A

USE OF REMOTE SENSING FOR ANALYSIS AND ESTIMATION OF VECTOR-BORNE DISEASE

by

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Abstract

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An epidemiological data of malaria cases were correlated with satellite-based vegetation health (VH) indices to investigate if they can be used as a proxy for monitoring the number of malaria cases. Mosquitoes, which spread malaria in Bangladesh, are very sensitive to environmental conditions, especially to changes in weather. Therefore, VH indices, which characterize weather conditions, were tested as indicators of mosquitoes' activities in the spread of malaria. Satellite data were presented by the following VH indices: Vegetation Condition Index (VCI), Temperature Condition Index (TCI), and Vegetation Health Index (VHI). They were derived from radiances and measured by the Advanced Very High Resolution Radiometer (AVHRR) flown on NOAA afternoon polar orbiting satellites. Assessment of sensitivity of the VH was performed using correlation and regression analysis. Estimation models were validated using of Jackknife Cross-Validation procedure. Results show that the VH indices can be used for detection, and numerical estimate of the number of malaria cases. During the cooler months (January–April) when mosquitoes are less active, the correlation is low and increases considerably during the warm and wet season (April-November), for TCI in early October and for VCI in mid September. All analysis and estimation model developed here are based on data obtained for Bangladesh

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Chapter 1

Introduction

1.1 Research motivations and problem statement

Climate can be used as a predictor for mosquito development. Information from the Advanced Very High Resolution Radiometer (AVHRR) on-board the National Oceanic and Atmospheric Administration's (NOAA) polar-orbiting meteorological satellites were used to estimate land surface temperature (LST) and atmospheric moisture. Cold cloud duration (CCD) data derived from the High Resolution Radiometer (HRR)

on-board the European Meteorological Satellite program's (EUMETSAT) and Meteosat satellite data were used to estimate rainfall. Temperature, atmospheric moisture and rainfall were independently derived from Meteorological data over Africa. These data were then used to test the accuracy of each methodology, so that the appropriateness of the two techniques for epidemiological research could be compared. Spatial information (SI) was a more accurate predictor of temperature, whereas Remote Sensing (RS) provide better surrogate for rainfall; both were equally accurate at predicting atmospheric moisture. The implications of these results for mapping short and long-term climate change and hence their potential for the study and control of disease vectors are considered.

Geographic information systems (GIS), global positioning systems (GPS), remote sensing, and spatial statistics are tools to analyze and integrate the spatial component of vector-borne disease epidemiology into research, surveillance, and control programs based on a landscape ecology approach. Landscape ecology, which deals with the mosaic structure of landscapes and ecosystems, considers the spatial heterogeneity of biotic and abiotic components as the underlying mechanism which determines the structure of ecosystems. The methodologies of GIS, GPS, satellite imagery, spatial statistics and the landscape ecology--epidemiology approach to vector-borne diseases and applications are reviewed. The remotely sensed data such as reflectance in the middle infra-red and the normalized difference vegetation index (NDVI) were processed to provide surrogate information on environment. As described by Ripron, the NDVI in the preceding month correlated with malaria across the 3 sites. Regression analyses showed that an NDVI threshold of 0.35-0.40 was required for more than 5% of the annual malaria cases to be presented in a given month. These thresholds were then extrapolated spatially with the temporal Fourier-processed NDVI data to define the number of months, in which malaria admissions could be expected across Kenya in an average year. The resulting maps were compared with the Butler's map of malaria transmission for Kenya, compiled from expert opinion. Conclusions are drawn on the appropriateness of remote sensing techniques for compiling national strategies for malaria intervention.

An increasing number of health studies have used remotely sensed data for monitoring, surveillance, or risk mapping, particularly of vector-borne diseases like malaria and dengue. Most of human health studies using remote sensing have focused on data from NOAA's Advanced Very High Resolution Radiometer (AVHRR), Landsat's Multispectral Scanner (MSS) and Thematic Mapper (TM) and France's Système Pour l'Observation de la Terre.

Vector-borne diseases (mosquito-borne diseases) have become a major international public health concern. Mosquito vectored diseases include protozoan diseases, i.e., malaria, dengue, dog heartworm and yellow fever. From all are among those malaria is the most widely spread and dengue intensified recently, creating a global problem. The malaria parasite (plasmodium) is transmitted by female Anopheles mosquitoes. Dengue is spread through the bite of an infected Aedes aegypti mosquito.

Malaria and dengue are understood to be both a disease and cause of poverty with significant measurable direct and indirect costs, having been shown to be a major constraint to economic development. For developing economies, this has meant that the gap in prosperity between countries with these diseases and countries without malaria has become wider every single year. Annual economic growth in countries with high vector-borne diseases transmission has historically been lower than in countries without malaria. Economists believe that vector-borne diseases are responsible for a growth penalty of up to 1.3% per year in some countries. When compounded over the years, this penalty leads to substantial differences in GDP between countries with and without malaria and severely restrains the economic growth of the entire region. The direct costs of malaria include a combination of personal and public expenditures on both prevention and treatment of the disease. Personal expenditures include spending on insecticide-treated nets (ITNs), doctor's fees, anti malarial drugs, transport to health facilities, support for the patient and sometimes an accompanying family member during hospital stays. Public expenditures include maintenance of health facilities and health care infrastructure, publicly managed vector control, education and research. In some countries with a heavy malaria burden, the disease may account for as much as 40% of public health expenditure, 30% to 50% of inpatient admissions, and up to 50% of outpatient visits. The indirect costs of malaria include lost of productivity or income associated with illness or death. This might be expressed as the cost of lost workdays or absenteeism from formal employment and the value of unpaid work done in the home by both men and women. In the case of death, the indirect cost includes the discounted future lifetime earnings of those who die. The simple presence of vector-borne diseases in a community or country also hampers individual and national prosperity due to its influence on social and economic decisions. The risk of contracting vector-borne diseases in endemic areas can deter investment, both internal and external, and affect individual and household decision-making in many ways that have a negative impact on economic productivity and growth.

Vector-borne diseases are spread by mosquitoes which create different types of epidemics and many are regarded as contributing factors, such as: living condition of the people, climate and landscape. The type of standing water in which the mosquito chooses to lay eggs depends upon the species. The presence of beneficial predators such as fish and dragonfly nymphs in permanent ponds, lakes and streams usually keep these bodies of water relatively free of mosquito larvae. However, swamps, clogged ditches and temporary pools and puddles are all prolific mosquito breeding sites. Other sites in which some species lay their eggs include tree holes and containers such as old tires, buckets, toys, potted plant trays and saucers and plastic covers or tarpaulins. Some of the most annoying and potentially dangerous mosquito species, such as the Asian tiger mosquito, come from these sites.

The People's Republic of Bangladesh lies between 20°34' and 26°38' north latitude, and 88°01' and 92°41' east longitude. Bangladesh has its borders with the Indian states of Mizuram, Tripura, Assam and West Bengal. The southern deltaic region faces the Bay of Bengal. It has a small inter-country border with Myanmar. Bangladesh has 64 districts within 6 administrative divisions: Barisal, Chittagong, Dhaka, Khulna, Rajshahi and Sylhet. It has a Population of 88 million with a population density of 868 persons per square kilometers. Eighty percent of total population lives in a rural area. Bangladesh mostly comprises of low, mostly flat alluvial plain; hills in southeast, intersected by numerous rivers and rivulets, canals, swamps and marshy lands. Bangladesh has a tropical monsoon climate, mild winter (October to March); hot, humid summer (March to June); and a humid, warm rainy monsoon period (June to October). The alluvial soil of Bangladesh is continuously enriched by heavy silt deposits during the rainy season. The country is prone to natural disaster, floods droughts, cyclones, and tidal bores, much of the country is routinely inundated during the summer monsoon season and faces the consequences of such disasters almost every year. Water-borne diseases prevalent in surface water; water pollution, especially of fishing areas, results from the use of commercial pesticides; ground water contaminated by naturally occurring arsenic; intermittent water shortages because of falling water tables in the northern and central parts of the country; soil degradation and erosion; deforestation; and severe overpopulation .

