus expect coastal plankton to be a major predictor variable for the spring occurrence of cholera. Because coastal plankton cannot be measured from satellites, we have used chlorophyll measurements as a surrogate for plankton abundance. Figure 5.2b shows the two seasonal peaks in cholera outbreaks for the Bengal region; the spring (March-April-May) season and the autumn (September-October-November) season. Peak river discharge occurs during summer (July-August-September) season, whereas the lowest discharge is observed in early spring (February-March-April) season. Chlorophyll has a single peak with seasonal maxima observed in autumn season. Figure 5.2a shows cross-correlation between seasonal chlorophyll concentration in the Bay of Bengal coastal zone (region between 20-22.5°N and 89-93°E) and spring cholera. Chlorophyll values in autumn show the highest correlation with next year's spring cholera incidence ($r = 0.83$; $p < 0.05$). This high correlation between autumn chlorophyll and spring cholera is encouraging as: (i) it supports the hypothesis of a coastal connection of spring cholera outbreaks; (ii) the highest chlorophyll concentration and variability is observed in the autumn season in the coastal Bay of Bengal region and (iii) provide several months' lead time for predicting spring cholera incidence.

In addition, low river discharge during dry season (February-March-April) and spring cholera incidence have a negative correlation ($r = -0.65$; $p < 0.01$), implying that higher dry-season discharge will lead to less plankton intrusion and subsequently, less cholera (Akanda et al., 2009). Currently, river discharge in the Ganges-Brahmaputra-Meghna (GBM) basin cannot be measured using remote sensing data. Consequently, we have used NCEP-NCAR air temperature during early winter months at the foothills of the Himalayas (27°-32°N; 77°-81°E), where these rivers originate, as a surrogate for low river discharge. Our working hypothesis is that higher air temperature in the Himalayan foothills during early winter (October-November-December) leads to more precipitation as rainfall, and consequently more discharge is likely (Rees and Collins, 2006; Dery et al. 2009) during low discharge season. Jian et al. (2009) reported a travel time of

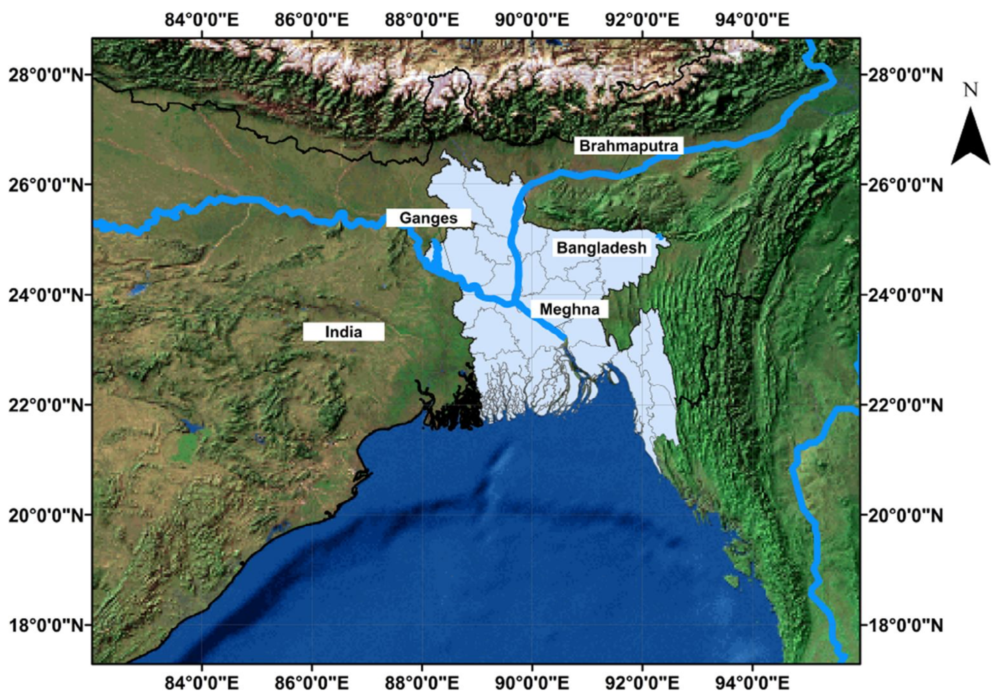

Figure 5.1a: Location of Bangladesh, Ganges, and Brahmaputra Rivers and the coastal zone.

about a month for the Ganges water to reach Bangladesh from its origin in the Himalayan foothills. Consequently, we expect to observe increased flow at the downstream of GBM outlet region during the low discharge season (correlation between early winter air temperature and low river discharge is 0.65; $p<0.01$). Figure 5.2b shows seasonal correlation between air temperature and spring cholera incidence; highest negative correlation is observed between early winter air temperature and spring cholera outbreaks ($r = -0.72$; $p < 0.05$). The presence of this negative relationship between spring cholera incidence and early winter air temperature can thus be used as a possible predictor variable for modeling spring cholera incidence.

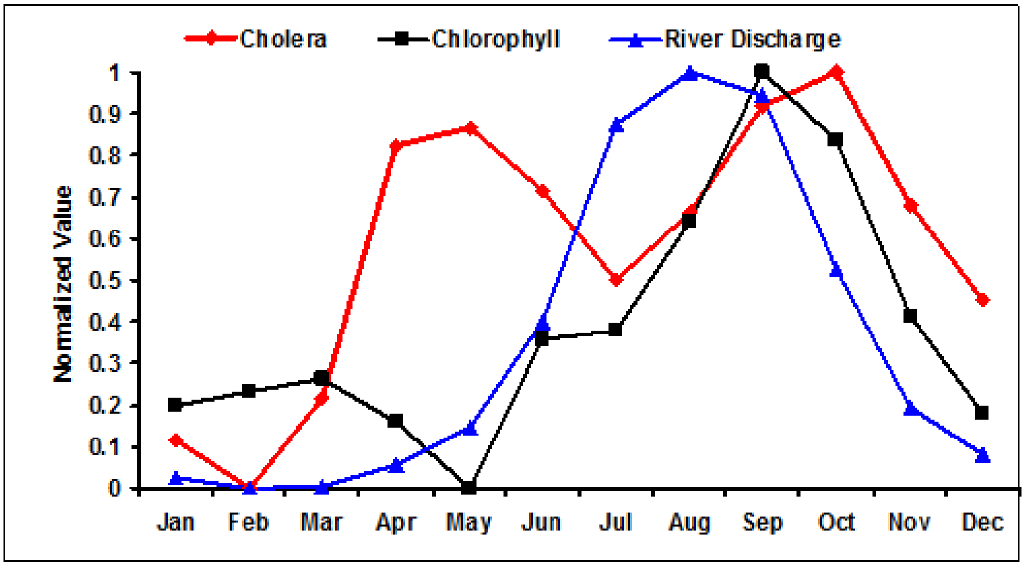

Figure 5.1b. Annual climatology of cholera, chlorophyll, and river discharge. The normalized data represent the scaled values from 0 to 1.

5.6 Results

5.6.1 Spring cholera incidence

We begin with a set of multiple regression models using relationships between predictand (spring cholera incidence) and two independent predictor variables [chlorophyll (Chl) and air temperature (AT)]. A key objective is to provide statistical prediction with one, two, and three months' lead time for predicting spring cholera outbreaks. We recognize that—given the statistical basis of the framework, length of available dataset, and uncertainty of measured data—we are not likely to have a single evaluation metric that will allow us to choose a particular model. Consequently, we select a model as robust, when it performs better than all competing models in at least six out of nine evaluation metrics in Table 4.

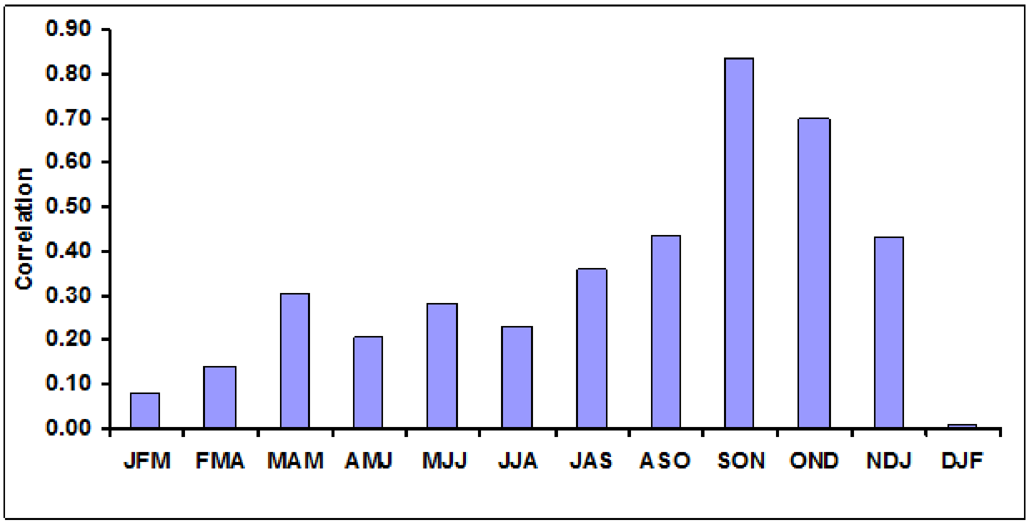

Figure 5.2a. Cross-correlation between spring cholera incidence and seasonal chlorophyll in the Bay of Bengal.

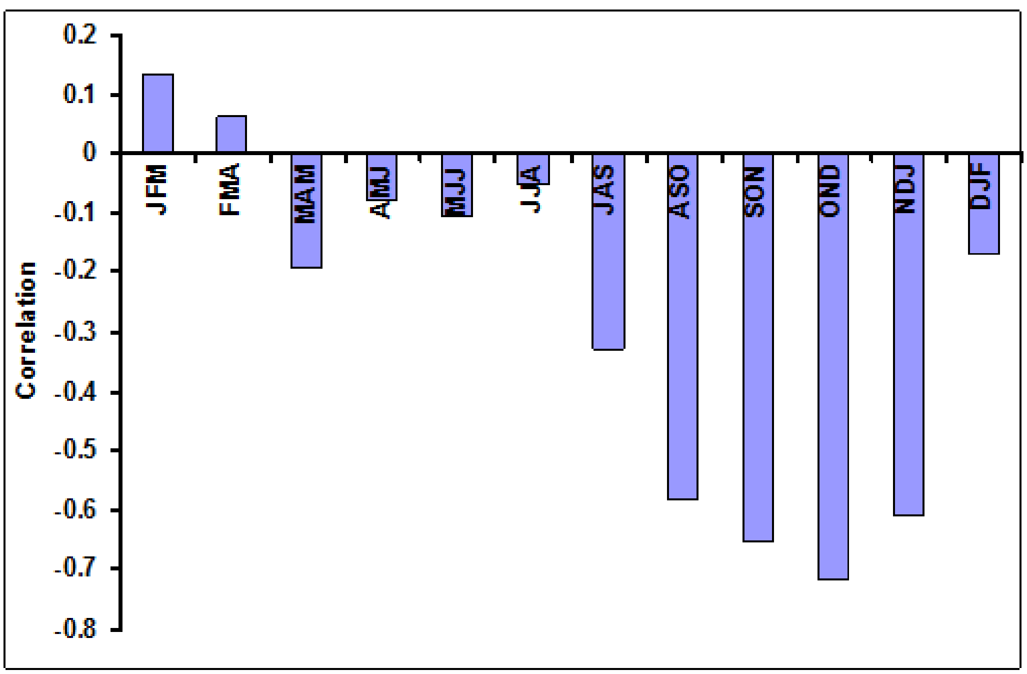

Figure 5.2b. Cross-correlation between spring cholera incidence in Bengal Delta and seasonal Himalayan air temperature.

Table 4. Model performance indicators

	Formula and meaning
Mean Absolute Error (MAE)	$=\frac{1}{n}\sum_{1}^{n}\lvert y_o - y_p \rvert$ Measures how close predictions are to observations. MAE close to zero implies perfect prediction model.
Root Mean Square Error (RMSE)	$=\sqrt{\frac{\sum_{1}^{n}\left(y_o - y_p\right)^2}{n}}$ Quantifies difference between predicted and the observed value. If RMSE is close to the average of the observations, then the prediction results are no better than the mean of the observations.
Bias	$=\frac{1}{n}\sum_{1}^{n} y_o - y_p$ Indicates whether there is a bias (positive: underprediction; negative: overprediction) between predicted and observed values.
Nash-Sutcliffe Efficiency (NSE)	$=1-\frac{\sum_{1}^{n}\left(y_o - y_p\right)^2}{\sum_{1}^{n}\left(y_o - \overline{y_o}\right)^2}$ Indicates predictive power of the model. The range of Nash–Sutcliffe efficiencies can range be from $-\infty$ to 1. NSE = 1 indicates perfect match of modeled to the observed data. NSE = 0 indicates that the model predictions are as accurate as the mean of the observed data. NSE < 0 suggests that the observed mean is a better predictor

	than the model.
Prediction Sum of Squares (PRESS)	Assesses model's predictive ability. PRESS, similar to the sum of squares error (SSE), is the sum of squares of the prediction error. PRESS differs from SSE in that each fitted value, y_{pi}, for PRESS is obtained by excluding the ith observation from the data set, then estimating the regression equation from the remaining n - 1 observations, then using the fitted regression function to obtain the predicted value for the ith observation (Minitab, 2009).
Adjusted r^2	$=1-\left[\frac{(1-R^2)(n-1)}{n-P-1}\right]$ A version of R^2, which has been adjusted to take into account the number of predictors (P) used in the model.
Predicted r^2	Similar to adjusted r^2, but calculated by removing each observations from the dataset, then estimating the regression equation, and then estimating adjusted R^2 for each removed observation scenario (Minitab, 2009). A predicted r^2 of 0.80 implies that the model can predict with 80% accuracy.
Note: y_o, y_p are observed and predicted values, respectively; n is the number of observations.	

5.6.1.1 Three-month prediction lead time model (3MX)

For a prediction lead time of three months for spring cholera incidence, four models (3M1, 3M2, 3M3, 3M4) using a combination of autumn chlorophyll and autumn air temperature are evaluated and the performance of the models is shown in Table 5. Mean observed spring cholera incidence for the last 11 years in the Bengal Delta is 21.83 ± 8.33. Using only autumn chlorophyll, model 3M1, we can achieve a prediction r^2 of 0.58, which implies that autumn chlorophyll has about 58% prediction power for predicting spring cholera incidence. Table 5 shows the nine model evaluation metrics for model 3M1. The Nash-Sutcliffe efficiency of model 3M1 is 0.71, which implies that the model is about 71% efficient in predicting spring cholera incidence. Model 3M2 uses only autumn air temperature and has a predicted r^2 of 0.40. However, when we combine autumn chlorophyll and autumn air temperature, model 3M3 shows significantly improved prediction power, achieving a predicted r^2 of 0.70, as well as better performance indicators than 3M1 and 3M2. On a closer look at the coefficients of the model 3M3 (Table 6), we observe that air temperature coefficient shows a negative sign, whereas the chlorophyll coefficient is positive. Although 3M3 has high prediction r^2, however, there is about 11% difference between predicted and observed r^2. In order to minimize the difference in r^2 as well as to increase the degrees of freedom, we developed another model using a ratio of autumn chlorophyll and autumn air temperature as a predictor (Model 3M4), which outperforms all preceding models, while minimizing the difference between predicted and observed r^2 (Table 5).

Table 5: Model performance indicators for predicting spring cholera incidence

Model	Parameters	Average	Std.	MAE	RMSE	Bias	NSE	PRESS	r^2 (Adj)	r^2 (Pred)
M0	Observed	21.83	8.33	x	x	x	x	x	x	x
3M1	Chl(SON)	21.86	7.00	3.50	4.32	-0.47	0.71	278	0.67	0.58
3M2	AT(SON)	21.84	7.11	3.20	4.14	0.89	0.73	271	0.60	0.40
3M3	Chl(SON), AT(SON)	21.75	7.70	2.70	3.89	-0.27	0.85	207	0.81	0.70
3M4	***CHL (SON)/AT(SON)***	***21.84***	***7.50***	***2.93***	***3.47***	***-0.02***	***0.85***	***160***	0.***82***	0.***78***
2M1	Chl(OND)	21.70	6.43	4.56	5.05	-1.01	0.60	412	0.55	0.40
2M2	AT(OND)	20.58	7.31	2.82	3.81	0.60	0.77	232	0.74	0.66
2M3	Chl(OND), AT(OND)	21.78	7.50	3.03	3.46	-0.90	0.81	251	0.76	0.63
2M4	Chl(SON), AT(OND)	21.58	7.63	2.86	3.21	0.41	0.84	231	0.79	0.66
2M5	Chl(OND), AT(SON)	21.58	7.55	2.99	3.37	1.35	0.82	249	0.75	0.64
2M6	***CHL (SON)/AT(OND)***	***21.83***	***7.99***	***1.94***	***2.34***	***0.17***	***0.87***	***120***	0.***85***	0.***82***
2M7	Chl (OND)/AT(OND)	21.81	7.46	3.24	3.54	-1.00	0.80	190	0.78	0.73
2M8	Chl (OND)/AT(SON)	21.25	7.29	3.39	3.85	-1.32	0.77	240	0.73	0.65
1M1	Chl(NDJ)	21.08	5.16	5.42	6.24	-0.76	0.38	623.00	0.31	0.10
1M2	AT(NDJ)	20.62	3.47	5.67	7.22	0.61	0.17	719.00	0.08	0.02
1M3	Chl(NDJ), AT(NDJ)	**20.83**	5.44	5.23	6.02	**0.40**	0.43	832.00	0.28	0.06
1M4	Chl(OND), AT(NDJ)	21.10	6.56	4.24	4.89	-0.91	0.62	539.00	0.52	0.33
1M5	*Chl(SON), AT(NDJ)*	*20.69*	***7.02***	***3.41***	***4.28***	*-0.43*	***0.71***	***332.00***	***0.63***	***0.50***
1M6	Chl(NDJ), AT(OND)	20.49	5.96	4.74	5.55	-0.62	0.51	823.00	0.38	0.03
1M7	Chl(NDJ), AT(SON)	21.60	6.40	4.30	5.09	-0.48	0.59	589.00	0.48	0.15

Note: **Boldface** shows best indicator value in the three-, two-, and one-month prediction lead time. *Italics* indicate selected model based on highest number of model performance indicators.
Autumn season (SON-September-October-November); Early Winter season (OND: October-November-December); Winter season (NDJ: November-December-January); Spring season (MAM: March-April-May); AT: Air temperature; Chol: Cholera incidence; Chl: Chlorophyll
MAE: Mean Absolute Error; RMSE: Root Mean Square Error; NSE: Nash Sutcliffe's Efficiency; PRESS: Prediction Sum of Squares. Std: Standard Deviation.

Table 6: Estimated model parameters for predicting spring cholera incidence

Model	Parameters	α (constant)	*p*-value (α)	β Chl	*p*-value (β)	β1 Chl/AT	*p*-value (β1)	γ (AT)	*p*-value (γ)	Range of Validity of Model			
3M1	Chl(SON)	-16.10	0.020	19.50	0.001	x	x	x	x	Chl >	0.83		
3M2	AT(SON)	153.00	0.001	x	x	x	x	-8.88	0.001	AT <	17.23		
3M3	Chl(SON), AT(SON)	80.98	0.001	11.20	0.001	x	x	-5.47	0.050	Chl >	0.49	AT -	7.23
3M4	**CHL (SON)/ AT(SON)**	**-10.70**	**0.030**	**x**	**x**	**245.00**	**0.001**	**x**	**x**	**Chl/AT>**	**0.04**		
2M1	Chl(OND)	-25.50	0.080	26.50	0.001	x	x	x	x	Chl >	0.96		
2M2	AT(OND)	91.00	0.001	x	x	x	x	-6.36	0.001	AT <	14.31		
2M3	Chl(OND), AT(OND)	56.70	0.010	9.95	*	x	x	-4.84	0.001	Chl >	0.49	AT +	5.70
2M4	Chl(SON), AT(OND)	48.30	*	9.37	*	x	x	-4.11	0.001	Chl >	0.44	AT +	5.15
2M5	Chl(OND), AT(SON)	91.30	0.001	13.33	0.001	x	x	-6.33	0.040	Chl >	0.47	AT -	6.85
2M6	**CHL (SON)/ AT(OND)**	**-3.54**	**0.001**	**x**	**x**	**138.00**	**0.001**	**x**	**x**	**Chl/AT>**	**0.03**		
2M7	Chl (OND)/ AT(OND)	-9.04	*	x	x	183.00	0.001	x	x	Chl/AT>	0.05		
2M8	Chl (OND)/ AT(SON)	-19.00	0.020	x	x	335.00	0.001	x	x	Chl/AT>	0.06		
1M1	Chl(NDJ)	-30.30	*	31.90	0.04	x	x	x	x	Chl >	0.95		
1M2	AT(NDJ)	60.50	*	x	x	x	x	-4.92	*	AT <	12.30		
1M3	Chl(NDJ), AT(NDJ)	-2.90	*	27.73	*	x	x	-2.62	*	Chl >	0.09	AT +	-0.10
1M4	Chl(OND), AT(NDJ)	-6.52	*	24.49	0.02	x	x	-1.96	*	Chl >	0.08	AT +	-0.27
1M5	Chl(SON), AT(NDJ)	-7.18	*	18.72	0.01	x	x	-0.93	*	Chl >	0.05	AT +	-0.38
1M6	Chl(NDJ), AT(OND)	35.48	*	19.33	*	x	x	-4.09	*	Chl >	0.21	AT +	1.84
1M7	Chl(NDJ), AT(SON	89.90	*	18.68	*	x	x	-6.61	*	Chl >	0.35	AT +	4.81

*Indicates *p*-value greater than 0.05.
Autumn season (SON-September-October-November); Early winter season (OND: October-November-December); Winter season (NDJ: November-December-January); Spring season (MAM: March-April-May); AT: Air temperature; Chol: Cholera incidence; Chl: Chlorophyll

Table 7: Model performance indicators for predicting autumn cholera incidence

Model	Parameters	Average	Std.	MAE	RMSE	Bias	NSE	PRESS	r^2 (Adj)	r^2 (Pred)
N0	Observed	21.42	9.43	x	x	x	x	x	x	x
N1	**MAM (Observed Chol)**	**21.43**	**7.60**	**4.47**	**5.47**	**0.95**	**0.65**	**900.00**	**0.64**	**0.57**
N2	Chol (MAM), FAA	21.12	8.05	3.72	4.81	-0.55	0.73	700.00	0.70	0.63
N3	***Chol (MAM), SST (JJA)***	***21.41***	***8.25***	***3.59***	***4.47***	***0.29***	***0.77***	***685.00***	***0.78***	***0.72***
N4	Chol (MAM), SST (JJA), FAA	20.41	8.19	3.84	4.58	0.36	0.75	791.00	0.75	0.68
N5	FAA	19.15	3.88	6.43	8.42	0.58	0.17	2049.00	0.13	0.04
N6	SST (JJA)	18.99	4.11	6.39	8.31	-0.48	0.19	2033.00	0.15	0.05
N7	SST (JJA), FAA	20.14	4.47	6.28	8.13	-0.25	0.22	2140.00	0.15	0.10

Spring season (MAM: March-April-May); Summer season (JJA: June-July-August); FAA: Flood Affected Areas; SST: Sea Surface Temperature: Chol: Cholera incidence; Chl: Chlorophyll

MAE: Mean Absolute Error; RMSE: Root Mean Square Error; NSE: Nash Sutcliffe's Efficiency; PRESS: Prediction Sum of Squares. Std: Standard Deviation.

Table 8: Estimated model parameters for predicting autumn cholera incidence

Model	Parameters	α (constant)	p-value (α)	β	*p*-value (β)	β1	*p*-value (β1)	γ	*p*-value (γ)	Range of validity of model
N1	Chol (MAM)	6.96	0.010	Chol 0.84	0.001					V
N2	Chol(MAM), FAA	4.93	0.050	Chol 6.73	0.001	FAA 0.0005	0.020			V
N3	**Chol (MAM), SST (JJA)**	**-272**	**0.007**	**Chol** 0.79	**0.001**	**SST** 10.42	**0.006**			**SST> 26.10-0.08 Chol**
N4	Chol (MAM), SST (JJA), FAA	-202	0.020	Chol 0.78	0.050	SST 7.77	*	FAA 0.0004	*	SST> 0.07 Chol + 2.6 × 10^{-5} FAA + 29
N5	FAA	17.3	*	FAA 0.0002	0.040					V
N6	SST (JJA)	-352	*	SST 13.9	0.029					SST> 25.29
N7	SST (JJA), FAA	-233	*	SST 9.31	*	FAA 0.0002	*			SST> 2.4 × 10^{-5} FAA + 30

*Indicates *p*-value greater than 0.05.
V denotes the value of predicted cholera outbreaks in spring can never reach below zero because of the parameter values.
Spring season (MAM: March-April-May); Summer season (JJA: June-July-August); FAA: Flood Affected Areas; SST: Sea Surface Temperature: Chol: Cholera incidence; Chl: Chlorophyll

5.6.1.2 Two- and one-month prediction lead-time model (2MX, 1MX)

Similar to section 6.1.1, we evaluated eight models, using several combinations of chlorophyll and air temperature, which may provide a prediction lead time of two months for spring cholera incidence. Of the eight models (Table 5), model 2M6, which uses a ratio of autumn chlorophyll and early winter air temperature, performed better in all performance indicators than did the rest of the models. Model 2M6 can predict spring cholera with prediction r^2 of 0.82; however, the model is valid only when the ratio of chlorophyll and air temperature is greater than 0.03 in the coastal Bay of Bengal region. Out of eight models in 2MX series, model 2M6 appears to be the most useful for predicting spring incidence at two months' lead time.

We have evaluated seven models, using different combinations of seasonal chlorophyll and air temperature, with one month prediction lead-time (Table 5: Models 1MX series). Based on our defined criteria for model selection, Table 5 indicates that model 1M5 has limited predictive abilities, compared to two and three month lead time models discussed before, with a predicted r^2 of 0.53 and an NSE of 0.71. In addition, a closer look at the model parameters (Table 6) shows that the prediction skill of model 1M5 is primarily coming from autumn chlorophyll and not from air temperature since the model coefficient for AT (γ - 0.93) is not statistically significant. This somewhat counterintuitive prediction accuracy for shorter lead time models is discussed in the following section.

5.6.1.3 Comparison of three-, two-, and one-month prediction models

On the basis of our chosen set of nine evaluation metrics and selection criteria, the best prediction of spring cholera incidence is achieved with a two-month prediction lead time using a ratio of autumn chlorophyll and air temperature. We compared models 3M4 and 2M6 and observed that all nine performance metrics are better in 2M6 than in 3M4. Figure 5.3 shows comparison of predicted and observed spring cholera incidence using 3M4 and 2M6 models. Both models are capable of predicting both high (1998, 2005) and low (2002, 2008) spring cholera incidence.

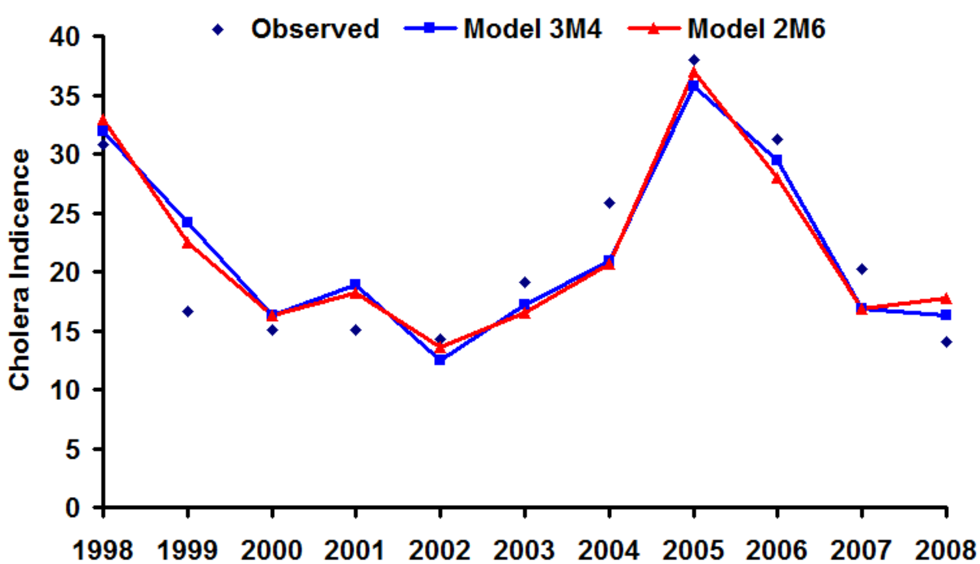

Figure 5.3. Spring observed and predicted cholera incidence using the 3M4 and 2M6 models.

Typically, one expects to see shorter lead time (e.g., one-month) prediction models to outperform longer lead time (e.g., two- and three-month) prediction models. However, based on nine chosen metrics, our one-month prediction lead-time models appear to perform worse. This prompts us to question the statistical nature of relationships among variables and to focus further on the transmission pathways of cholera: the seasonality and internal dynamics of phytoplankton and the resulting bacterial growth in coastal Bay of Bengal (detailed discussion in Section 7).

5.6.2 Autumn cholera outbreaks

Our proposed modeling framework explicitly recognizes the biannual cholera outbreaks in the Bengal Delta region and their underlying macro-environmental controls to develop separate prediction models for each peak (Akanda et al. 2011). Autumn cholera in the Bengal Delta is attributed to widespread flooding in upstream regions of Bangladesh through monsoon discharge in the GBM Rivers (Akanda et al., 2009). The current generation of remote sensing products cannot reliably estimate river discharge at the spatial and temporal scale we desire for cholera prediction. However, a high correlation is observed between spring and autumn cholera incidence (r = 0.82; p <0.05). This correlation breaks down from preceding autumn cholera to next year's spring cholera incidence (r = 0.38), suggesting a one-way spring-to-autumn relationship (not autumn to spring) between the seasonal outbreaks (Akanda et al. 2011). Therefore, as a starting point, we have used 23 years (1985-2007) of available data to predict autumn cholera incidence using the persistence between spring and autumn cholera incidence time series. Table 7 shows models (NX), where observed spring cholera incidence is used for predicting autumn cholera incidence. Figure 5.4 shows that model N1 satisfactorily predicts autumn cholera incidence by using only spring incidence as predictor variable.

We now explore the influence of flood affected areas (FAA) and SST as macro-environmental variables to predict autumn cholera incidence, as proposed by Akanda et al (2009). We examined mixed models by incorporating persistence between spring and autumn cholera incidence, and the macro-environmental variables (annual FAA and early summer, June-July-August, SST). SST data (from 1985-2007) have been extracted from Advanced Very High Resolution Radiometer (AVHRR) for the coastal region of Bay of Bengal (region between 20-22.5°N and 89-93°E). The best regression model was obtained using spring cholera incidence and summer SST, yielding an adjusted r^2 of 0.78 and a predicted r^2 of 0.72, with a lowest PRESS value in the developed models in Table 7. Table 7 shows that model N3 comprising the two variables performs better than all other models in this category. Figure 5.4 shows that model N3 adequately captures the variability of predicted autumn cholera over the study period. Table 8 shows the characteristic details of estimated model parameters for predicting autumn cholera incidence. On the basis of these findings, we suggest a persistence-based model (N1) or mixed model (N3) for predicting autumn cholera outbreaks, depending upon the availability of quality data.

Akanda et al. (2011) provides a plausible physical mechanism behind the persistence of the autumn peak following the spring peak. Once the cholera bacteria are introduced into the system during spring through coastal intrusion, floods can spread this contamination over a much larger area and cause sanitary conditions to deteriorate further, leading to autumn cholera outbreaks. One of the major advantages of model N1 is that the prediction of autumn cholera incidence can be done using only remote sensing chlorophyll and air temperature at the foothills of the Himalayas from the previous autumn, providing almost a year-long prediction lead time. This is a very encouraging finding and needs to be further validated as longer remote sensing data become available.