In addition to water-borne, vector-borne diseases (mosquito-borne diseases) have become a major international public health concern.

From vector-borne diseases, malaria and dengue affect the health and wealth of nations and individuals alike. Although socioeconomic indicator such as poverty living conditions, sanitation, public health, etc., environmental conditions are a major contributor to development of vector-borne epidemics.

Although the government of Bangladesh takes measures to eradicate the diseases, but it still prevails in many places. These diseases are causing deaths and creating big labor and economic problem for the country. In order to reduce the consequences of vector-borne epidemics, especially in the years of their intensification, the Government needs to know in advance potential for the development of epidemics.

However the number of weather stations in Bangladesh is not sufficient. There are only 34 stations for the total area of 107,570 square kilometers. With an average of one weather station per 100 sq. km, weather data could potentially provide useful information about mosquito development and activity.

Therefore the goal of this dissertation is to investigate possibility of using RS data for estimating potential for mosquito-borne diseases. Specific tasks include the development of spatially and temporally consistent indices to be used for the detection, surveillance and numerical estimate of development of malaria and dengue in Bangladesh. It is well known that variations in the epidemic intensify from year to year and is increasingly weather dependent. Wet and warm weather normally stimulates mosquito multiplication and triggers to increase in the number of people bitten by mosquito which is potentially favorable for development of epidemics.

1.2 Thesis organization

Chapter two will provide overview of Vector-borne diseases and Remote Sensing (RS)

Chapter three will explain environmental satellites. RS data was collected from environmental satellites to predict malaria of all divisions of Bangladesh.

Chapter four will present landscape, climate, malaria and dengue in study area, Bangladesh.

Chapter five will explain the methodology of using three types of data (satellite, malaria statistics and ground data).

Chapter six will analyze coastal divisions. Here describes correlation of malaria cases with satellite data and metrological data. We also developed a regression model for predicting malaria cases.

Chapter seven will analyze highland and forest cover divisions.

Chapter eight will elaborately analyze malaria cases of Bangladesh for period 1992-2001. The developed model will be used to predict malaria cases using RS data.

Chapter nine will provide analysis of malaria case for Bangladesh for period 19982-1991.

Chapter ten will describe analysis of dengue in Dhaka city, Bangladesh. Here we used trend analysis and RS data to predict epidemics.

In chapter eleven will show validation of developed model for Chittagong division and whole Bangladesh.

In chapter twelve we will summarize and conclude this work and layout some future research.

Chapter 2

Vector-borne Disease

2.1 Introduction

Vector-borne diseases (mosquito-borne diseases) have become a major international public health concern. Mosquito vectored diseases include protozoan diseases, i.e., malaria, dengue, Dog heartworm and Yellow fever. From all of them, malaria is the most widely spread while dengue has recently intensified, creating a global problem. The malaria parasite (plasmodium) is transmitted by female Anopheles mosquitoes. Dengue is spread through the bite of an infected Aedes aegypti mosquito.

2.2 Overview of Vector-Borne disease

Malaria and dengue are understood to be both a disease of poverty and have significant measurable direct and indirect costs, having been shown to be a major constraint to economic development. For developing economies this means that the gap in prosperity between countries with these diseases and without has widened every single year. Annual economic growth in countries with high vector-borne disease transmission has historically been lower than in the countries without them. Economists believe that vector-borne diseases are responsible for a growth penalty of up to 1.3% per year in some countries [45, 49]. When compounded over the years, this penalty leads to substantial differences in GDP between countries with and without malaria and severely restrains the economic growth of the entire region. The direct costs of malaria include a combination of personal and public expenditures on both prevention and treatment of the disease. Personal expenditures include individual or family spending on insecticide-treated nets (ITNs), doctor's fees, anti malarial drugs, transport to health facilities, support for the patient and sometimes an accompanying family member during hospital stays. Public expenditures include spending by government on maintaining health facilities and health care infrastructure, publicly managed vector control, education and research. In some countries with a heavy malaria burden, the disease may account for as much as 40% of public health expenditure, 30% to 50% of inpatient admissions, and up to 50% of outpatient visits. The indirect costs of malaria include lost productivity or income associated with illness or death. This might be expressed as the cost of lost workdays or absenteeism from formal employment and the value of unpaid work done in the home by both men and women. In the case of death, the indirect cost includes the discounted future lifetime earnings of those who die. The simple presence of vector-borne diseases in a community or country also hampers individual and national prosperity due to its influence on social and economic decisions. The risk of contracting vector-borne diseases in endemic areas can deter investment, both internal and external, and affect individual and household decision making in many ways that have a negative impact on economic productivity and growth [22, 23, 34, and 38].

Malaria affects individuals in 102 countries and is responsible for over 300 to 500 million clinical cases and more than a million deaths each year. Approximately 40% of the world's population, mostly those living in the world's poorest countries, is at risk of malaria. During the 1950s and 1960s, a vigorous campaign to eradicate malaria was waged through out the world with great success. There are more than 2,500 known species of mosquitoes worldwide. Out of that, only around 50 to 60 species of Anopheles mosquitoes are capable to transmit infection. Since the inception of the global Malaria Eradication Program in 1961 [15], malaria blood slide results and related indicators have been at the center of the malaria eradication strategy worldwide, and have been used to analyze the malaria situation in Bangladesh. In 1969, the global malaria strategy changed from eradication to control, yet the surveillance practices of the malaria eradication era continue to be used in Bangladesh. Bangladesh is not unique in this respect. Following the Amsterdam Ministerial Conference in 1992, a change from specialized information systems to integrated ones was seen as essential, together with ''a radical redefinition of the information that should be collected''[1]. In many instances, however, general health services continue to follow traditional eradication screening criteria, long after the eradication strategy has been abandoned. The global prevalence of dengue has grown dramatically in recent decades. Dengue fever, dengue hemorrhagic fever (DHF) and dengue shock syndrome (DSS) occur in over 100 countries and territories and threaten the health of more than 2.5 billion people in urban, peri-urban and rural areas of the tropics and subtropics. The disease is endemic in Africa, the Americas, the Eastern Mediterranean, South-East Asia and the Western Pacific. Although the major disease burden is in South-East Asia and the Western Pacific, rising trends are also reflected in increased reporting of dengue fever and DHF cases in the Americas. Prior to 1970, only nine countries in the world had experienced DHF epidemics; by 1995 the number had increased more than four-fold. In the 1950s and average of 908 DHF cases per year were reported to the World Health Organization (WHO). For the period 1990-1998, the average has increased to 51,099. In 1998, a total of 1.2 million cases of dengue and DHF were reported to WHO including 15,000 deaths [9, 11, 49, 51]. Dengue is also a mosquito vectored disease like malaria. Dengue is spread through the bite of an infected Aedes aegypti mosquito. Dengue carrying mosquitoes breed in stored, exposed, water collection systems. The favored breeding places are: barrels, drums, jars, pots, buckets, flower cases, plants saucers, tanks, discarded bottles tins, tires, water coolers, etc and a lot more places where rainwater collects or is stored [2]. The history of the dengue outbreak of Bangladesh began in 1964 but it was an epidemic since 2000. There are many deaths caused by dengue in 2000, 2001 and 2002.

The populations most at risk of epidemics are those living in highlands, arid and desert-fringe zones, as well as those living in areas where successful control measures have not been consolidated or maintained [47,48].

2.3 Mosquito, Malaria, Dengue and Environment

Mosquito

Mosquitoes have been the bane of mankind for millennia. In 300 B.C., Aristotle referred to mosquitoes as "empis" in his "Historia Animalium" where he documented their life cycle and metamorphic abilities [37]. They can disrupt work, ruin vacations and reduce the pleasure of gardening. They are capable of transmitting diseases such as malaria, yellow fever, filariasis, and dengue to man, encephalitis to man and horses, and heartworm to dogs.

There are over 2500 different species of mosquitoes throughout the world. Common types of mosquitoes found in Oklahoma are placed in the genera Aedes, Anopheles, Culex, and Psorophora.