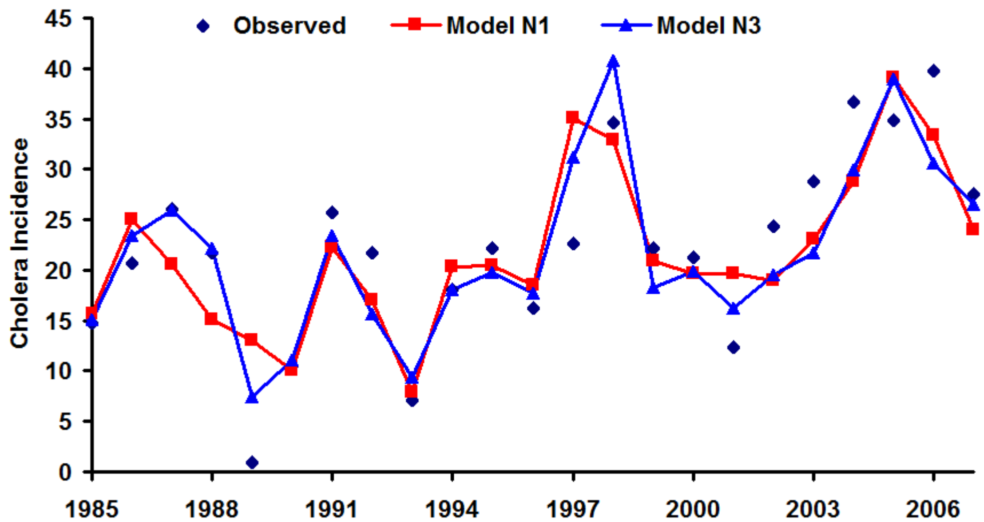

Figure 5.4. Autumn observed and predicted cholera incidence using N1 and N3 models

On the other hand, model N3 combines persistence with macro-environmental variables to predict autumn cholera incidence, which provides a physically plausible mechanistic explanation of the role of the variables used in this model. Although flood affected areas has been associated with autumn cholera outbreaks by Akanda et al. (2009), our analysis suggests that flood affected areas has limited predictive ability (Table 7). This may be due to the aggregated form of the annual time series, which is a lumped measure of annual flood inundation. As finer-resolution flood affected areas data become available, the proposed modeling scheme can be refined.

5.7 Discussion

We have shown that remotely sensed coastal chlorophyll and upstream Himalayan air temperature measurements can be used to statistically predict spring cholera incidence in the Bengal Delta region with three-month (78% accuracy) and two-month (82% accuracy) prediction lead time. Autumn cholera can be predicted with a three-month lead time (72% accuracy) using two separate multiple regression models. Clearly, these prediction accuracies are remarkably good. Yet, we need to be cognizant of the statistical nature of the modeling framework, the perennial struggle to separate causality from correlation, and the limitations imposed by the length of the available dataset. Consequently, we need to understand the possible physical linkages and pathways as to how and why chlorophyll levels in the autumn of one year may be related to next year's spring cholera outbreaks. Figure 5.5 provides a summary schematic for the prediction of biannual cholera incidence in the Bengal Delta. The modeling framework starts with prediction of spring cholera (M-series models) using two remotely sensed macro-environmental variables (preceding autumn chlorophyll in coastal Bay of Bengal and air temperature in the foothills of the Himalayas) and then uses seasonal persistence and other macro variables (SST) to predict cholera incidence in autumn (N-series models).

One of the plausible pathways for relating coastal macro-environmental processes with spring cholera incidence is shown in Figure 5.6. We hypothesize that decomposition of phytoplankton after autumn increases zooplankton, which upon degradation, together with phytoplankton, results in CDOMs (colored

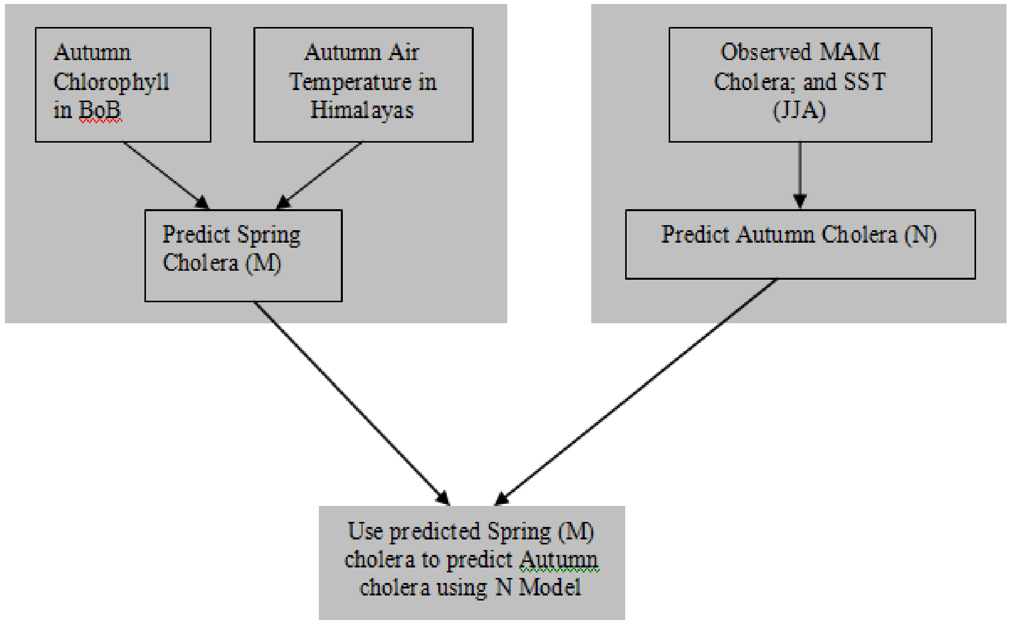

Figure 5.5. Prediction modeling framework of cholera outbreaks using remotely sensed variables in Bangladesh.

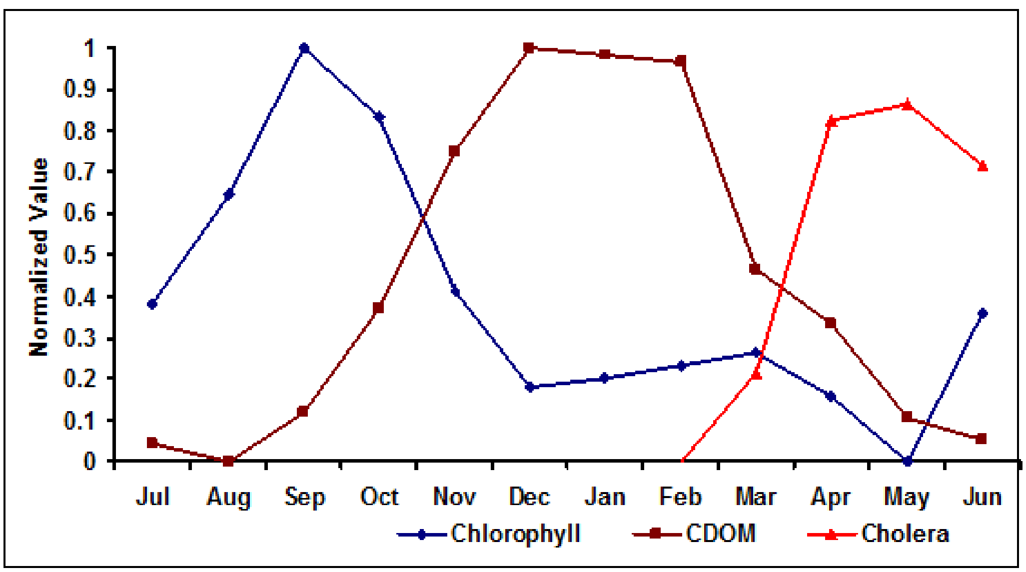

Figure 5.6. A plausible pathway relating coastal macro-environmental processes with spring cholera outbreaks.

dissolved organic material) in the winter (December-January-February) season. For this hypothesis to be valid, one would expect to see a strong correlation between the autumn chlorophyll and winter CDOMs (r = 0.79; p <0.05). Similarly, correlation between winter season CDOMs and spring cholera incidence is found to be statistically significant (r = 0.71; p <0.05). CDOMs are commonly known as the fraction of the bulk dissolved organic carbon pool, and have been widely recognized as the decomposed product of phytoplankton (e.g. Sharp, 1977; Bjornsen, 1988). The relationship of phytoplankton and CDOMs is the subject of several recent studies in various coastal regions of the globe (Smith and Demaster, 1996; Yamashita and Tanoue, 2004; Henderson et al., 2008). Carder et al. (1989) suggested that the increase in CDOMs observed in the Gulf of Mexico was a consequence of the collapse of an earlier coastal phytoplankton bloom. Rochelle-Newall and Fisher (2002) observed that decomposition of phytoplankton in the presence of bacteria results in an increase of CDOMs.

Laboratory experiments conducted by Worden et al. (2006) suggest that cholera bacteria can survive in CDOM-rich waters after the phytoplankton bloom biodegrades. Therefore, it is reasonable to expect that the decay of phytoplankton in autumn transforms the released nutrients as CDOMs in winter season. Recent laboratory studies indicated that *Vibrio cholerae* can grow rapidly in the presence of dissolved organic material (Mourino Perez et al., 2003; Worden et al. 2006; Eiler et al., 2007). Laboratory analysis by Eiler et al. (2007) suggested an increase of about 75% of *Vibrio cholera* population, when CDOMs were increased from 0% to 100% in coastal water samples. Moran and Zepp (1997) reported that removal processes of CDOMs are through bacterial consumption of organic material, which strengthens the possible favorable conditions for bacteria feeding upon CDOMs. The highest seasonal correlation is observed between winter season CDOMs and spring cholera incidence (r=0.63; $p<0.05$), with the correlation decreasing thereafter, suggesting that CDOMs and spring cholera incidence together provide a plausible physical pathway as to how these two variables are related.

As complementary evidence, we show spatial maps of autumn chlorophyll for the lowest (2002) and highest (2005) spring cholera years. Figure 5.7 shows autumn chlorophyll in 2001 (representing the lowest spring cholera incidence in 2002) and 2004 (representing the highest spring cholera incidence in 2005) in coastal Bay of Bengal. The first visual observation is that autumn chlorophyll is very high during 2004 as compared to 2001. Figure 5.7c indicates the percent change of chlorophyll between Figs. 5.7a and 5.7b. On an average, there is approximately 50% more chlorophyll in coastal Bay of Bengal in 2004 compared to 2001. Taken together, these findings suggest that autumn chlorophyll may have a strong physical association with spring cholera incidence. This phenomenological link, where degradation of phytoplankton leads to CDOMs, gives us a plausible pathway of coastal processes contributing to the growth of bacterial reservoirs of cholera in the coastal zone of the Bay of Bengal. The biological transformation of chlorophyll to CDOMs and its transport into estuarine areas during the dry season, and the associated time delay, provide a plausible explanation as to why seasonal November-December-January chlorophyll models at one-month lag (1M series) are not able to predict cholera incidence satisfactorily compared to the two- or three-month lead-time models.

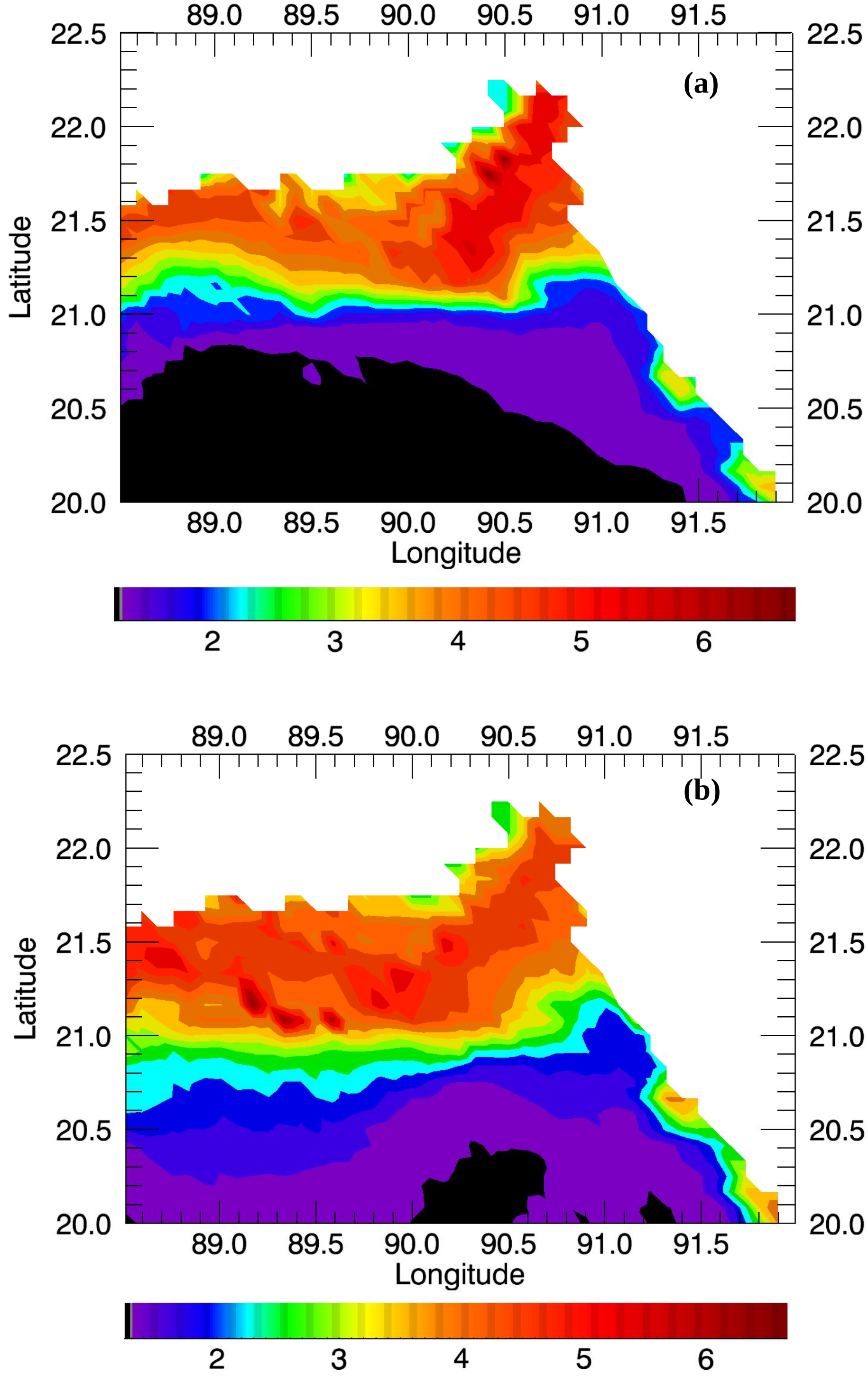

Figure 5.7. Spatial chlorophyll (mg/m^3) in coastal Bay of Bengal in autumn in (a) 2001 (low spring cholera in spring of 2002) and (b) 2004 (low spring cholera in spring of 2005);

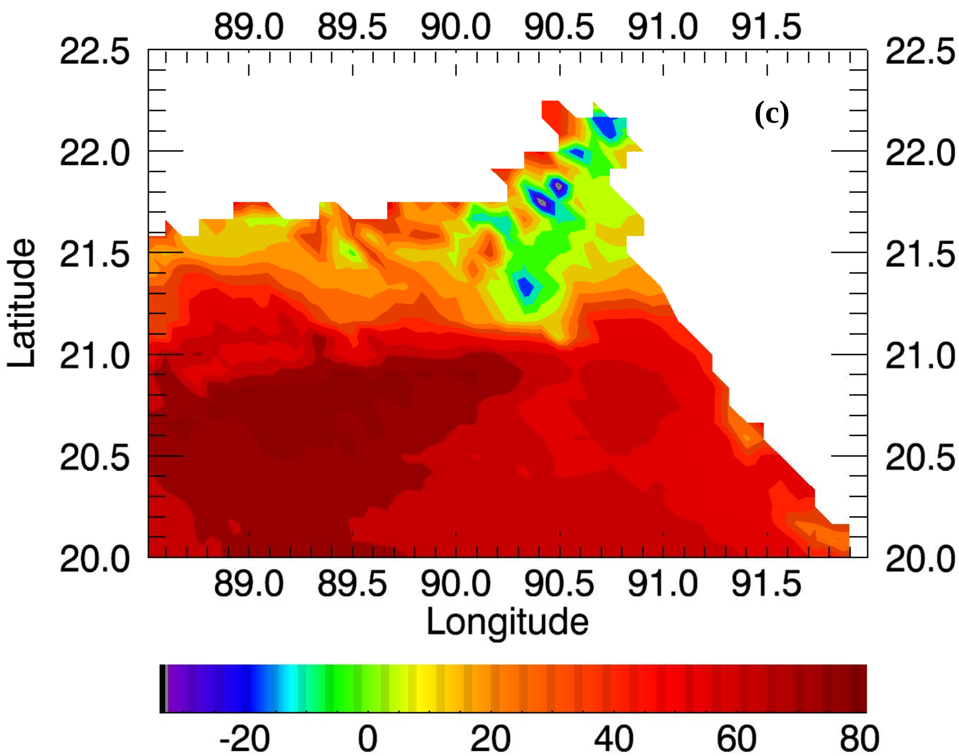

Figure 5.7. Spatial chlorophyll (mg/m^3) in coastal Bay of Bengal in autumn (c) percent difference in each pixel between 2001 and 2004.

This is perhaps one of the first studies to quantitatively link available remote sensing data to predict cholera outbreaks with several months prediction lead time. Two key findings from this study are: (1) Cholera outbreaks can be predicted using two-seasonal modeling strategies with a prediction lead time of several months to a year, depending on the choice of macro-environmental variables. Spring cholera can be predicted up to three months in advance, whereas autumn cholera can be predicted up to one year in advance using remote sensing data. Such prediction lead times will have tangible impacts in designing appropriate cholera intervention, mitigation, and prevention measures for resource-constrained regions. (2) A physically plausible phenomenological explanation is provided regarding the pathways of geophysical transformation (such as from plankton to CDOMs to bacterial growth to cholera outbreaks) of macro-environmental processes leading to conditions favorable for cholera outbreaks.

These results are promising; yet, we must be cognizant of possible caveats and limitations that warrant further investigation. Our results are based on eleven years of remote sensing data; as more data become available, the proposed approach needs to be further validated and refined. The idea of environmental cholera transmission was proposed in 1970s (Colwell et al., 1977) and reported in a series of subsequent publications (e.g., Tamplin et al. 1990; Colwell & Huq, 1994; Lipp et al., 2002; Akanda et al., 2009) that continue to be refined as more observational data become available and as the roles of different abiotic, biotic, and hydroclimatological factors affecting cholera transmission are clarified. Chlorophyll estimates from satellite remote sensing provide an indirect measurement of phytoplankton abundance and a quantitative measure of space-time distribution of phytoplankton. However, chlorophyll alone cannot provide a direct connection to *V. cholera;* although it can help determine timing and location of phytoplankton blooms that are followed by zooplankton blooms. By analyzing plankton samples for major groups of phytoplankton and zooplankton, a tighter relationship needs to be established between plankton types and quantitative estimates of *V. cholerae*. Our ongoing research will address some of these questions in the future. Our results demonstrate that satellite data over a range of space and time scales can be very effective in developing a cholera prediction model with several months' lead time. Such prediction lead time will have tangible impacts to design and implement effective cholera intervention and mitigation strategies for various resource constrained and cholera affected regions of the world.

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Chapter 6

Satellite Water Impurity Marker (SWIM) for predicting seasonal cholera outbreaks

Abstract

Prediction of outbreaks of cholera, a deadly water related disease, remains elusive. Since coastal brackish water provides a natural ecological niche for cholera bacteria and because a powerful evidence of new biotypes is emerging, it is highly unlikely that cholera will be fully eradicated. Therefore, it is necessary to develop cholera prediction model with several months' of lead time. Satellite based estimates of chlorophyll, a surrogate for phytoplankton abundance, has been associated with proliferation of cholera bacteria. However, survival of cholera bacteria in a variety of coastal ecological environment put constraints on predictive abilities of chlorophyll algorithm since it only measures greenness in coastal waters. Here, we propose a new remote sensing reflectance based statistical index: Satellite Water Impurity Marker, or SWIM. This statistical index estimates impurity levels in the coastal waters and is based on the variability observed in the difference between the blue (412nm) and green (555nm) wavelengths in coastal waters. The developed index is bounded between clear and impure water and shows the ability to predict cholera outbreaks in the Bengal Delta with a predicted r^2 of 78% with two months lead time. We anticipate that a predictive system based on SWIM will provide essential lead time allowing effective intervention and mitigation strategies to be developed for other cholera endemic regions of the world.

6.1 Context, Motivation and Objectives

Cholera, an acute water-borne diarrheal disease, continues to be a significant global health threat. The ongoing seventh pandemic of cholera, which started in 1960s, has been reported in over 50 countries and has affected more than 7 million people (*Gleick, 2008*). The disease remains one of the most prevalent water-related infections in many tropical regions of the world, specifically in coastal areas of South Asia, Africa, and Latin America. Several studies (e.g., *Jutla et al., 2010; Magny et al., 2008; Huq and Colwell, 1996; Colwell, 1996*) have suggested that major cholera outbreaks around the globe have originated in coastal regions, indicating a strong link between coastal environments and cholera outbreaks. The life cycle of the bacterium *V. cholerae,* causative agent for the disease outbreak, is intricately linked to macro-environmental (hydrological, ecological, climatic, and coastal) and micro-environmental (microbiological, genetic, and human intestinal) processes, which have vastly different spatial and temporal scales of interacting variables. While appropriate micro-environmental processes are necessary for epidemics, macro-environmental processes set the stage for initial disease outbreaks and create conditions that allow the disease to become endemic to the region. Since macro-environmental processes provide a natural ecological niche for *V. cholerae* and because powerful evidence of new biotypes is emerging, it is highly unlikely that cholera will be fully eradicated. Consequently, it is necessary to develop cholera prediction models with several months' lead-time for planning effective intervention and mitigation strategies.

Phytoplankton abundance--because of its relationship with zooplankton and cholera bacteria as well as its ease of estimation over large areas using satellite-derived chlorophyll- has been analyzed to understand cholera and coastal connection as well as to estimate disease outbreak in several parts of the globe (*Magny et al. 2008; Lobitz et al., 2000; Jutla et al., 2010*). Although space-time variability of phytoplankton abundance over large oceanic region may provide a phenomenological linkage to cholera outbreaks; however, survival of cholera bacteria depends on a range of coastal ecological variables and conditions including phytoplankton (*Tamplin et al., 1990*), zooplankton (*Colwell and Huq., 1996*), salinity (*Miller et al., 1982*) and organic material (*Mourino Perez et al., 2003; Worden et al. 2006; Eiler et al., 2007*). Our previous study (*Jutla et al., 2011a*), indicated that chlorophyll alone can predict disease outbreak with about 58% accuracy for the Bengal Delta. In addition, chlorophyll is estimated using a maximum ratio based logarithmic cubic polynomial model with a non-linear combination of reflectance data from 443, 490, 510, and 555nm wavelengths, with an estimation error in excess of 30% (*Gregg and Casey, 2005, McClain et al., 1998*). Consequently, it is unlikely that chlorophyll alone would be able to provide operationally feasible prediction capabilities for cholera outbreaks with reasonable accuracy. Therefore, a new model is needed for an effective early warning system for cholera with several months' lead time and better prediction accuracy.

Chlorophyll algorithm has been developed, calibrated and validated to estimate greenness in marine waters. The primary use of greenness is to estimate phytoplankton abundance. Marine waters also contain organic matter, detritus, zooplankton and non-green flora and fauna which are not represented in the chlorophyll algorithm, but are known to be contributing factors to the growth and proliferation of cholera bacteria. In this case, combination of satellite measured reflectance can capture wide variations in the biological growth than chlorophyll algorithm alone in the marine waters (e.g., phytoplankton functional groups: Brown and Yoder, 1994, Subramaniam et al., 2002; organic matter: Carder et al., 1991; harmful algae: Cannizzaro et al., 2008). Consequently, here we explore satellite measured reflectance, which have an error of about 5% (*McClain et al., 1998*), to detect statistical conditions in coastal waters that can be associated with disease outbreaks. An overarching objective of the study is to: develop an index using combination of satellite observed reflectance in visible wavelength range which can identify spatial and temporal conditions in coastal regions that can predict cholera outbreaks with one to two months lead time. The desired attributes for such an index include: (i) applicability over different regions of the globe; and (ii) ability to predict cholera outbreaks with satisfactory accuracy with one to two months in advance.

Remote sensing data have been successfully used to derive various indices for a range of geophysical processes (e.g., *Rouse et al, 1973, Jackson et al., 1983, Townshend et al, 1985*; Gao*, 1996; Chen et al., 2005*). Two major advantages of indices are that they can: (i) quantify spatial and temporal variability of a process over large areas without including a detailed description of the underlying physical processes and in-situ measurements; and (ii) aid in visualizing the process being monitored and modeled over large areas. Typically, indices are constructed using carefully chosen spectral information. Normalized Density Vegetation Index (NDVI) is probably the most widely used index and is used to represent the state of vegetation. Mathematically, NDVI is the ratio of difference in near infrared bands over the sum of the infrared bands. NDVI values for a given pixel result in a number which ranges from minus one (-1) to plus one (+1). If there are no green leaves then the NDVI value is zero. A pixel with NDVI of 0.4 will imply less vegetation cover than a pixel with a value of 0.8. Similarly, *Wang and Qu (2007)* developed a new index to monitor soil moisture and vegetation based on three spectral bands of MODIS. *Chen et al (2005)* suggested a index for mapping lichen-dominated biological soil crusts in desert areas using LANDSAT data. *Kraneili (2001)* developed Aerosol Free Vegetation Index for monitoring vegetation changes using five near infrared wavelengths for LANDSAT. Normalized Density Water Index, using three wavelengths, is widely used to delineate the water bodies across the globe (*Mcfeeters, 1996; Gao, 1996*). The utility of such indices is that, in the absence of a local data sources and a comprehensive understanding of related physical drivers, the index can spatially quantify the state of the process with a reasonable accuracy. This make remote sensing based indices very effective in quantifying and communicating spatial characteristics of related physical processes.

6.2 Data

Cholera epidemiological data were collected from the International Centre for Diarrheal Disease Research, Bangladesh, perhaps the longest and most comprehensive cholera datasets available in the world (Longini et al. 2002). For this study, the coastal water zone of the Bay of Bengal is defined as the region between 20-22.5°N and 88.5-93°E, based on bathymetry data (*Barua et al., 2005*). We have used Sea-viewing Wide Field-of-view Sensor (SeaWiFS) monthly reflectance for five bands (412, 443, 490, 510, 555nm) at 9-km resolution, obtained from NASA/Goddard Earth Sciences/Distributed Active Archive Center for twelve-year period (September 1997- September 2010). More-detailed description about these products, sensors, estimation algorithms, and accuracy are available elsewhere (*Martin, 2004; Uz and Yoder, 2004*).

6.3 Concept and Development of SWIM

We propose the **S**atellite **W**ater **I**mpurity **M**arker for **c**holera, or SWIM, which is an empirical index, developed with an objective of detecting conditions favorable for growth of cholera bacteria that will eventually lead to a disease outbreak. The functional form of SWIM is

$$SWIM = \left[\frac{R_{rs}555 - R_{rs}412}{R_{rs}555 + R_{rs}412}\right].100 \qquad [6.1]$$

where, $R_{rs}412$ and $R_{rs}555$ are the satellite measured visible range reflectances at 412nm and 555nm, respectively. The basic premise of SWIM is the variability in the difference between the blue (412nm) and green (555nm) wavelengths, which may determine the level of impurity in the water; this impurity may further be related with growth of *V. cholerae* bacteria and subsequently, cholera incidence. Pure water absorbs all colors but reflects blue color (*Morel and Prieur, 1977; Morel et al., 2007*). Similarly, reflectance wavelength at 555nm is most sensitive to the green color, or, presence of the impurity in terms of plankton and other pigments (*Morel and Prieur, 1977)*. Figure 6.1 provides a schematic understanding of SWIM. In the two extreme conditions, if the water has no contaminants, then $R_{rs}555$ should approach to zero; and in case of perfectly impure water, $R_{rs}412$ should be zero. By definition, SWIM can have limits between -100 to 100. A value of -100 represent clear water and +100 is the most impure water. In coastal regions, we do not expect it to approach either of the two extreme conditions since there will always be some impurity present in the water.

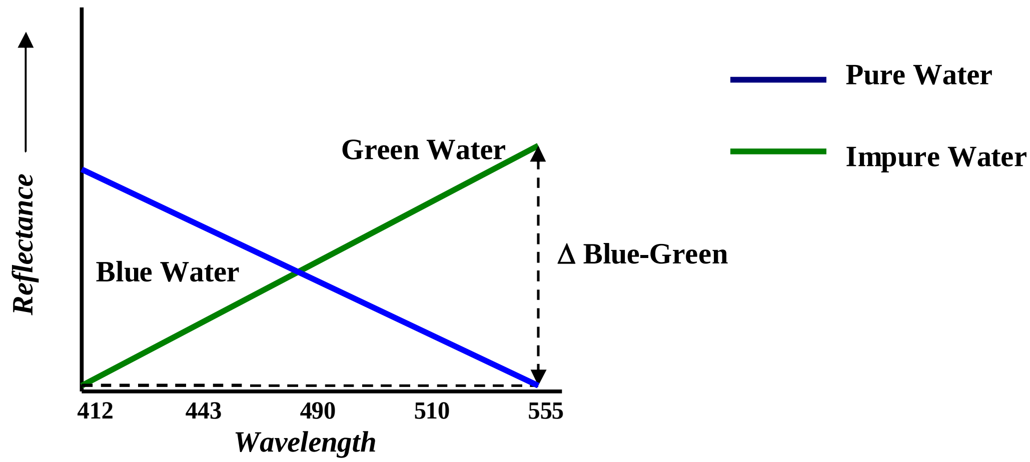

Figure 6.1: Concept of Satellite Water Impurity Marker, or SWIM

The behaviour of blue and green wavelengths (similar to Figure 6.1) has been reported in several other studies. Cannizzaro et al (2008) observed that the wavelength spectra shifts from blue to green as the amount of impurities increase from offshore to coastal waters in the Gulf of Mexico. They reported that transitioning to the waters with high chlorophyll and other impurities results in increases values of reflectance of the green wavelength. Cunnigham et al (2011) reported similar trends, between the blue and green wavelengths, along the coast of South Georgia, near Falkland Islands. In order to test the proposed concept of SWIM, we plotted seasonal (average of three months) satellite derived reflectance for coastal Bay of Bengal (Figure 6.2). It indicates that the seasonal reflectance from the green (555nm) wavelength is highest in the October-November-December (OND) and lowest in May-June-July (MJJ). A complete reversal is observed in the blue wavelength (412mn), which has lowest in October-November-December (OND) season and highest in the May-June-July (MJJ) season. The inverse relationship indicates that our stated basis for SWIM (from Figure 6.1) is valid. To provide a more physical explanation, coastal Bay of Bengal experiences high monsoonal rainfall in the May-June-July season (*Ahmed and Karmakar, 1993*) and the freshwater accumulation on the surface of the ocean water may be the reason why blue (clear) water appears to dominate in the bay with increased reflectance in the blue colors than the greens. On the other hand, river discharge brings terrestrial nutrients in coastal waters, aiding in production of plankton (phytoplankton, zooplankton, organic material) *(Jutla et al., 2011; Arker et al., 2005; Harding and Perry, 1997; Pennock and Sharp, 1985; Revenlante and Gilmartim, 1976; Bidigare et al., 1993; Lohrenz et al., 1990*). This results in greater value of reflectance in green wavelengths in October-November-December (OND) and an opposite effect in the blue wavelength.