Aedes mosquitoes are painful and persistent biters, attacking humans during daylight hours. They do not normally enter homes. Aedes mosquitoes are strong fliers and are known to fly many miles from their breeding sources. Aedes and also Psorophora mosquitoes do not breed in ponds, lakes or extremely stagnant water, so, control efforts during rain periods should be directed at eliminating temporary standing water pools. These are sometimes called "floodwater" mosquitoes because flooding is important for their eggs to hatch. Aedes mosquitoes have abdomens with pointed tips. They include such species as the yellow-fever mosquito (Aedes aegypti) and the Asian tiger mosquito (Aedes albopictus). They are strong fliers, capable of traveling great distances (up to 75 miles/81 km) from their breeding sites. They persistently bite mammals (especially humans), mainly at dawn and in the early evening.

Culex mosquitoes are painful and persistent biters at dusk and after dark. They prefer to attack domestic and wild birds rather than man, cows, and horses. They will enter homes in search of blood meals. Some Culex species are known to transmit encephalitis (sleeping sickness) to man and horses. The Culex mosquitoes develop in standing or very stagnant water. They cannot survive the wave action of open bodies of water or the movement of water in flowing streams. Culex mosquitoes are often found in containers that hold water, e.g. tanks, troughs, barrels, tin cans, tires, etc. Culex are generally weak fliers and do not move far from home, although they have been known to fly up to two miles. Culex usually lives only a few weeks during the warm summer months [50]. Those females which emerge in late summer search for sheltered areas where they "hibernate" until spring. Warm weather brings them out in search of water on which to lay their eggs.

Culiseta mosquitoes are moderately aggressive biters, attacking in the evening hours or in shade during the day.

Anopheles tends to breed in bodies of permanent fresh water. Anopheles mosquitoes also have abdomens with pointed tips. They include several species, such as the common malaria mosquito (Anopheles quadrimaculatus), that can spread malaria to humans. Anopheles mosquitoes are the only mosquito which transmits malaria to humans.

Vector-borne diseases are spread by mosquitoes which create different types of epidemics many factor contribute to the epidemics, living condition of the people, climate and landscape. The type of standing water in which the mosquito chooses to lay eggs depends upon the species. The presence of beneficial predators such as fish and dragonfly nymphs in permanent ponds, lakes and streams usually keep these bodies of water relatively free of mosquito larvae. However, swamps, clogged ditches and temporary pools and puddles are all prolific mosquito breeding sites. Other sites in which some species lay their eggs include tree holes and containers such as old tires, buckets, toys, potted plant trays and saucers and plastic covers or tarpaulins. Some of the most annoying and potentially dangerous mosquito species, such as the Asian tiger mosquito, come from these sites. The female mosquito lays 30-150 eggs every 2-3 days. The average life span of a mosquito is 2-3 weeks. It can be longer in ideal living conditions [21, 28, 30, 31]. Human blood is needed to nourish these eggs and Anopheles shows the most regular cycles of blood feeding and egg lying.

Anopheles mosquitoes enter the house between 5 p.m. and 9.30 p.m. and again in early hours of morning. They start biting by late evening and the peak of biting activity is at midnight and early hours of morning.

Mosquito Development

The mosquito goes through four separate and distinct stages in its development cycle: Egg, Larva, Pupa, and Adult.

Typical Life Cycle of Mosquitoes shown in **Figure 2.1**.

Egg: Eggs are laid one at a time or attached together to form "rafts." They float on the surface of the water. Anopheles, Ochlerotatus and Aedes, as well as many other genera, do not make egg rafts, but lay their eggs one at a time. Anopheles lay their eggs on the water surface while many Aedes lay their eggs on damp soil that will be flooded by water. Most eggs hatch into larvae within 48 hours; others might withstand subzero winters before hatching. Water is a necessary part of their habitat [26, 27].

Larva: The larva (plural - larvae) lives in the water and comes to the surface to breathe. Larvae shed (molt) their skins four times, growing larger after each molt. Most larvae have siphon tubes for breathing and hang upside down from the water surface. Anopheles larvae do not have a siphon and lie parallel to the water surface to get a supply of oxygen through a breathing opening. The larvae feed on microorganisms and organic matter in the water [31, 32]. During the fourth molt the larva changes into a pupa. Mosquito larvae, commonly called "wigglers," live in water from 4 to 10 days depending on water temperature.

Pupa: The pupa stage is a resting, non-feeding stage of development, but pupae are mobile, responding to light changes and moving (tumble) with a flip of their tails towards the bottom or protective areas. This is the time the mosquito changes into an adult. Mosquito pupae, commonly called "tumblers," live in water from 1 to 4 days, depending upon species and temperature

Adults: The newly emerged adult rests on the surface of the water for a short time to allow itself to dry and all its body parts to harden. The wings have to spread out and dry properly before it can fly. Blood feeding and mating does not occur for a couple of days after the adults emerge.

When adult mosquitoes emerge from the aquatic stages, they mate, and the young adult female seeks a blood meal. The young adult female mosquito taking her first blood meal does not transmit diseases. It is the older female who may have picked up a disease organism in an earlier blood meal that can transmit the disease during a subsequent blood meal. Plant nectar is the principle food source for the male.

Malaria

Malaria is a protozoa disease transmitted by the Anopheles mosquito, caused by minute parasitic protozoa of the genus Plasmodium, which infect human and insect hosts alternatively. It is a very old disease and prehistoric man is thought to have suffered from

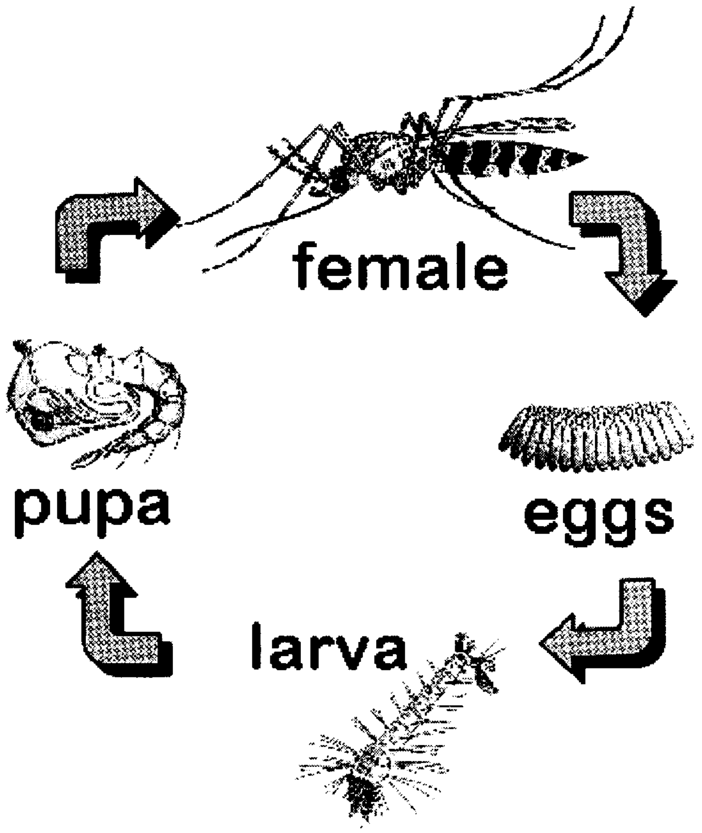


Figure 2.1 Typical life cycle of mosquitoes

malaria. It probably originated in Africa and accompanied human migration to the Mediterranean shores, India and South East Asia. In the past it used to be common in the marshy areas around Rome and the name is derived from the Italian, (mal-aria) or "bad air"; it was also known as Roman fever. Today some 500 hundred million people in Africa, India, South East Asia and South America are exposed to endemic malaria and it is estimated to cause two and a half million deaths annually, one million of which are children [3, 12].