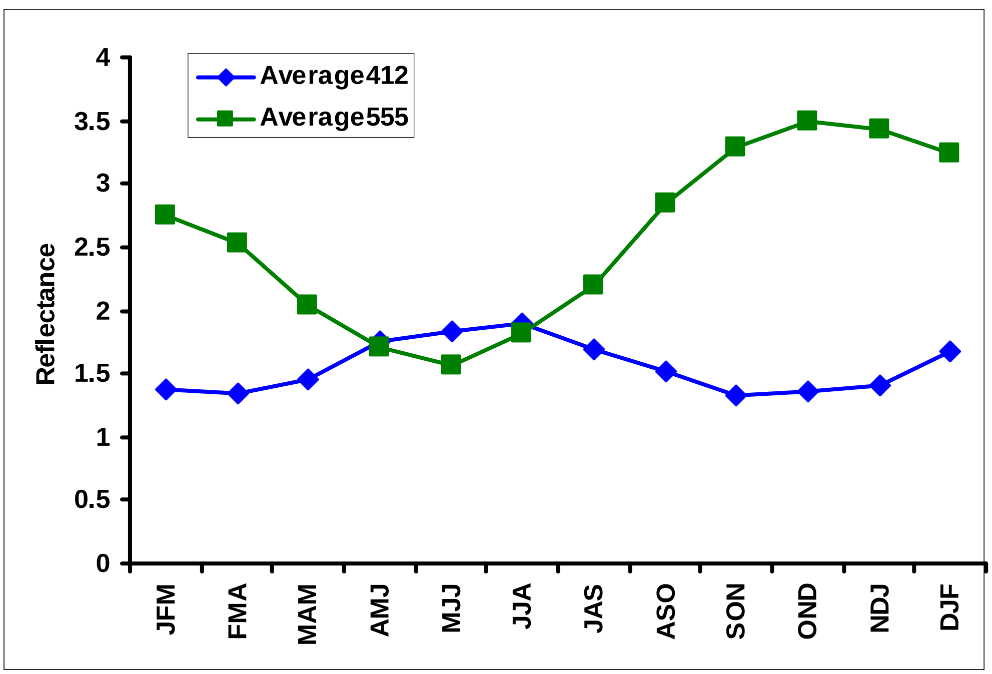

Figure 6.2: Seasonal climatology of 412nm and 555nm wavelengths in the coastal Bay of Bengal

6.4 Application of SWIM to predict cholera outbreaks

The next step will be to determine applicability and relationship of SWIM with cholera incidence in the Bengal Delta. Cholera outbreaks in the Bengal Delta show two seasonal peaks: one in spring (defined as the average of March-April-May months) and another in fall (defined as the average of September-October-November months) (*Akanda et al., 2009*). One recent study, Akanda et al. (2011), identified two seasonal and spatial asymmetric hydroclimatic conditions that aid cholera outbreaks in this region. Low river discharge in the spring months enable the intrusion of bacteria laden coastal water inland, resulting in spring cholera outbreaks. On the other hand, monsoon floods create the environmental conditions conducive for fall outbreaks by widespread contamination of the region's water resources with the cholera bacteria. Therefore, the applicability of SWIM-enabled prediction appears to be limited to the spring outbreaks.

In order to determine the relationship between SWIM and spring cholera incidence, we averaged calculated SWIM values over coastal Bay of Bengal (88.5-920E; 20-22.50N) and determined seasonal correlation with spring cholera incidence. The highest correlation between spring cholera and seasonal SWIM is observed during early winter (average of October-November-December: $r=0.83$, $p<0.05$) season (Figure 6.3). The correlation value decreases after early winter. The linear correlation between OND SWIM and spring cholera incidence is shown in figure 6.3b. The high correlation between early winter SWIM and next years' spring cholera incidence is encouraging since it (i) provides sufficient lead time for prediction models before disease outbreaks and (ii) indicates that bacterial growth may be the function of the variety of coastal conditions, and not just chlorophyll.

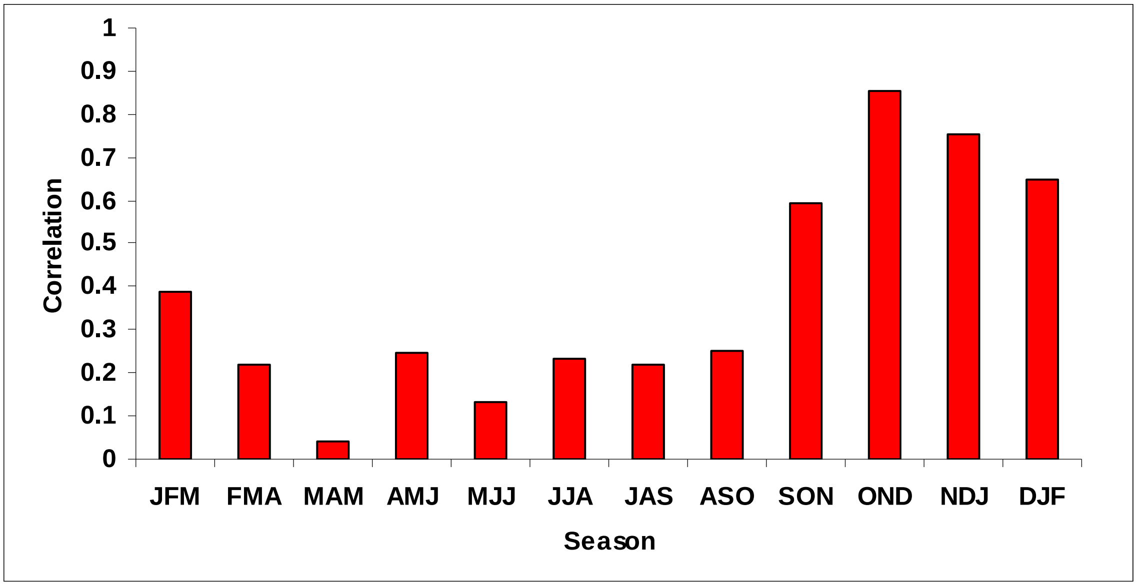

Figure 6.3a : Correlation between seasonal Coastal SWIM and spring cholera incidence.

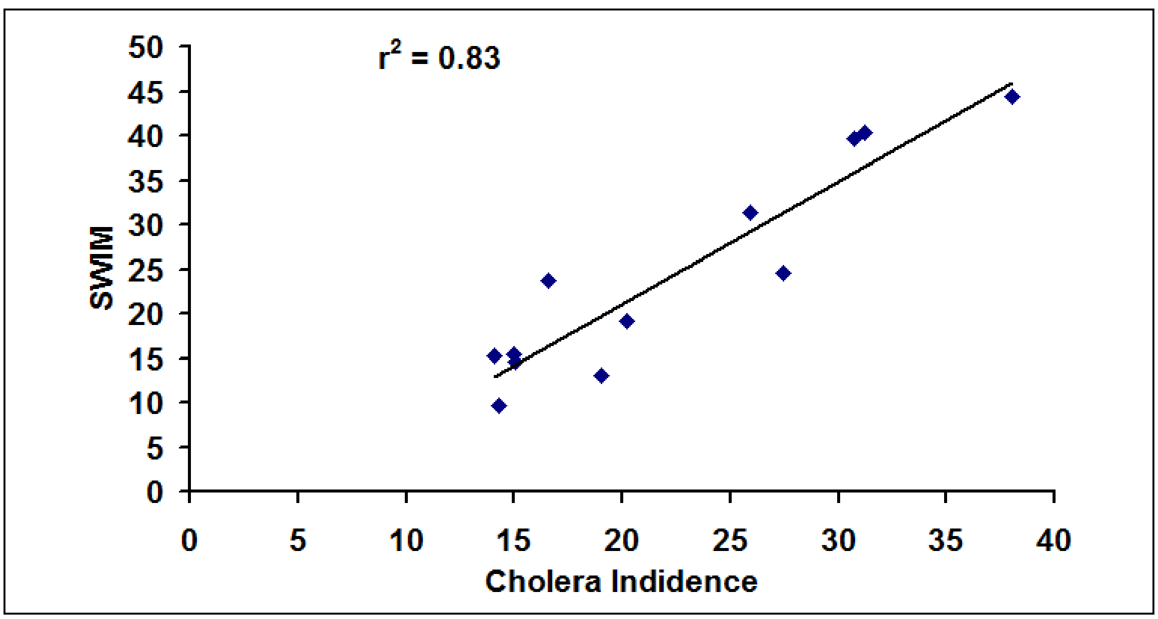

Figure 6.3b: Correlation between OND Coastal SWIM and spring cholera incidence.

We have developed linear regression models to predict spring cholera incidence using early winter season SWIM values. Table 9 shows fitted model performance statistics and parameters for Model M1 for Bengal cholera incidence. Root Mean Square

Error (RMSE) and bias for model M1 is 2.5% and -0.59% respectively. Figure 6.4a shows the observed and predicted spring cholera incidence using model M1 which yielded predicted r^2 of 78% and an adjusted r^2 of 82%.

Table 9: SWIM based model performance statistics and parameters

Model		**α**	**β**	**Predicted r^2**	**Adjusted r^2**	**RMSE**	**Mean**	**Bias**
	Observed Bengal Cholera						22.3%	
M1	Predicted Bengal Cholera	8.71 (0.002)	1.43 (0.001)	78%	82%	2.5%	22.9%	-0.59%
	Observed Mozambique Cholera						1421 Cases	
M2	Mozambique Cholera	-3443 (0.008)	520 (0.001)	57%	70%	350 Cases	1352 Cases	90 Cases
p-values of parameters are shown in parenthesis								

Model M1 appears to perform satisfactorily for Bengal Cholera, but the concept of SWIM needs validation. Validation cannot be done on the 12 year limited dataset from the Bengal Delta. Statistically, jackknifing experiments should be performed to validate the model, however, with 12 data points; it will be difficult to set up such experiments. Moreover, predicted r^2 is calculated leaving one observation out and then estimating the predicted value of the left out observation (details in Chapter 5) using the developed model. However, if our hypothesis of SWIM is valid, then we should be able to apply the concept of index to other cholera endemic regions of the world and can still predict outbreak of disease. Therefore, for validation, we chose Mozambique, a cholera endemic region, where 11 years of cholera case data are available. In Mozambique, we observe a seasonal peak in the months of December-January- February or winter season (Jutla et al., 2010). However, Mozambique cholera data is available as the cases of cholera observed and not as percent incidence. Since the dataset is only for 11 years, the changes in population during this timeframe are assumed to be negligible. Model M2 was constructed using July-August-September, summer season's SWIM for Mozambique for predicting cholera cases in the winter season. Adjusted r^2 for the model is 70%, which along with results in Figure 6.4b, is encouraging. Table 9 indicates that the regression model was able to fit cholera cases with a predicted r^2 of 57%, thus validating the concept and applicability of SWIM. These results indicate that SWIM may have adequate potential for predicting global cholera outbreaks using only satellite measured reflectance.

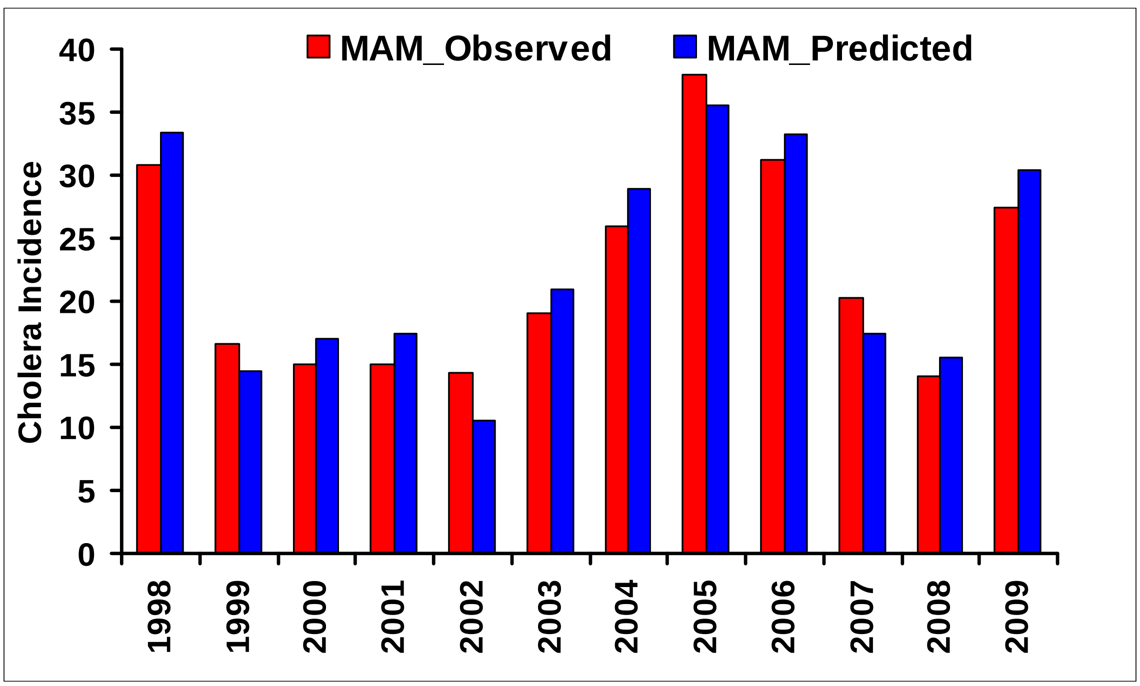

Figure 6.4a: Observed and predicted spring cholera outbreaks in Bengal Delta

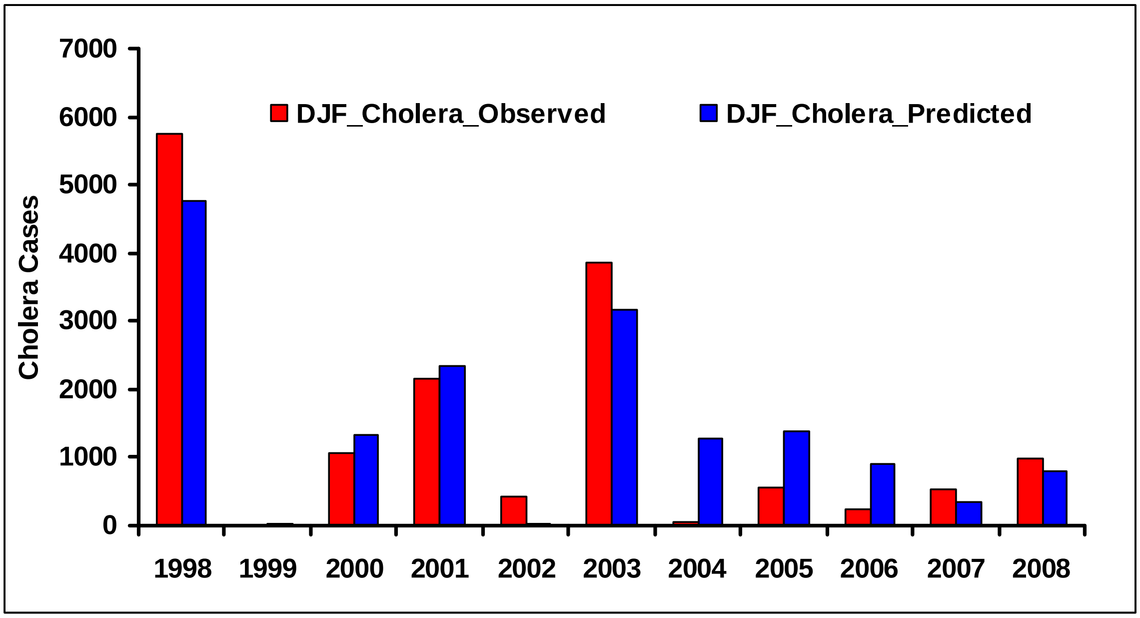

Figure 6.4b: Observed and predicted spring cholera outbreaks in Mozambique

It should be noted that Mozambique cholera data are counts, therefore, Poisson regression or a negative binomial type models should be fitted to the data. However, linear regression have been used for the sake of simplicity and with the objective of validating the concept of SWIM.

6.5 Discussion and Summary

The objective of the study was to develop a satellite reflectance based index that has the capabilities to capture the biological growth that may affect cholera bacteria and then relate such index with cholera incidence in disease endemic regions. Using our proposed SWIM, we show that it is possible to predict cholera outbreaks in South Asia and Southeastern Africa with satisfactory prediction accuracy. The index is based on the variability in the difference in reflectances of two wavelengths, 412nm and 555nm over coastal waters. Our basic hypothesis is that blue (412nm) wavelength represents clear water and green (555nm) wavelength represents water with impurities. These impurities can be phytoplankton, zooplankton or organic matter. The range of the index is from -100 to 100, although it is not expected that the index will achieve either of the two extremes in the real world scenario.

We anticipated that the developed index must be applicable over other disease prone regions. SWIM has shown satisfactory capabilities for predicting cholera outbreaks in two disease endemic regions. It can predict cholera incidence in Bangladesh and Mozambique with overall prediction accuracies of 78% and 57%, respectively. Figure 6.5 presents complementary evidence to our results, showing the spatial variation of SWIM values in coastal Bay of Bengal during highest and lowest cholera years within the analysis period. SWIM values (Figure 6.5a) are very high in the early winter season of 2004 during the onset of the epidemic outbreak of spring 2005. Figure 6.5b shows that SWIM values in the early winter of 2001 are much lower than average, before the anomalously low cholera incidence in spring of 2002. It should be also noted that about 97% of pixels in Figure 6.5a (year 2004) have higher values than in Figure 6.5b (year 2000), suggesting a region-wide coastal process as opposed to an inflated influence by particular regions.

Since, survival of cholera bacteria depends on variety of coastal ecological conditions that include phytoplankton (Tamplin et al., 1990), zooplankton (Colwell and Huq., 1996), salinity (Singleton et al., 1982) and organic material (Mourino Perez et al., 2003; Worden et al. 2006; Eiler et al., 2007), it is expected that chlorophyll alone will not provide sufficient prediction capabilities for cholera outbreaks. The concept of SWIM is such that it has the potential to capture wide variety of impurities present in coastal waters. As an example, Cunningham et al (2011) observed that degradation of diatoms, a type of phytoplankton, produces false chlorophyll values using standard chlorophyll algorithm which are currently employed by SeaWiFS. However, the optical properties of decaying diatoms produce a spectral peak in the green reflectance wavelength (~555nm), which is merely an impurity at that stage. On the other hand, lack of impurities show a characteristic peak at blue wavelengths (~412nm). It implies that the difference between the two wavelengths may be useful to capture wide range of water impurities (biological growth).

Our results indicate that SWIM values in the early winter season are related with cholera outbreaks in following spring season (i.e., two months lead time between SWIM and cholera outbreak). The question remains as to what may happen in early winter season that is related with spring cholera outbreaks? In our previous study on the relationship of chlorophyll with cholera outbreaks (Jutla et al., 2011a), we hypothesized that degradation of phytoplankton and zooplankton during early winter season aids in growth of organic matter, which then help in growth of cholera bacteria in coastal waters. Within this context, SWIM values in early winter season may indicate the process of degradation of plankton and the beginning of the increase in organic matter in coastal waters. Thereafter, intrusion of bacteria-laden coastal water due to low river discharge may be responsible for cholera outbreaks along the coastal regions of Bengal Delta.

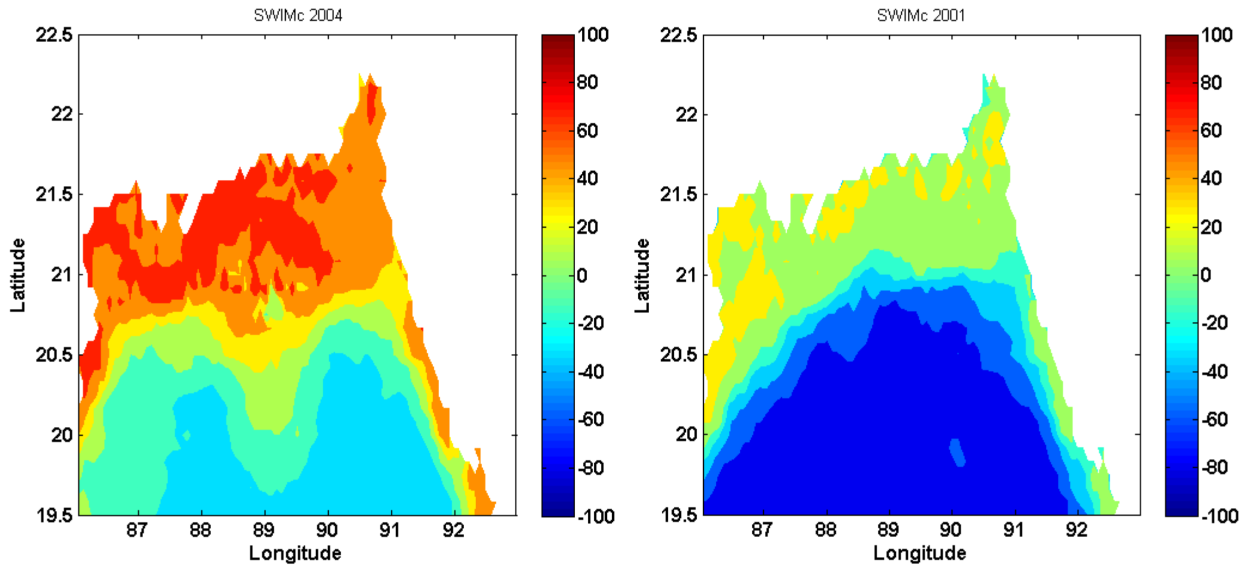

Figure 6.5: SWIM during October-November –December in (a) 2004 (high cholera in spring of 2005) and (b) 2001 (low cholera in spring of 2001).

Since the available dataset is limited, the question of separability of correlation from causation will arise regarding the concept of SWIM and its prediction abilities for cholera outbreaks. In order to negate such possibility, we also tested SWIM in a coastal region, which has no to sporadic cholera outbreaks. If the concept of SWIM is physically tangible, then we should expect to see negative (clear water with fewer impurities) values of SWIM in such regions. Such a finding will suggest that the coastal connection hypothesis (Akanda et al., 2011; Colwell et al., 1996) of cholera outbreaks as proposed in some regions may not be true for this particular location. A recent outbreak of cholera in Haiti is a perfect example to demonstrate the concept and applicability of SWIM. Origin of cholera outbreaks, whether it is imported or indigenous, in Haiti in 2010 has been widely debated in literature (Enserink, 2010, 2011; Waldor 2010, Chin 2011). Figure 6.6 shows that SWIM is entirely negative during the outbreak year of 2010. This implies the presence of clear coastal water as opposed to the impure water that is observed in case of the Mozambique Bay and the Bay of Bengal. Therefore, SWIM values indicate that coastal environments of Haiti may not be responsible for cholera outbreaks in that region. Our observations are further strengthened by the official finding that the Haiti cholera outbreaks were indeed initiated by a foreign carrier (Enserink, 2011: Chin et al., 2011). Taken together with the prediction of cholera outbreaks in two disease prone regions, it may be concluded that SWIM has the potential to be useful for predicting cholera outbreaks in other disease prone regions with active coastal zones.

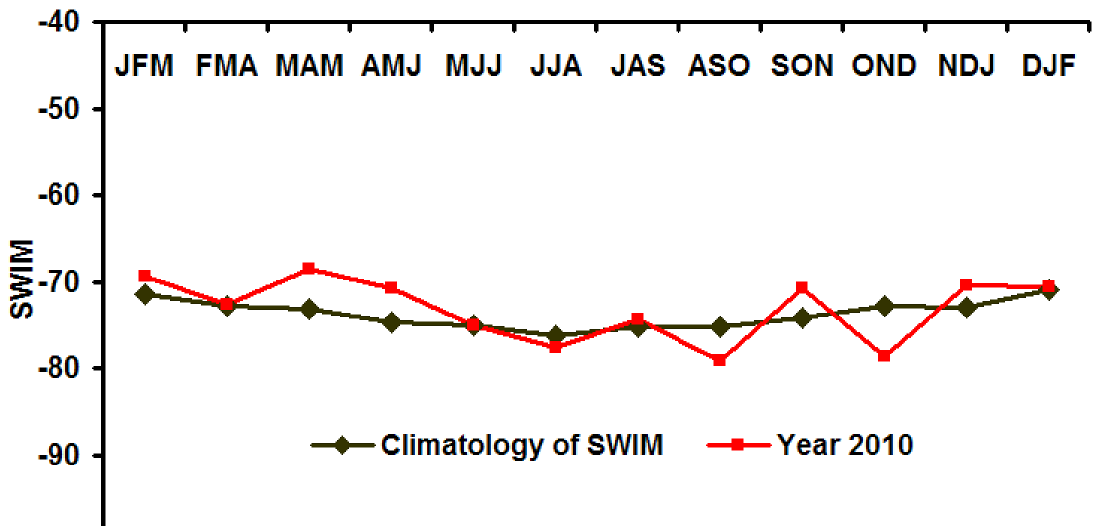

Figure 6.6: SWIM values along the coast of Haiti

The results from application of SWIM to predict cholera incidence are encouraging, yet we are cognizant of the limitations posed by the limited dataset and the apparent separation of causation from correlation. One may argue that the term "prediction" used in this chapter is misleading since we are comparing the modeled values with the observed values. While this is partially true, yet, our models are predictive in nature since the variable used (SWIM) has a lead time of about two months with cholera outbreaks. To overcome this criticism, we have explored other regions (Mozambique and Haiti) for applicability of the concept of SWIM. As more satellite data becomes available, we will keep testing our modeling framework for its robustness. Our results are based on twelve years of remote sensing data; as more data become available, the proposed approach needs to be further validated and refined. The idea of environmental cholera transmission was proposed as early as 1975 (Colwell, 1977) and reported in a series of publications (e.g., Tamplin et al. 1990; Colwell & Huq, 1994; Lipp et al., 2002; Akanda et al., 2009) that continue to be refined as more observational data become available and as the roles of different abiotic, biotic, and hydroclimatological factors affecting cholera transmission are clarified. SWIM estimates from satellite remote sensing provide an indirect measurement of impurities present in the coastal waters. It alone cannot provide a direct connection to *V. cholerae*, but can help determine timing and location of presence of impurities in the coastal waters that contributes to the eventual growth and propagation of the causative agent. Our results demonstrate that satellite data over a range of space and time scales can be very effective in developing cholera prediction models for the Bengal Delta and Sub-Saharan Africa. We anticipate that our modeling framework will provide essential lead time ahead of epidemic outbreaks that will help develop effective intervention and mitigation strategies for cholera-endemic regions of the world.

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Chapter 7

Summary, Research Contributions and Future Research

7.1 Summary of the Research

The overall goal of the proposed research was to develop a framework for predicting cholera outbreaks with two to three months lead time, using primarily remote sensing data. To achieve this goal, three closely related research objectives were outlined as to: (i) determine the space-time structure of chlorophyll in the Bay of Bengal; (ii) understand the role of freshwater discharge in creating seasonality and relationships among phytoplankton and SST; and (iii) develop a cholera prediction modeling framework.

Space-time characterization of chlorophyll established relationship between cholera and plankton abundance over a range of scales. Using daily SeaWiFS chlorophyll data, we have established that chlorophyll time series is a white noise process for pixel (~10km) to band (~100 km) scales. Such large temporal variations of pixel level chlorophyll concentration put a practical constraint on the design and implementation of in-situ plankton measurements for coastal areas. Results of chlorophyll variability at the monthly time scale are more encouraging. Chlorophyll in the coastal band shows a distinct annual cycle while such a cycle is not apparent for offshore regions. For the coastal bands, monthly chlorophyll time series shows significant memory; yet at the pixel scale (9 km) it does not exhibit much persistence in time. With increased spatial averaging, temporal persistence of monthly chlorophyll increases. An aggregated monthly chlorophyll concentration for the coastal band - with a spatial averaging scale of

1296 km^2 or larger -is likely to provide a lower limit on spatial scale of plankton measurements for a useful prediction lead time for a potential cholera outbreak model.

Plankton production in the Bay of Bengal is a complex geophysical process. Results indicate that observed positive correlation between SST and chlorophyll in the Bay of Bengal and other major freshwater basins globally are primarily caused by terrestrial nutrient inputs from river discharge. An important aspect of the study is that it provides a new and physically meaningful explanation as to why despite higher SST, more phytoplankton are found in the coastal areas where freshwater discharge is high. The observed positive correlation between SST and chlorophyll in the Bay of Bengal is in fact not causal, and should not form the basis to infer or construct prediction models for cholera outbreaks. Cholera prediction models may benefit from including data on terrestrial nutrient influx and subsequent phytoplankton and zooplankton blooms.

This is perhaps one of the first studies to quantitatively link available remote sensing data to predict cholera outbreaks with several months prediction lead time. Key findings from the phenomenological modeling framework are: (1) Cholera outbreaks can be predicted using two-seasonal modeling strategies with a prediction lead time of several months to a year, depending on the choice of macro-environmental variables. Spring cholera can be predicted up to three months in advance, whereas autumn cholera can be predicted up to one year in advance using remote sensing data. Such prediction lead times will have tangible impacts in designing appropriate cholera intervention, mitigation, and prevention measures for resource-constrained regions. (2) A physically plausible phenomenological explanation is provided regarding the pathways of geophysical transformation (such as from plankton to CDOMs to bacterial growth to cholera outbreaks) of macro-environmental processes leading to conditions favorable for cholera outbreaks.

A reflectance based index, Satellite Water Impurity Marker (SWIM) was developed for predicting cholera outbreaks in vulnerable regions. The index is the combination of blue and green wavelengths where the difference between the two yields a unique value within the range of -100 to 100. The developed index has shown potential to predict cholera outbreaks in Bengal Delta with prediction lead time of about two months and about 78% prediction accuracy.

7.2 Research Contributions

The major contribution of the research is the quantitative evaluation of the satellite based prediction modeling architecture for cholera outbreaks with a lead time of two to three months. Although statistical in nature, the prediction models have shown that satellites have tremendous potential to predict cholera outbreaks (~75% prediction in Bengal) in the data scarce regions. The research also challenged the existing notion that increase in SST will increase chlorophyll and therefore will have increase in the cholera outbreaks. The results from this research clearly showed that the observed positive association between SST and chlorophyll in the Bay of Bengal and other major freshwater basins globally are primarily caused by terrestrial nutrient inputs from river discharge.

The research resulted in over eleven publications, one research grant from National Institutes of Health and twenty-five conference proceedings. To disseminate our understanding on the water-related diseases, we also organized a special session in American Geophysical Union's Fall meeting (Dec 11-17, 2010) titled

Hydroepidemiology: Connections of Human Health with Hydrology which focused on understanding macro-scale controls on outbreaks of several water-related diseases.

7.3 Possible Caveats

The prediction results from this research (more than 75% accuracy) are promising; yet, we are cognizant of possible caveats and limitations that warrant further investigation. Our results are based on twelve years of remote sensing data; as more data become available, the proposed approach needs to be further validated and refined. The idea of environmental cholera transmission was proposed in 1970s (Colwell et al., 1977) and reported in a series of subsequent publications (e.g., Tamplin et al. 1990; Colwell & Huq, 1994; Lipp et al., 2002; Akanda et al., 2009) that continue to be refined as more observational data become available and as the roles of different abiotic, biotic, and hydroclimatological factors affecting cholera transmission are clarified. Chlorophyll estimates from satellite remote sensing provide an indirect measurement of phytoplankton abundance and a quantitative measure of space-time distribution of phytoplankton. However, chlorophyll alone cannot provide a direct connection to *V. cholera;* although it can help determine timing and location of phytoplankton blooms that are followed by zooplankton blooms. By analyzing plankton samples for major groups of phytoplankton and zooplankton, a tighter relationship needs to be established between plankton types and quantitative estimates of *V. cholerae*. Our future research will address some of these questions in the future. Our results demonstrate that satellite data over a range of space and time scales can be very effective in developing a cholera prediction model with several months' lead time. Such prediction lead time will have tangible impacts to design and implement effective cholera intervention and mitigation strategies for various resource constrained and cholera affected regions of the world.