While it was recognized that the Anopheles mosquito played a key role in the transmission of the disease it was not until 1948 that all the stages in its life cycle were identified. The parasite undergoes a development stage in the mosquito and the female of the species requires a blood meal to mature her eggs. She bites a human and injects material from her salivary glands, which contains primitive malarial parasites called sporozoites, before feeding. These sporozoites circulate in the blood for a short time and then settle in the liver where they enter the parenchymal cells and multiply; this stage is known as pre-erythrocytic schizogony. After about 8 days there may be many thousands of young parasites known as merozoites in one liver cell, the cell ruptures and the free merozoites enter red blood cells [28, 37].

Malarial Parasite

There are four species of the genus plasmodium responsible for the malarial parasite infections that commonly infect man,

1. Plasmodium falciparum,
2. Plasmodium vivax,
3. Plasmodium malariae and

4. Plasmodium ovale.

The most important of these is Plasmodium falciparum because it can be rapidly fatal and is responsible for the majority of malaria related deaths. Malaria occurs in most tropical regions of the world with Plasmodium falciparum predominating in Africa, New Guinea and Haiti. Plasmodium vivax is more common on the Indian sub-continent and Central America with the prevalence of these two infections roughly equal in Asia, Oceania and South America. Plasmodium malariae is found in most endemic areas especially sub-Saharan Africa but much less frequently. Plasmodium ovale is relatively unusual outside Africa although some cases are now being identified in other regions (e.g. Southern States of India).

The parasite undergoes a development stage in the mosquito and the female of the species requires a blood meal to mature her eggs. She bites a human and injects material from her salivary glands, which contains primitive malarial parasites called sporozoites, before feeding. These sporozoites circulate in the blood for a short time and then settle in the liver where they enter the parenchymal cells and multiply; this stage is known as pre-erythrocytic schizogony. After about 8 days there may be many thousands of young parasites known as merozoites in one liver cell, the cell ruptures and the free merozoites enter red blood cells. In the case of P. vivax, and P.ovale the liver cycle continues and requires a course of primaquine to eliminate it. P.falciparum on the other hand does not have a continuing liver cycle [28, 37].

In the red blood cells the parasites develop into two forms, a sexual and an asexual cycle. The sexual cycle produces male and female gametocytes, which circulate in the blood and are taken up by a female mosquito when taking a blood meal. The male and female gametocytes fuse in the mosquito's stomach and form oöcysts in the wall of the stomach. These oöcysts develop over a period of days and contain large numbers of sporozoites, which move to the salivary glands and are ready to be injected into man when the mosquito next takes a meal. In the asexual cycle the developing parasites form schizonts in the red blood cells which contain many merozoites, the infected red cells rupture and release a batch of young. Life cycle of the malarial parasite is shown in **Figure 2.2.**

Malaria life cycle

The life cycle of malaria is complex with developmental stages and corresponding symptoms differing according to the Plasmodium species involved. sporozoites, the infective stage of plasmodia, are injected from the salivary glands of infected mosquitoes during feeding. Following inoculation, the sporozoites disappear from the blood within 30 minutes. Many are destroyed by white blood cells, but some enter liver cells.

Exoerythrocytic Phase: Sporozoites that enter liver cells multiply asexually in a process called exoerythrocytic schizogony. Thousands of uninucleate merozoites form, displacing the nucleus of the liver cell, but causing no inflammatory reaction in the liver. Eventually, invaded liver cells rupture, releasing thousands of merozoites into the bloodstream. This occurs 6 to 16 days after initial infection depending on the infecting Plasmodium species [28].

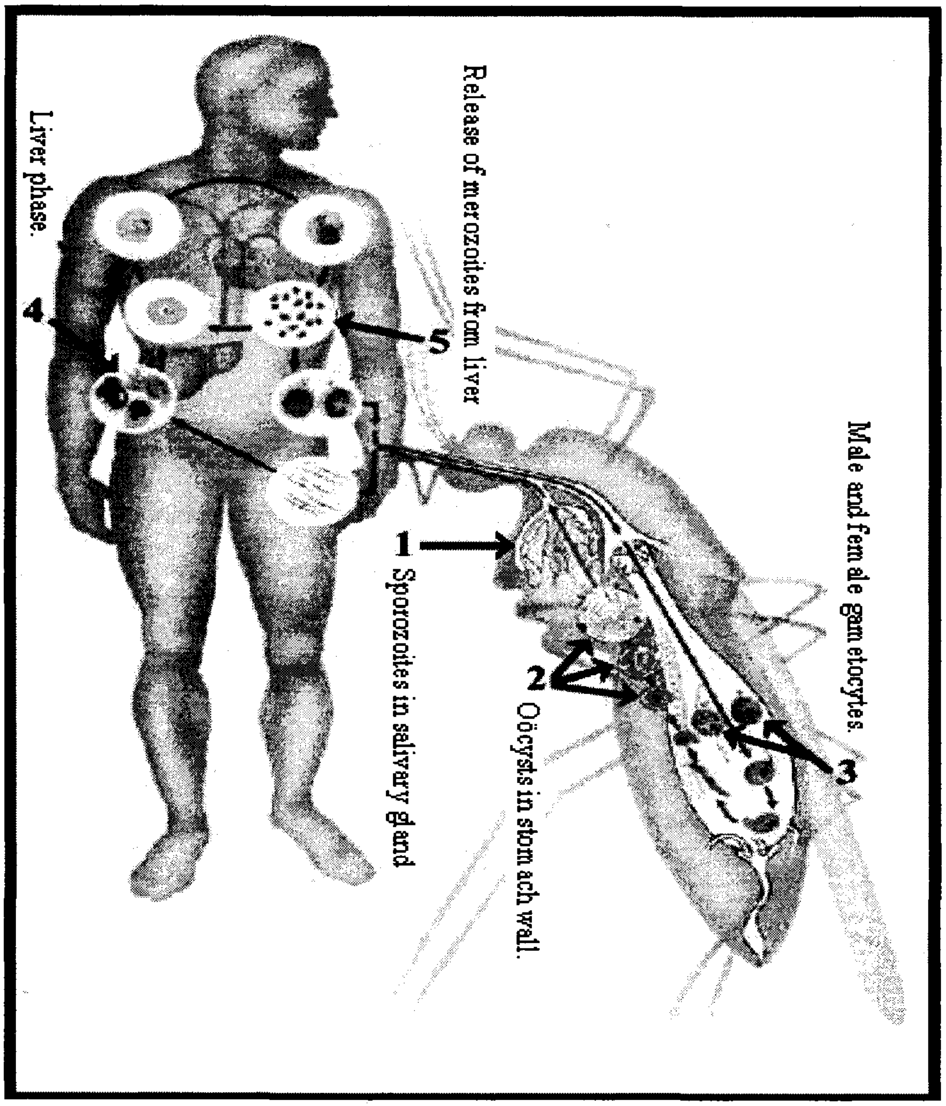


Figure 2.2 Schematic explanation of the life cycle of the malarial parasite (http://iri.ldeo.columbia.edu/iri/programs/training/bamako1999/report/malaria.cycle)

Dormant or Hypnozoite Phase: All infections due to Plasmodium falciparum and Plasmodium malariae have a single exoerythrocytic form. All infected liver cells parasitized with P. falciparum and P. malariae rupture and release merozoites at about the same time. In contrast, Plasmodium vivax and Plasmodium ovale have two exoerythrocytic forms. The primary type develops, causes liver cell rupture, and releases merozoites just as described Plasmodium falciparum and Plasmodium malariae. The other form, which develops concurrently, is known as the hypnozoite. Sporozoites that enter liver cells differentiate into hypnozoites that remain dormant for weeks, months, or years [35]. At some future time, the hypnozoites activate and undergo exoerythrocytic schizogony, forming a wave of merozoites that invade the blood and cause a delayed case or a clinical relapse.

Erythrocytic Phase: Released merozoites invade red blood cells (erythrocytes), where they develop into trophozoites. After a period of growth, the trophozoites divide and develop, eventually forming 8-24 merozoites in each red blood cell. When this process is complete, the host red blood cells rupture, releasing mature merozoites. The symptoms associated with malaria occur at this point. The merozoites then invade fresh erythrocytes and another generation of parasites develops in the same manner. This process occurs repeatedly during the course of infection and is called eryrthrocytic schizogony. The length of this development cycle differs according to the species of parasite, varying from 48 hours in vivax, ovale, and falciparum malaria, to 72 hours in P. malariae infections. In the early stages of infection there is no characteristic periodicity as groups of parasites develop at different times. The febrile episodes caused are inconsistent. Later, the erythrocytic schizogony development cycle becomes synchronized, and the febrile paroxysms become more consistent [12]. Some merozoites differentiate into sexual forms (female macrogametocytes, male microgametocytes) and develop in invaded red blood cells.