7.4 Future Research: An Integrated Modeling Framework for Cholera Prediction

A population based modeling framework to provide an adaptive understanding and prediction of cholera dynamics where “macro” (hydrological, ecological, climatic and coastal processes) and “micro” (microbiological, genetic, and human intestine scale processes) environmental conditions should be developed. One of the approaches to understand effects of macro environmental controls on cholera dynamics is by using the Susceptible-Infected-Recovered (SIR) based epidemiological models (*e.g., Codeco, 2001; Joh et al., 2009*). The basic idea of SIR models is to compute the theoretical number of people infected with a contagious illness over time and how the disease spread through a given population using various parameters. More details of SIR models can be found in Kermack and McKendrik (1972). Within the framework, we suggest a new class of SIR (Susceptible-Infected-Recovered) model, where macro-environmental factors inform traditional SIR model - will allow us to examine different facets of cholera dynamics. Our proposed model, **Macro-SIR**, will integrate macro-environmental and micro-environmental determinants of cholera occurrences and transmission. It will synthesize existing knowledge and new information from hydroclimatology, ecology, and remote sensing. Cholera based SIR models usually start with the premise that cholera bacteria are transmitted via human to human interaction. Recently, role of indirect transmission via environmental reservoir has been introduced in SIR models (e.g., Codeco, 2001; Joh et al., 2009). Studies have highlighted the role of environmental conditions for creating seasonality in cholera (*Koelle et al., 2005; Pascual et al., 2008*) but did not elaborate on plausible physical mechanisms related to seasonality of outbreaks. Similarly, Bertuzzo et al. (2008; 2009) incorporated an SIR-type framework with a spatially distributed cholera transmission model, but the seasonality of transmission in that model was introduced with ***a-priori*** knowledge or assumption of the distribution of infections. Despite its ubiquitous nature and its importance in the timing of the outbreaks, the seasonality of cholera is not well understood (*Fisman 2007*). To our best knowledge, currently there are no models that can predict cholera outbreaks several months ahead. Issues of seasonality and prediction lead time for cholera are particularly important for the endemic areas of the Bengal Delta where cholera exhibits two peaks per year. To examine the origin of such seasonal patterns, one may focus on relative roles of two routes of transmission – primary or environmental transmission, **Tr (P)**, and secondary or person to person transmission, **Tr (S)**, - for cholera (*Miller et al., 1985*). Most SIR models focus on the secondary transmission mechanisms, Tr(S), as shown in Figure 2.6. Few studies included, Tr (P), as an environmental reservoir (e.g., *Codeco 2001; Jensen et al 200*6). Traditional SIR models presume exponential decay for bacteria in the reservoir even though this phenomenon is not frequently observed (*Joh et al., 2009*). The Macro-SIR modeling framework may be used to evaluate the roles of macro- and micro-environmental drivers in creating and sustaining primary and secondary transmission mechanisms for cholera outbreaks and promoting epidemic and endemic cholera.

The dynamics of direct disease transmission in humans have been studied using variants of SIR models. In these models, primarily micro-environmental conditions are emphasized and basic reproductive ratio (defined as “the number of secondary cases caused by a small number of infected individuals” Joh et al., 2009) is used as a central concept (*Joh et al., 2009; Dietz 1993*). But, these models cannot create seasonality unless some of the model parameters are ***a-priori*** chosen to vary seasonally. Such is the case for a recent study by *Pascual et al (2008)* where a complex SIR type model is used with susceptible fraction and transmission rate as ***a-priori*** chosen seasonally varying parameters. In the absence of plausible physical mechanisms to explain this choice of seasonally varying parameters, predictive capabilities of these models remain uncertain. For example, *Pascual et al (2008)* reported only 7% improvement in predictive capability when effects of El-Nino are included in their model. In a related study, *Koelle et al (2005)* reported low frequency variations in transmission rate to be negatively correlated with rainfall in Northeast India ($r = -0.797$, $p < 0.05$, lag = 14 months). There are no plausible hydroclimatological explanations for such a lagged relationship between rainfall and cholera transmission.Instead of ***a-priori*** choosing transmission mechanisms (primary or secondary) that create and sustain seasonality in cholera, one can use an adaptive modeling framework (such as Figure 2.6). In a Macro-SIR framework, pathogen dynamics and within human transmission dynamics may be explicitly coupled. It recognizes that seasonality of cholera may be dependent on geography and climate (e.g., dual peak in the Bengal delta and single peak in Mozambique) and transmission rates must be estimated based on regional macro-environmental drivers. Such a regionalized approach will allow one to accurately estimate transmission that will result in better prediction.

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Appendix A

On Predicting Cholera Outbreaks: Where is the next Haiti?

Abstract

Despite significant advances in knowledge on *Vibrio cholerae*, recent cholera outbreak in Haiti indicated that the disease remains a global threat. Here, we present a forward thinking framework for developing cholera prediction models in the endemic (ER) and non-endemic regions (NER). The sharp contrast in mortality rates between ER and NER exists not because we do not know how to treat cholera patients, but because of a persistent "knowledge barrier" between ER and NER. We proposed a pragmatic and adaptive framework which hypothesizes that convergence of three enabling situations- Inception, Conditions, and Transmission- are necessary for cholera outbreak to become an epidemic. Based on observations, it can be reasonably hypothesized that the next cholera epidemic will occur in tropical NER following disaster that devastates water and sanitation infrastructure during season with climatic and environmental conditions conducive to cholera proliferation.

Introduction and Objectives

In the mid-1800s, John Snow- a British physician, documented the relationship between cholera and contaminated drinking water. Cholera, an acute waterborne diarrheal disease, has since been the subject of intense study for microbiologists, epidemiologists, clinicians, and environmental scientists. Despite advancements in understanding the causative agent, *Vibrio cholerae*, the disease has remained a global threat. The World Health Organization estimates that annually, 3 to 5 million people are affected worldwide by cholera and over one hundred thousand cases result in death. Because *V. cholerae* is a natural inhabitant of the aquatic environment [1] and growing evidence of emerging biotypes, it is unlikely that cholera will ever be eradicated [2].

The disease remains one of the most prevalent waterborne infections in many regions of the world, specifically in South Asia, Sub-Saharan Africa, and Latin America. Observational records suggest that the vast majority of cholera outbreaks have originated in coastal regions, indicating a strong correlation between the environment and the disease [3-6]. Despite significant advances in our knowledge of *V. cholerae*, we still cannot adequately predict when and where the next cholera epidemic will strike. Prediction of the timing, location, and probability of an outbreak is essential for the effective design and implementation of intervention strategies.

Here, we examine the current status of cholera prediction, identify potential knowledge gaps and provide a framework for prediction and intervention strategies for mitigation. In our study, cholera Endemic Regions (ER) are defined as regions where recurrence of the disease is continual for at least ten consecutive years, while Non-Endemic Regions (NER) experience sporadic and sudden outbreaks. Accordingly, Bangladesh and several coastal Sub-Saharan countries (such as South Africa, Congo, Mozambique, Ghana etc.) are ER (Figure 1a: red colored) and blue colored regions in Figure 1a (Afghanistan, Angola, Haiti, Malaysia, Pakistan etc) are NER. A key difference between ER and NER is fatality rate; for example, the mortality rate for an ER is 1% or lower, while NER rates can exceed 6% (6.4% in Haiti in 2010 and 6% in Madagascar in 2000). More than 3% mortality has been recorded for several NER over the last five years, including Zimbabwe (4.3% in 2008-09), Angola (4% in 2006-07), Nigeria (3.8% in 2010) and Sudan (3.3% in 2006-07).

Discussion

The sharp contrast in mortality rates between ER and NER exists not because we do not know how to treat cholera patients, but because of a persistent "knowledge barrier" between ER and NER. Most of our current knowledge on cholera and effectiveness of interventions is based on surveillance and treatment data from ER. For example, we have a relatively advanced understanding of the ecology, microbiology, and pathology for *Vibrio Cholerae* derived from South Asia [1]. Oral rehydration therapy has reduced the cholera mortality rate from over 30% to less than 1% within a few decades [7]. But at this time, we cannot reliably predict where a cholera outbreak will occur. Furthermore, we have not managed to translate information and experience from ER to implement effective intervention strategies in NER that could significantly reduce potential mortality rates. The current state of knowledge thus raises the following question: Can we use our existing understanding of cholera dynamics and successful interventions in the ER to predict and mitigate the next NER cholera outbreak?

Determining future outbreaks in NER remains a difficult challenge, primarily due to the complex interplay of multiple environmental, human and pathogen factors that obscure causal and transmission pathways. Consequently, identification of a comprehensive causal pathway for the next NER outbreak will remain a scientific puzzle for years to come. Here, we propose a pragmatic and adaptive framework to address this puzzle. This framework hypothesizes that convergence of three enabling situations (Figure 1b) – Inception (I), Conditions (C), and Transmission (T) – are necessary for a cholera outbreak to become an epidemic.

Two opposing views currently exist regarding inception of the disease: indigenous or imported? The indigenous view argues that *V. cholerae* is ubiquitous in natural environments and given appropriate conditions, the number of bacteria will increase in aquatic ecosystems- such as coastal rivers and inland water bodies- and trigger an epidemic through human exposure The imported view argues that in a NER, inception is initiated by imported bacteria from an ER via a human host- either an infected cholera patient or an asymptomatic carrier [8].

While the recent cholera outbreak in Haiti has been linked to the destruction of water and sanitation infrastructure due to the January 2010 earthquake and continued unhygienic living conditions in refugee camps, a similar disaster in Pakistan in 2005 did not lead to a massive cholera outbreak. However, following the 2010 floods in Pakistan, over 600,000 people sought treatment for diarrheal diseases. The acute nature of the crisis in Pakistan and a shortage of cholera vaccines were reported [9]. A key difference between Pakistan 2005 and 2010 disasters appears to be the environmental conditions for bacterial growth and proliferation (C). The 2005 Pakistan disaster occurred just before winter in a mountainous region, with extreme cold conditions that were not conducive to proliferation and spread of *Vibrio cholerae* bacteria. Conversely, the 2010 floods in Pakistan provided the necessary growth conditions and proliferation pathways for cholera transmission.

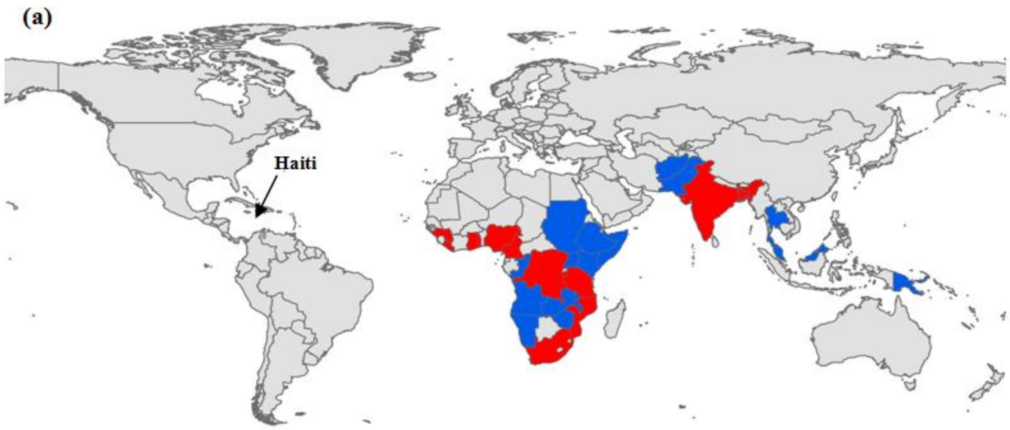
Convergence of inception (I) and conditions (C) cannot result in an outbreak without viable transmission (T) pathways. This was especially evidenced by Louisiana in 2005; despite Hurricane Katrina, a cholera outbreak did not occur. Furthermore, over the past five years, 44 cases of cholera have been reported in the United States, but none led to an outbreak because of the existence of a robust water and sanitation infrastructure and effective prevention methods to halt spread of the disease. Consequently, cholera outbreaks in NER share a common thread, namely a significant interruption or destruction of water and sanitation infrastructure caused by a natural calamity (Pakistan in 2010; Haiti in 2010) or severe political unrest (Angola in 2007; Zimbabwe in 2008; Congo DR in 2008). It has become reasonably clear that crippled water and sanitation infrastructures- the basics of public health and hygiene- have enabled cholera transmission (T) in these aforementioned NER outbreaks.

Conclusions

We conclude that a combination of inception (I), transmission (T) pathways, and conducive environmental conditions (C) is necessary to trigger a cholera outbreak in NER (Figure 1b). Within this framework, could outbreaks of cholera in Haiti have been predicted after the devastating earthquake of January 2010? Indigenous or imported pathways of transmission are both plausible for Haiti. Based on the coastal connection for cholera in ER, it can be argued that *V. cholerae* is present in the tropical coastal aquatic environments of Haiti. However, because cholera has not been officially reported for in over 50 years, the indigenous inception view is questionable. Contrastingly, because many individuals from ER countries traveled to Haiti for aid and relief missions after the earthquake, one could support the viability of the imported inception viewpoint. Although analysis of strains from the recent Haiti outbreak showed similarity to strains from South Asia [9], such strains were also isolated in East Africa. (Based on the plausibility of both viewpoints, one can argue that inception, as an enabling situation, was not a limiting factor for cholera outbreak in Haiti. However, inception cannot proceed further without supporting conditions and transmission pathways. The ambient environmental conditions in fall season and crippled water and sanitation infrastructure after the earthquake provided the convergence of three enabling situations in October 2010 for an outbreak to become an epidemic in Haiti. Accordingly, one could argue that using the ICT framework, one could have predicted with high probability that Haiti would have a cholera epidemic in fall 2010.

Based on observations, it can be hypothesized that the next cholera epidemic will occur in a tropical NER following a disaster that devastates water and sanitation infrastructure during a season with climatic and environmental conditions conducive to cholera proliferation. The challenge remains to develop a prediction model for NER such that we can accurately assess: where is the next Haiti? A cholera prediction model for NER will focus on identifying the appropriate environmental conditions conducive to cholera outbreaks and the existence of enabling transmission mechanisms.

After a major natural disaster strikes a coastal town or significant civil disorder seriously damages living conditions of a population center in the tropical belt, a cholera tracking mechanism should be initiated to monitor climate and environment surrounding vulnerable areas, including refugee camps and areas of flooding, by methods of satellite remote sensing [6]. Water and sanitation infrastructure conditions and density of displaced populations should be assessed. If convergence of environmental conditions and transmission pathways are predicted with high probability, cholera epidemic warnings can be issued. Investment in such a cholera warning system will (a) synthesize current understanding of cholera microbiology, epidemiology and hydroclimatolgy; (b) utilize recent developments in satellite remote sensing and other automated data sources; and (c) translate intervention and mitigation strategies from ER to NER in order to reduce the case-mortality ratio and control the extent of the outbreak.