Vector Phase: Anopheles mosquitoes feeding on infected hosts ingest sexual forms developing in red blood cells. The female macrogametocytes and male microgametocytes mature in the mosquito's stomach and combine forming a zygote that undergoes mitosis. The products of mitosis are ookinetes, which force themselves between the epithelial cells to the outer surface of the stomach, and form into small spheres called oocysts. The oocysts enlarge as the nucleus divides, eventually rupturing and releasing thousands of motile sporozoites into the body cavity [16]. The sporozoites migrate to the salivary glands, making the female mosquito infective.

The vector phase of the life cycle, called sporogony, is complete in 8 to 35 days depending on species and environmental conditions.

World distribution of Malaria

The worldwide distribution of malaria is illustrated by the map in **Figure 2.3**. Malaria transmission occurs in more than 100 countries. Regions include Africa, Asia, islands of the South, west, and central Pacific Ocean, Latin America, certain Caribbean islands, and Turkey. These areas, all between 45^0 N and 40^0 S latitude, possess tropical or subtropical zones wherein anopheles mosquito habitats exist.

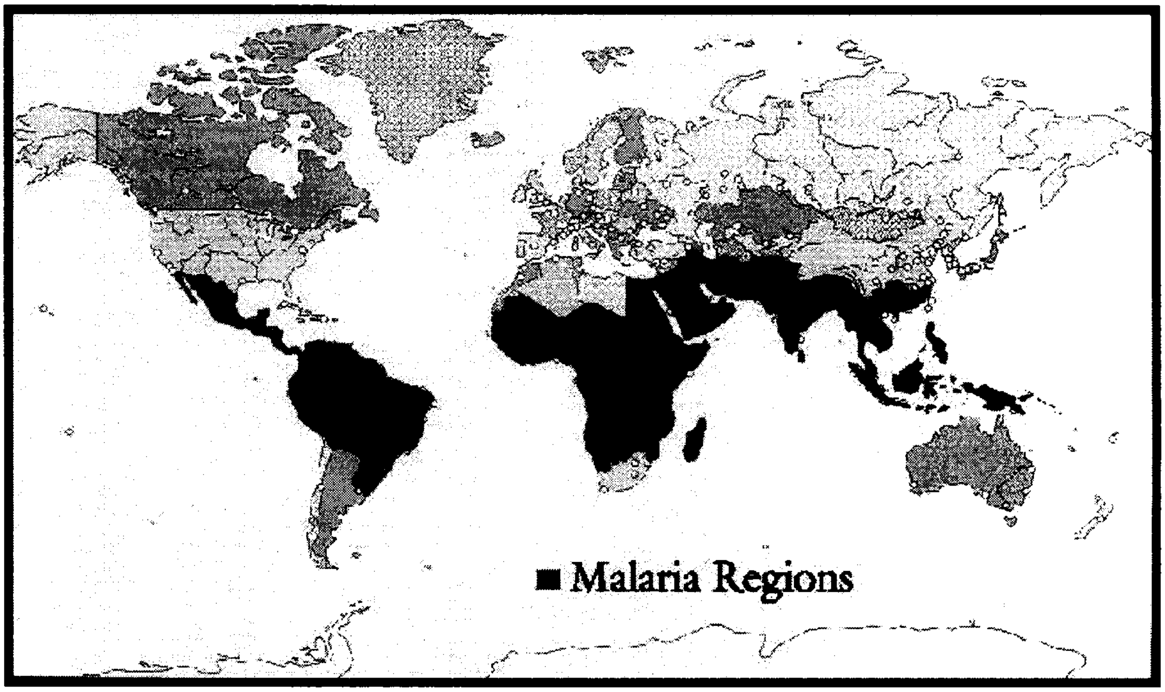


Figure 2.3 Distribution of malaria (http://iri.ldeo.columbia.edu/iri/programs/training/bamako1999/report/malaria.regions)

Malaria Epidemiological Types

Five major epidemiological types of malaria have been defined which are:

i) Malaria of Forested Hills,

ii) Malaria of Forest Fringe,

iii) Malaria of Plain Border Belt Areas,

iv) Malaria of Plain Rural Areas and

v) Malaria of Urban Areas

Dengue

Dengue is also a mosquito vectored disease like malaria. Dengue fever is transmitted by the Asian tiger mosquito. It is also transmitted by Aedes aegypti in the tropics. Dengue-carrying mosquitoes breed in stored, exposed, water collection systems. Dengue fever is caused by a virus that produces a range of illnesses, from viral flu to hemorrhagic fever. It is especially dangerous for children.

The global prevalence of dengue has grown dramatically in recent decades. The disease is now endemic in more than 100 countries in Africa, the Americas, the Eastern Mediterranean, South-East Asia and the Western Pacific. South-East Asia and the Western Pacific are most seriously affected. Before 1970, only nine countries had experienced DHF epidemics, a number which had increased more than four-fold by 1995. Some 2500 million people – two fifths of the world's population - are now at risk from dengue [46, 54]. WHO currently estimates there may be 50 million cases of dengue infection worldwide every year. In 1998 alone, there were more than 616,000 cases of dengue in the Americas, of which 11,000 cases were DHF. This is greater than double the number of dengue cases which were recorded in the same region in 1995 [55, 56]. Not only is the number of cases increasing as the disease is spreading to new areas, but explosive outbreaks are occurring.

Dengue outbreak history: [52]

1780: First Dengue epidemic in Philadelphia described by 'Rush'.

1897: Death occurred during dengue epidemic in Australia.

1928: Death occurred during epidemics were reported in Louisiana.

1950: Epidemic DHF first appeared in Southeast Asia.

1953: DHF was first recognized in Philippines.

1958: Epidemic in Thailand.

1963: Epidemic for the first time in India.

1964: Dengue epidemic first occurred in Bangladesh.

1970: DHF reported in Myanmar.

1980s: Epidemic in India, Sri Lanka, China, Taiwan, Indonesia, Malaysia, Myanmar, Thailand and Vietnam.

1981: Out Break in more severe form of DHF in Cuba.

1985: A series of epidemic in China and Maldives.

Transmission of dengue

Dengue viruses are transmitted to humans through the bites of infective female Aedes mosquitoes. Mosquitoes generally acquire the virus while feeding on the blood of an infected person. Once infective a mosquito is capable of transmitting the virus to susceptible individuals for the rest of its life, during probing and blood feeding. Infected female mosquitoes may also transmit the virus to the next generation of mosquitoes by transversal transmission i.e. via its eggs, but the role of this in sustaining transmission of virus to humans has not yet been delineated. Humans are the main amplifying host of the virus, although studies have shown that in some parts of the world, monkeys may become infected and perhaps serve as a source of virus for uninfected mosquitoes. The virus circulates in the blood of infected humans for 2-7 days, at approximately the same time as they have fever; Aedes mosquitoes may acquire the virus when they feed on an individual at this time [53].

Characteristics of dengue

Dengue fever is a severe, flu-like illness that affects infants, young children and adults but rarely causes death. The clinical features of dengue fever vary according to the age of the patient. Infants and young children may have a non-specific febrile illness with rash. Older children and adults may have either a mild febrile syndrome or the classical incapacitating disease with abrupt onset and high fever, severe headache, pain behind the eyes, muscle and joint pains, and rash. Dengue hemorrhagic fever is a potentially deadly complication that is characterized by high fever, hemorrhagic phenomena—often with enlargement of the liver and in severe cases, circulatory failure. The illness commonly begins with a sudden rise in temperature accompanied by facial flush and other non-specific constitutional symptoms of dengue fever [56]. The fever usually continues for 2-7 days and can be as high as 40-41° C, possibly with febrile convulsions and hemorrhagic phenomena [18]. In moderate DHF cases, all signs and symptoms abate after the fever subsides. In severe cases, the patient's condition may suddenly deteriorate after a few days of fever; the temperature drops, followed by signs of circulatory failure, and the patient may rapidly go into a critical state of shock and die within 8-24 hours, or quickly recover following appropriate volume replacement therapy.

Environment

40 years ago, classic insect-borne diseases like malaria, yellow fever and dengue were thought to have been nearly eradicated on the Earth.But then the unexpected happened - insect-borne diseases began to reemerge. Part of that is because some of the insects and microbes they carry have developed resistance to the insecticides and medicines used to control them .An important factor for epidemics of vector-borne diseases is change – in nature, in government and in society. Factors that may precipitate a malaria epidemic fall into two categories: natural (climatic variations, natural disasters), and man-made (conflicts and wars, agricultural projects, dams, mining, logging, failure of control measures). Most of these factors make the physical environment more suitable for mosquitoes hatching. Other factors, such as local conflicts or development projects, produce massive population movements that expose non-immune populations to the malaria parasite. There is some evidence that this may already be taking place. But the warmer weather can do more. In some areas, it transforms rivers into puddles, while in others, it triggers rain and floods that leave behind stagnant pools. In both cases, the standing water serves as a perfect breeding ground for mosquitoes. Hotter weather also shortens the mosquitoes' breeding cycle, speeding up their reproduction rate and it lengthens the season during which mosquitoes abound. In warmer weather, mosquitoes are more active. Hotter temperatures ever reach inside mosquito's gut and intensify the reproduction rate of disease-causing microbes, thereby increasing the likelihood that a single bite will cause infection [17]. Changes in human society can also contribute to insect –borne disease. In many diseases an insect may only one of several links in the chain of disease transmission. To large extent malaria epidemics are predictable, through

a combination of socioeconomic and meteorological information and local epidemiological knowledge. Man-made epidemics, in particular, can be predicted with considerable precision, for example in relation to development projects, such as irrigation projects, fish pounds, dams, etc. Multi-sectoral action at the planning stage can help prevent them from occurring.Vegetation cover; temperature and precipitation are the factors that may affect malaria transmission [19, 38, 39]. We showed potential links between environment factors and malaria in the **Table 2.1.**

Table 2.1 Links between environment factors and malaria

Factor	Mapping opportunity
Vegetation/crop type	Breeding/resting/feeding habitats; Crop pesticides vector resistance
Vegetation green-up	Timing of habitat creation
Deforestation	Habitat creation (for vectors requiring sunlit pools) Habitat destruction (for vectors requiring shaded pools)
Flooded forests	Mosquito habitat
Flooding	Mosquito habitat
Permanent water	Breeding habitat for mosquitoes
Wetlands	Mosquito habitat
Soil moisture	Vector breeding habitat
Canals	Dry season mosquito-breeding habitat; ponding ; leaking water

Three principal environmental factors that should be considered in malaria epidemiology are temperature, humidity, and rainfall.

Temperature

The life cycles of Plasmodium as well as at the Anopheles mosquito depend on temperature. The optimal temperature for Plasmodium reapplication within the mosquito is 27^{o} C [26]. Higher temperature increase the number of times female mosquitoes bite and lay eggs. The intersections of the ranges of minimum and maximum temperature for parasite and vector development determine the impact of changes in temperature on malaria transmission. The minimum temperature for mosquito development is between 8-10°C, the minimum temperatures for parasite development are between 16-20°C with P. vivax (It can exist in places with an average summer temperature of only 16ºC) surviving at lower temperatures than Plasmodium falciparum [13, 28] (Plasmodium falciparum needs an average ambient temperature of at least 20ºC). The optimum temperature for mosquitoes is 25-27°C, and the maximum temperature for both vectors and parasites is 40°C. There are some areas where the climate is optimal for malaria and Anopheles mosquitoes are present, but there is no malaria. This is called "Anophelism without malaria" which can be due to the fact that the Anopheles mosquitoes present do not feed primarily on humans or because malaria control techniques have eliminated the parasite. If any changes, whether environmental or otherwise, were to occur to bring another species to the area that does act as a vector for human malaria, then the potential for outbreaks of malaria is very high since there is no immunity in the human population there. The 'extrinsic phase' is the period necessary for a mosquito to become infective for man after it has ingested the sexual forms of the parasite from another man.

Precipitation

Precipitation is a factor which affects the behavior of Anopheles mosquitoes. There must be a certain level of precipitation in order to provide the stagnant water pools for the female mosquito to lay her eggs. Too little precipitation, and stagnant water can not be found. Anopheline mosquitoes breed in water habitats, thus requiring just the right amount of precipitation in order for mosquito breeding to occur. Little is known about the biology of this aquatic phase [27]. However it is known that different Anopheline mosquitoes prefer different types of water bodies in which to breed. Too much rainfall, or rainfall accompanied by storm conditions can flush away breeding larvae. The amount and intensity of precipitation, the time in the year, and whether it is the wet or dry season, malaria survival is affected. Rainfall also affects malaria transmission because it increases relative humidity and modifies temperature, and it also affects where and how much mosquito breeding can take place.

Some contend that the amount of rainfall may be secondary in its effects on malaria to the number of rainy days or the degree of wetness that exists after a rain event [50]. The degree of wetness can be calculated by the following equation: (# of wet days in a month)*(total rainfall) / (# of days in the month). Malaria has also been found to be dependent on the groundwater level.

Humidity

Anopheles mosquitoes are also affected by humidity. Plasmodium parasites are not affected by relative humidity, but the activity and survival of Anopheline mosquitoes are. If the average monthly relative humidity is below 60% [28], it is believed that the life of the mosquito is so shortened that there is no malaria transmission.

Wind

Wind may play both negative and positive roles in the malaria cycle because very strong winds can decrease biting by mosquitoes, while at the same time extending the length of the flight of the mosquito. During a monsoon, wind has the potential to change the geographic distribution of mosquitoes.

Climate and vector succession

In addition to changing the amount and rate of transmission of the vectors and parasites that are already in a certain location, changing the climate of an area can allow the introduction of different vectors and parasites that may be more efficient. Since P. malariae and P. ovale have longer extrinsic cycles, some mosquitoes do not live long enough to transmit them. However, if environmental conditions change in ways that would increase the survival time of those mosquitoes, then they would be able to transmit other species of malaria that were not present in that area before.

Epidemics

Epidemics of malaria are caused by a disturbance of the equilibrium between host, parasite and vector. Najera et al. (1998) define three different types of epidemics. Type I epidemics are caused by meteorological conditions, which create temporary epidemics that will eventually revert back to the previous condition. Type II epidemics are caused by landscape changes or colonization of sparsely populated areas that create a new equilibrium level of endemicity. And type III epidemics are caused by interruptions in measures that were controlling malaria [14, 17, and 20].

Meteorologically stimulated epidemics normally last only one season of transmission. Many areas experience epidemics caused by meteorological changes that occur in interannual cycles. These cycles, which have been well illustrated by ENSO (El Niño Southern Oscillation), have been found in many parts of the world to follow the paraquinquennial cycle, which means epidemics happen every 5 to 7 years, however, in some areas the period of the cycle is longer. Because of the periodicity of cycles caused by meteorological factors, there should be a way to predict epidemics based on the risk factors related to epidemics including: a sudden increase in the number of non-immunes that are exposed to malaria, a rapid increase in vectorial capacity (increased density of vectors or invasion of a more efficient vector), land-use change, and failure of control efforts.

Vivax and falciparum cause different types of epidemics. Vivax epidemics occur mainly in the areas with only seasonal transmission and show a bimodal peak, the second peak caused by relapses, whereas falciparum epidemics grow slowly and then explode causing only one peak of transmission.

Climate Change and Malaria

The effects of temperature on both the vectors and parasites of malaria are easily seen in the latitudinal and altitudinal boundaries to malaria transmission. However, these boundaries seem to be changing as many highland areas have experienced malaria epidemics in the past few years. It has been hypothesized that increasing temperatures could be part of the reason why malaria can now survive at higher altitudes. Many other confounding factors, however, could be causing the increase in malaria in these areas.