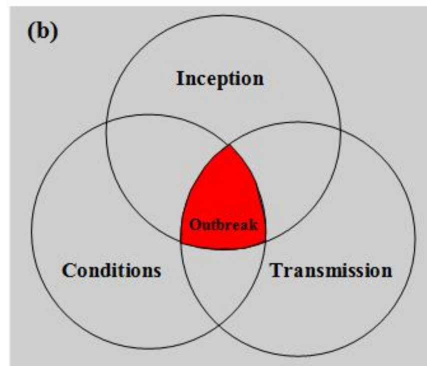


Figure 1: (a) Reported Global Cholera Outbreaks in last 12 months. Blue and red regions are the non-endemic and endemic regions respectively. *Data Source: World Health Organization Global Health Database;* (b) Inception-Conditions-Transmission Framework

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Appendix B

LIST OF PUBLICATIONS

This research thesis has resulted in or significantly contributed to following publications:

<u>*Articles Already Published*</u>

1. Akanda, A.S., Jutla, A.S. and Islam, S. 2009. Dual peak cholera transmission in Bengal Delta: A hydroclimatological explanation, *Geophysical Research Letters*, 36, L19401.
2. Jutla, A.S., Akanda, A.S. and Islam, S. 2010. Tracking Cholera in Coastal Regions using Satellite Observations. *Journal of American Water Resources Association*, 46(4): 651-662.
3. Akanda, A.S., Jutla, A.S., de Magny, G.C., Alam, M., Siddique, A.K., Sack, R.B., Huq, A., Colwell, R.R. and Islam, S. 2011. Hydroclimatic Influences on Seasonal and Spatial Cholera Transmission Cycles: Implications for Public Health Intervention in the Bengal Delta, *Water Resources Research*, 47, W00H07.
4. Jutla, A.S., Akanda, A.S, Griffiths, J., Islam, S. and Colwell, R.R. 2011. Warming oceans, phytoplankton, and river discharge: Implications for cholera outbreaks. *American Journal of Tropical Medicine and Hygiene,* doi:10.4269/ajtmh.2011.11.

<u>*Articles Submitted / In Revision*</u>

5. Jutla, A.S., Akanda, A.S. and Islam, S. 2011. Satellite Remote Sensing of Space-Time Plankton Variability in the Bay of Bengal: Connections to Cholera Outbreaks. *Remote Sensing of Environment* (Minor Revision)
6. Akanda, A.S., Jutla, A.S., Gute, D.M., Evans, T. and Islam, S. 2011. Reducing Cholera Burden through Proactive Intervention. *Bulletin of the World Health Organization* (Submitted).
7. Akanda, A.S., Gute, D.M., Jutla, A.S., and Islam, S. 2011. Understanding and Predicting Bengal Cholera Outbreaks Through an Epidemiologic Application of Macro-Scale Hydroclimatic Drivers, *Epidemiology* (Submitted).
8. Jutla, A.S., Akanda, A.S. and Islam, S. 2011. Predicting cholera outbreaks in South Asia using satellite derived macro-scale environmental determinants. *Environmental Modeling and Software*. (Submitted).
9. Jutla, A.S., Akanda, A.S., Mazumdar, M., Colwell, R.R., and Islam, S. 2011, Predicting Cholera Outbreaks: Where is the next Haiti? (*Submitted)*

<u>*Articles In Preparation*</u>

10. Akanda, A.S., Jutla, A.S., Eltahir, E. and Islam, S. 2011. A Spatially Explicit and Seasonally Varying Cholera Prevalence Model using Macro-Scale Hydroclimatic Forcings (*In Preparation*).

11. Jutla, A.S., Akanda, A.S. and Islam, S. 2011. Predicting Cholera Outbreaks in South Asia and Sub-Saharan Africa using Satellite Water Impurity Marker (*In Preparation*).

APPENDIX C

ABSTRACTS OF PUBLICATIONS

1. Dual Peak Cholera Transmission in Bengal Delta: A Hydroclimatological Explanation

Cholera has reemerged as a global killer with the world witnessing an unprecedented rise in cholera infection and transmission since the 1990s. Cholera outbreaks across most affected areas show infection patterns with a single annual peak. However, cholera incidences in the Bengal Delta region, the native homeland of cholera, show bi-annual peaks. The mechanisms behind this unique seasonal dual peak phenomenon in cholera dynamics, especially the role of climatic and hydrologic variables, are not fully understood. Here, we show that low flow in the Brahmaputra and the Ganges during spring is associated with the first outbreaks of cholera in Bangladesh; elevated spring cholera outbreaks are seen in low discharge years. Peak streamflow of these rivers, on the other hand, create a different cholera transmission environment; peak flood volumes and extent of flood-affected areas during monsoon are responsible for autumn cholera outbreaks. Our results demonstrate how regional hydroclimatology may explain the seasonality and dual peaks of cholera incidence in the Bengal Delta region. A quantitative understanding of the relationships among the hydroclimatological drivers and seasonal cholera outbreaks will help early cholera detection and prevention efforts.

2. Tracking Cholera in Coastal Regions using Satellite Observations

Cholera, an acute water-borne diarrheal disease, continues to be a significant health threat across the globe. The pattern and magnitude of the seven global pandemics suggest that cholera outbreaks primarily originate in coastal regions and spread inland through secondary means. Cholera bacteria show strong association with zooplankton and phytoplankton abundance in coastal ecosystems. This review study investigates relationship(s) between cholera incidences and coastal processes and explores the utility of using remote sensing data to track coastal plankton blooms and subsequent cholera outbreaks in vulnerable regions. Most of the studies over the last several decades have primarily focused on the microbiological and epidemiological understanding of cholera outbreaks, however, successful identification and mechanistic understanding of large scale climatic, geophysical and oceanic processes governing chlorophyll-cholera relationships is important for developing any predictive model for disease outbreak. Development of a holistic understanding of these processes requires long and reliable chlorophyll dataset, which is now available through satellites. We have presented a plausible pathway relating cholera, sea surface temperature, chlorophyll, and terrestrial hydrology through river discharge and satellite estimated coastal plankton abundance. Remote sensing, with its unprecedented spatial and temporal coverage, has capabilities to monitor coastal processes and track potential cholera outbreaks in endemic regions.

3. Hydroclimatic Influences on Seasonal and Spatial Cholera Transmission Cycles: Implications for Public Health Intervention in the Bengal Delta

Cholera remains a major public health threat in many developing countries around the world. The striking seasonality and annual recurrence of this infectious disease in endemic areas remain of considerable interest to scientists and public health workers. Despite major advances in the ecological and microbiological understanding of *Vibrio cholerae*, the causative agent of the disease, the role of underlying large-scale hydroclimatic processes in propagating the disease for different seasons and spatial locations is not well understood. Here, we show that the cholera outbreaks in the Bengal Delta region, are propagated from the coastal to the inland areas and from spring to fall by two distinctly different, pre- and post-monsoon, transmission cycles influenced by coastal and terrestrial hydroclimatic processes, respectively. A coupled analysis of the regional hydroclimate and cholera incidence reveals a strong association of the space-time variability of incidence peaks with seasonal processes and extreme climatic events. We explain how the asymmetric seasonal hydroclimatology affects regional cholera dynamics by providing a coastal growth environment for bacteria in spring, while propagating the disease to fall by monsoon flooding. Our findings may serve as the basis for “climate-informed” early warnings, and prompting effective means for intervention and preempting epidemic cholera outbreaks in vulnerable regions.

4. Warming oceans, phytoplankton, and river discharge: Implications for cholera outbreaks

Phytoplankton abundance is inversely related to sea surface temperature (SST). However, a positive relationship is observed between SST and phytoplankton abundance in coastal waters of Bay of Bengal. This positive relationship has been proposed as an important element in understanding cholera dynamics. It has led to an assertion that in a warming climate scenario, rise in SST may increase phytoplankton blooms and, therefore, cholera outbreaks. This study has two objectives: (i) explain why a positive SST-phytoplankton relationship exists in the Bay of Bengal and (ii) understand the implications of such a relationship on cholera dynamics. We used regression and wavelet analysis on satellite derived chlorophyll, a surrogate for phytoplankton abundance, and SST in Bay of Bengal as well as in three other major coastal regions (Amazon, Orinoco, and Congo rivers basin) with the high-discharge. We found clear evidence of two independent physical drivers for phytoplankton abundance. The first, primarily based on literature, is the phytoplankton blooming produced by the upwelling of cold, nutrient-rich deep ocean waters. The second, which explains positive relationship between SST and phytoplankton abundance in the Bay of Bengal, is the blooming of coastal phytoplankton from terrestrial nutrients discharge during high river discharges. The reported positive association between SST and phytoplankton for the Bay of Bengal may not be causal. Therefore, caution should be used when associating SST with phytoplankton and subsequent cholera outbreaks in regions where freshwater discharge rivers are a predominant mechanism for phytoplankton production.

5. Satellite Remote Sensing of Space-Time Plankton Variability in Bay of Bengal: Connections to Cholera Outbreaks

Cholera bacteria exhibit strong association with coastal plankton. Characterization of space-time variability of chlorophyll, a surrogate for plankton abundance, in Northern Bay of Bengal is an essential first step to develop any methodology for tracking cholera outbreaks in the Bengal Delta region using remote sensing. This study quantifies the space-time distribution of chlorophyll in Bay of Bengal region using ten years of satellite data. Variability of chlorophyll at daily scale, irrespective of spatial averaging, resembles white noise. At a monthly scale, chlorophyll shows distinct seasonality and chlorophyll values are significantly higher close to the coast than in the offshore regions. At pixel level (9 km) on monthly scale, on the other hand, chlorophyll does not exhibit much persistence in time. With increased spatial averaging, temporal persistence of chlorophyll increases and lag one autocorrelation stabilizes around 0.60 for 1296 km^2 or larger areal averages. Spatial analyses of chlorophyll suggest that coastal Bay of Bengal has a stable sill at 100 km. Offshore regions, on the other hand, do not show a stable sill. This study puts a lower limit on space-time averaging of satellite measured plankton at 1296 km^2-monthly scale to track cholera outbreaks from space in Northern Bay of Bengal.

6. Reducing Cholera Burden through Proactive Intervention

With the ever-expanding geographic reach of the seventh pandemic and alarming fatality rates in newly affected regions, it is apparent that global cholera prevention strategies are failing. However, the disease burden could be significantly reduced if the established preventive measures could be implemented ahead of time with the advanced knowledge of impending outbreaks in a particular region. A spatially explicit cholera prediction model based on environmental and climatic signatures can potentially provide the critical lead-time to deploy medical and human resources and mount preventive interventions in vulnerable areas to save lives and reduce the cholera disease burden during and following epidemic outbreaks.

7. Understanding and Predicting Bengal Cholera Outbreaks Through An Epidemiologic Application of Macro-Scale Hydroclimatic Drivers

The coastal floodplains of the Bengal Delta have a long history of cholera outbreaks, with temporal peaks occurring during the spring in coastal areas and during the fall in inland locations. The highly populated proximal areas to the corridors of the major rivers of the region, the Ganges-Brahmaputra-Meghna (GBM) system, bear the brunt of both waves of outbreaks, experiencing a biannual incidence pattern. Previous studies focusing on environmental and hydroclimatic drivers of cholera dynamics have not highlighted the spatio-temporal nature of population vulnerability in floodplain areas due to the influence of these large-scale drivers. Here we show that the seasonal and interannual patterns of cholera transmission mechanisms are strongly influenced by estuarine salinity and inland flood inundation patterns that may set the ecological and environmental 'stage' for epidemic outbreaks over large geographic regions. We argue that a major segment of the population in floodplain areas remain vulnerable to the dual peak cholera transmission mechanisms associated with these large-scale drivers. An epidemic outbreak of cholera compounded with the concurrent appearance of droughts or floods may thus seriously overburden the public health response system in Bangladesh.

8. Predicting cholera outbreaks using satellite derived macro-scale environmental determinants

There is growing evidence that outbreaks of several water-related diseases are potentially predictable by using satellite derived macro-scale environmental variables. Cholera remains one of the most prevalent water-related infections in many tropical regions of the world. Macro-environmental processes provide a natural ecological niche for *Vibrio cholerae* and because powerful evidence of new biotypes is emerging, it is highly unlikely that cholera will be fully eradicated. Consequently, to develop effective intervention and mitigation strategies, it is necessary to develop cholera prediction models with several months' lead time. Three observations motivate us to explore the use of satellite data derived macro-scale environmental variables to develop a cholera prediction model: (a) almost all cholera outbreaks originate near the coastal areas; (b) cholera bacteria exhibit a strong relationship with coastal plankton; and (c) cholera bacteria cannot be measured easily and regularly over large areas. Using chlorophyll as a surrogate for plankton bloom in coastal areas, recent studies have postulated a relationship between chlorophyll and cholera incidence. Here, we show that seasonal cholera outbreaks in the Bengal Delta can be predicted two to three months in advance with an overall prediction accuracy of over 75% by using satellite-derived chlorophyll and air temperature data. Such high prediction accuracy is achievable because the two seasonal peaks of cholera are predicted using two separate models representing distinctive macro-scale environmental processes. We have shown that interannual variability of pre-monsoon cholera outbreaks can be satisfactorily explained with coastal plankton blooms and a cascade of hydro-coastal processes. Post-monsoon cholera outbreaks, on the other hand, are related to macro-scale monsoon processes and subsequent breakdown of sanitary conditions. Our results demonstrate that satellite data over a range of space and time scales are effective in developing a cholera prediction model for the Bengal Delta with several months' lead time. We anticipate our modeling framework and findings will provide the impetus to explore the utility of satellite derived macro-scale variables for cholera prediction in other cholera prone regions.

9. A Spatially Explicit and Seasonally Varying Cholera Prevalence Model With Distributed Macro-Scale Environmental and Hydroclimatic Forcings

Despite major advances in the ecological and microbiological understanding of *Vibrio cholerae*, the causative agent of the deadly diarrheal disease cholera, the role of underlying large-scale processes in the progression of the disease in space and time is not well understood. Here, we present a semi-mechanistic spatially explicit coupled hydroclimatology-epidemiology model for understanding regional scale cholera prevalence in response to large scale hydroclimatic and environmental forcings. The model simulations show that environmental cholera transmission is modulated by two spatially and seasonally distinct transmission mechanisms - influenced by dry and wet season hydroclimatic determinants. The semi-distributed model is applied to the Ganges-Brahmaputra-Meghna Basin areas in Bangladesh to simulate spatially explicit cholera prevalence rates, validated with long-term cholera data from Dhaka and shorter-term records from regional surveillance locations. The model reproduces the variability of cholera prevalence at monthly, seasonal, and interannual timescales and highlights the role of asymmetric large scale hydroclimatic processes as dominant controls. Our findings have important implications for formulating effective cholera intervention, and for understanding the impacts of changing climate patterns on seasonal transmission.

10. Predicting seasonal cholera outbreaks using a global index: Satellite Water Impurity Marker (SWIM)

Cholera remains a significant health threat across the globe. Since coastal brackish water provides a natural ecological niche for *Vibrio cholerae* and because powerful evidence of new biotypes is emerging, it is highly unlikely that cholera will be fully eradicated. Therefore, it is necessary to develop cholera prediction model with several months' of actionable lead time. Satellite based estimates of plankton have been associated with proliferation of cholera bacteria. However, survival of cholera bacteria in variety of coastal ecological environment puts physical constraints on predictive abilities of plankton abundance for cholera outbreaks. Here, we propose a new remote sensing reflectance based statistical index: Satellite Water Impurity Marker, or SWIM, which has shown potential to predict cholera outbreaks in two endemic regions (South Asia and Sub-Saharan Africa). This statistical marker is based on the variability observed in the difference between the blue (412nm) and green (555nm) wavelengths in coastal waters and cholera incidence. The developed marker has the ability to predict cholera outbreaks in the Bengal Delta with a predicted r^2 of 78% with two months lead time. The marker was validated in the coastal Mozambique region, where we obtained a predicted r^2 of 57% with two months' lead time. We anticipate that a predictive system based on SWIM will provide essential lead time allowing effective intervention and mitigation strategies to be developed for other cholera-endemic regions of the world.

11. On Predicting Cholera Outbreaks: Where is the next Haiti?

Despite significant advances in knowledge on *Vibrio cholerae*, recent cholera outbreak in aiti indicated that the disease remains a global threat. Here, we present a forward thinking ramework for developing cholera prediction models in the endemic (ER) and non-endemic regions (NER). The sharp contrast in mortality rates between ER and NER exists not because we do not know how to treat cholera patients, but because of a persistent "knowledge barrier" between ER and NER. We proposed a pragmatic and adaptive framework which hypothesizes that convergence of three enabling situations- Inception, Conditions, and Transmission- are necessary for cholera outbreak to become an epidemic. Based on observations, it can be reasonably hypothesized that the next cholera epidemic will occur in tropical NER following disaster that devastates water and sanitation infrastructure during season with climatic and environmental conditions conducive to cholera proliferation.