In addition to predictions of the effects of climate change on malaria, studies which identify factors that are most responsible for any changes in malaria are important in order to understand the complexities of malaria in the actual world. There are many variables that affect malaria transmission in addition to climatic changes, such as environmental modification (e.g. deforestation, increases in irrigation, swamp drainage), population growth, limited access to health care systems, and lack of or unsuccessful malaria control measures. Some studies have been done on the subject, yielding differing results as to which factor or factors are most responsible for the increase in malaria. Most of the studies, however, do not take into account all of the factors that are related to malaria transmission. This makes it difficult to assess the true determinants of malaria in each area.

Time-series studies

Mean temperature, night-time temperature, temperature in combination with rainfall, and mean November and December temperature, were found to be related to malaria in Zimbabwe, the Debre Zeit sector of Ethiopia, Rwanda, and the Northwest Frontier Province in Pakistan, respectively [3, 34, and 36]. In Pakistan, rainfall along with humidity in December, predicted malaria rates fairly well. In a more qualitative study, climate and forest clearing were alleged to be related to malaria rates in the Usambara Mountains of Tanzania. One study in the highlands of Kenya claimed that climate was not a factor in malaria transmission there because average temperature and rainfall did not change during the time that malaria rates changed. According to the study, deforestation might have been a reason behind changes in malaria transmission in the highlands of Kenya [3, 36].

Another study in Kenya found that soil moisture correlated with the human-biting rate of malaria vectors with a two-week time lag which was explained as the length of time it takes for mosquito larvae to develop. This same study also found that soil moisture correlates with entomological inoculation rate (which is the product of the human-biting rate and the proportion of female mosquitoes carrying infective parasites in their salivary glands ready to be delivered to the next host) with a six-week time lag. Six weeks is the amount of time necessary for the development of the infective parasites in the mosquito plus the length of time the mosquito survives.

The seasonal periodicity [28] of malaria is shown in **Table 2.2**.

Table 2.2 The seasonal periodicity of malaria

Zone	Average monthly temperature hottest month	Average monthly relative humidity
Temperate	16-20° C	Never lower than 70%
Subtropical	20-25° C	Never lower than 50%
Tropical	25° C or more	During some month lower than 50%
Equatorial	Never lower than 25° C	Never lower than 70%

2.4 Remote Sensing and Vector-Borne Disease

Climate can be used as a predictor for mosquito development. Since investigation into the utility of remote sensing (RS) and meteorological data, for the prediction of spatial variation in monthly climate across continental Africa in 1990. Information from the Advanced Very High Resolution Radiometer (AVHRR) of the National Oceanic and Atmospheric Administration's (NOAA) polar-orbiting meteorological satellites was used to estimate land surface temperature (LST) and atmospheric moisture. Cold cloud duration (CCD) data derived from the High Resolution Radiometer (HRR) on-board the European Meteorological Satellite program's (EUMETSAT) and Meteosat satellite data were used to estimate rainfall. Temperature, atmospheric moisture and rainfall surfaces were independently derived from Meteorological data over Africa. These data were then used to test the accuracy of each methodology, so that the appropriateness of the two techniques for epidemiological research could be compared. Spatial information was a more accurate predictor of temperature, whereas RS provided a better surrogate for rainfall; both were equally accurate at predicting atmospheric moisture. The implications of these results for mapping short and long-term climate change and hence their potential for the study and control of disease vectors are considered.

Geographic information systems (GIS), global positioning systems (GPS), remote sensing, and spatial statistics are tools to analyze and integrate the spatial component of vector-borne disease epidemiology into research, surveillance, and control programs based on a landscape ecology approach. Landscape ecology, which deals with the mosaic structure of landscapes and ecosystems, considers the spatial heterogeneity of biotic and abiotic components as the underlying mechanism which determines the structure of ecosystems [2]. The methodologies of GIS, GPS, satellite imagery, spatial statistics and the landscape ecology--epidemiology approach to vector-borne diseases and applications are reviewed [73].

The remotely sensed data such as temperature, reflectance in the middle infra-red, rainfall, and the normalized difference vegetation index (NDVI) were processed to provide surrogate information on the environment. The NDVI in the preceding month correlated with malaria across the 3 sites. Regression analyses showed that an NDVI threshold of 0.35-0.40 was required for more than 5% of the annual malaria cases to be presented in a given month [60, 84]. These thresholds were then extrapolated spatially with the temporal Fourier-processed NDVI data to define the number of months, in which malaria admissions could be expected across Kenya in an average year. The resulting maps were compared with the Butler's map of malaria transmission for Kenya, compiled from expert opinion. Conclusions are drawn on the appropriateness of remote sensing techniques for compiling national strategies for malaria intervention.

An increasing number of health studies have used remotely sensed data for monitoring, surveillance, and risk mapping, particularly of vector-borne diseases like malaria and dengue. Most of human health studies using remote sensing have focused on data from NOAA (National Oceanic and Atmospheric Administration)'s Advanced Very High Resolution Radiometer (AVHRR), Landsat's Multispectral Scanner (MSS) and Thematic Mapper (TM) and France's Système Pour l'Observation de la Terre [78].

Chapter 3

Environmental Satellites

3.1 Introduction

Beginning in the early 1960s, meteorological, or weather, satellite programs have been an important focus of government agencies. In the United States, the National Aeronautics and Space Administration (NASA), NOAA, and the Department of Defense (DoD) have all been involved in the developing and operating weather satellites. In Europe, the European Space Agency (ESA) and EUMETSAT (European Organization for the Exploitation of Meteorological Satellites) operate the meteorological satellite system.

The world's first Environmental satellite was launched from Cape Canaveral, Florida, on April 1, 1960. Named "TIROS" for Television Infrared Observation Satellite, this was NASA's first experimental step to determine if satellites could be useful in the study of the Earth and whether they could continue operating for an extended period of time. The first series of TIROS satellites was followed by a series that began with the October 1978 launch of TIROS-N, an experimental spacecraft that served as a model for the operational follow-on series: NOAA-6 through NOAA-17. The technological improvements integrated into this series of satellites, the current ATN or Advanced TIROS series (the launch of NOAA-17 is planned for 2004), have provided higher resolution images, and more day and nighttime data for both local and global areas than the earlier series [81, 87, 88, 98]. The series proved extremely successful, with one satellite operating for almost five years and several operating more than three years.

An operational system of meteorology satellites flying in low-Earth orbit (about 450-470 nautical miles [833-870 kilometers] altitude) began operating in 1970. These satellites were called the Improved TIROS Operational System (ITOS) at launch and NOAA once they were checked out and became operational. The primary objective of this series of sun-synchronous satellites was to provide improved infrared and visual observations of Earth cloud cover for use in analyzing weather and forecasting. Other objectives included measuring snow and ice and the sea surface, and gathering information on the vertical structure of temperature and moisture in the atmosphere on a regular daily basis. Six of the eight satellites in this series were launched and operated successfully, with one operating more than four years. On August 28, 1964 the U.S. launched a second generation spacecraft known as the NIMBUS satellite. This vehicle was placed into a sun synchronous orbit with an inclination of 98.48°, perigee of 450 km and an apogee of 924 km. The Nimbus carried advanced TV cameras including a sophisticated cloud mapping system and an infrared radiometer which allowed weather pictures to be taken at night. Seven Nimbus satellites were placed into orbit by 1978. This was the direct forerunner of the advanced weather forecasting system we have today [69, 79].

Environmental satellites are similar in that they gather information about the nature and condition of the Earth's land, sea and atmosphere by remote sensing. They accomplish this task with sensors which observe the Earth in various discrete bands of the electromagnetic spectrum. They are different in that the systems are designed to observe different phenomena and have sensors which gather data in different spectral bands with different resolutions [91]. When data from space systems is merged with that obtained from other ground and airborne sensors, resultant products are of significantly better quality than those produced from only one source.

3.2 Type of environmental satellite

Environmental satellite system is composed of two types of satellites:

- geostationary operational environmental satellites (GOES) for national, regional, short-range warning and "now-casting," and
- Polar-orbiting environmental satellites (POES) for global, long-term forecasting and environmental monitoring.

Both types of satellites are necessary for providing a complete global weather monitoring system.

GOES satellites provide the kind of continuous monitoring necessary for intensive data analysis. They circle the Earth in a geosynchronous orbit, which means they orbit the equatorial plane of the Earth at a speed matching the Earth's rotation [4, 24, 83]. This allows them to hover continuously over one position on the surface. The geosynchronous plane is about 35,800 km (22,300 miles) above the Earth, high enough to allow the satellites a full-disc view of the Earth. Because they stay above a fixed spot on the surface, they provide a constant vigil for the atmospheric "triggers" for severe weather conditions such as tornadoes, flash floods, hail storms, and hurricanes. When these conditions develop the GOES satellites are able to monitor storm development and track their movements [59, 62]. GOES satellite imagery is also used to estimate rainfall during the thunderstorms and hurricanes for flash flood warnings, as well as estimates snowfall accumulations and overall extent of snow cover. Such data help meteorologists issue winter storm warnings and spring snow melt advisories. Satellite sensors also detect ice fields and map the movements of sea and lake ice. The Geostationary Operational Environmental Satellites (GOES) are operated by the U.S. National Oceanographic and Atmospheric Administration (NOAA). GOES is a series of meteorological geostationary orbiting satellites that provide weather prediction data for the western hemisphere and particularly for the U.S. GOES imagery is accessible to over 10,000 ground stations in 80 nations and provides continuous storm tracking, cloud analysis, surface temperature mapping, data of floods, rain, snow, pollution, and solar flare activity.

The POES satellite system offers the advantage of daily global coverage, by making nearly polar orbits roughly 10.1 times daily. Since the number of orbits per day is not an integer the sub orbital tracks do not repeat on a daily basis, although the local solar time of each satellite's passage is essentially unchanged for any latitude. Currently in orbit we have a morning and afternoon satellite, which provide global coverage four times daily. National Oceanic and Atmospheric Administration (NOAA) Advanced Television Infrared Observation Satellite (Advanced TIROS) [82,97]. The NOAA/TIROS satellites provide images of cloud cover, snow, ice, and sea surface, plus temperature and moisture at various levels in the atmosphere for weather analysis and forecasting. GOES satellites can collect data for almost the entire Earth, and when two operate simultaneously, as this system is designed, environmental data for any region of the Earth is collected at least twice every 8 hours. This series of satellites has experienced only one launch failure, and almost all of the satellites have greatly exceeded their two-year expected lifetime. NOAA-8, launched in March 1983, was the first to carry search and rescue transponders. This international humanitarian system, with 29 participating nations, allows aircraft, ships, and people in distress who carry transmitters or beacons to signal the satellite, which then transmits the signal to a terminal on the ground where rescue operations begin. As was true with the earlier satellites, NASA is responsible for development, launch, and checkout of the satellites [89, 95].

The POES system includes the Advanced Very High Resolution Radiometer (AVHRR) and the Tiros Operational Vertical Sounder (TOVS). Because of the polar orbiting nature of the POES series satellites, these satellites are able to collect global data on a daily basis for a variety of land, ocean, and atmospheric applications. Data from the POES series supports a broad range of environmental monitoring applications including weather analysis and forecasting, climate research and prediction, global sea surface temperature measurements, atmospheric soundings of temperature and humidity, ocean dynamics research, volcanic eruption monitoring, forest fire detection, global vegetation analysis, search and rescue, and many other applications. Sun synchronous, polar orbiting, low Earth orbiting (LEO) weather satellites provide daily, full world coverage and higher resolution imagery than that available from geostationary satellites [5, 25, 57, 65]. Only the United States, Russia and China operate polar, low Earth orbiting, sun synchronous weather satellites. A sun synchronous orbit is one in which the satellite passes over a particular part of the Earth at the same time every day.

At present, an international plan is being promoted to establish a global meteorological satellite system as a part of the World Weather Watch (WWW) Program of the World Meteorological Organization (WMO) with cooperation of Japan, the United States and European countries. When this plan is realized, the geostationary meteorological satellites

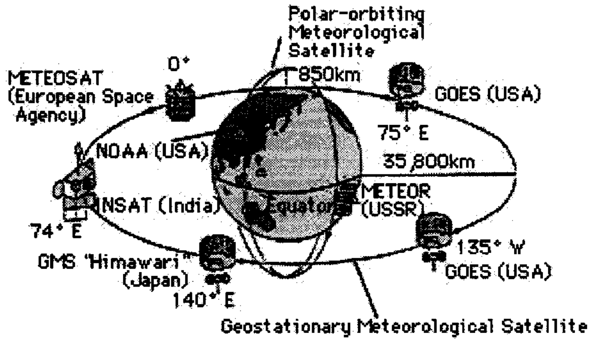


Figure 3.1 Geostationary meteorological satellites and polar-orbiting environmental satellites (http://www.ipo.noaa.gov/)

and polar-orbiting environmental satellites will be incorporated into one global system shown in **Figure 3.1**.

3.3 Advanced Very High Resolution Radiometer (AVHRR)

The AVHRR provides four- to six-band multi spectral data from the NOAA polar-orbiting satellite series. The AVHRR is a radiation-detection imager that can be used for remotely determining cloud cover and the surface temperature. Note that the term surface can mean the surface of the Earth, the upper surfaces of clouds, or the surface of a body of water [6, 58, 64, and 75]. This scanning radiometer uses 6 detectors that collect different bands of radiation wavelengths. There is fairly continuous global coverage since June 1979, with morning and afternoon acquisitions available. The AVHRR measures clouds over the ocean and land in 5 visible and near IR bands. The resolution is about 1.1 km at nadir and about 4 km at the edge of the scan which is about 2700 km wide. This provides 25° longitude of surface coverage within the scan width, with the central 15° providing the most useful data. Imagery from the AVHRR on each spacecraft is directly available to users with appropriate receivers [6, 61, 64, and 72]. The imagery is transmitted in two operational modes. The first is direct readout of any two of the five spectral bands to ground receiving stations of the Automatic Picture Transmission (APT) class at 4 km resolution. The second mode is direct readout of all five spectral channels to ground receiving stations of the High Resolution Picture Transmission (HRPT) class around one km resolution. The AVHRR is a radiation-detection imager that can be used for remotely determining cloud cover and the surface temperature. Note that the term surface can mean the surface of the Earth, the upper surfaces of clouds, or the surface of a body of water. This scanning radiometer uses 6 detectors that collect different bands of radiation wavelengths. The first AVHRR was a 4-channel radiometer, first carried on TIROS-N (launched October 1978). This was subsequently improved to a 5-channel instrument (AVHRR/2) that was initially carried on NOAA-7 [94] (launched June 1981). The latest instrument version is AVHRR/3, with 6 channels, first carried on NOAA-15 launched in May 1998.

3.4 Data Sets

AVHRR data provide opportunities for studying and monitoring vegetation conditions in different ecosystems including forests, tundra, and grasslands. Applications include agricultural assessment; land cover mapping, producing image maps of large areas such as countries or continents and tracking regional and continental snow cover [7, 8, 66]. AVHRR data are also used to retrieve various geophysical parameters such as sea surface temperatures and energy budget data. An AVHRR onboard NOAA satellite is most appropriate for the above applications due to the availability of the spectral information for vegetation studies, operational global daily coverage, and the long-term continuous observational period [70, 77, and 90]. Additionally, AVHRR data are readily available at a nominal cost, whereas the high resolution data from LANDSAT (land remote sensing satellite system) and SPOT (Systeme Probatoire d'Observation de la Terre) are costly and cover only limited regions of the globe episodically.

AVHRR data are acquired in two formats:

High Resolution Picture Transmission (HRPT)

Local Area Coverage (LAC)

HRPT data are full resolution image data transmitted to a ground station as they are collected [68, 74, 93]. The average instantaneous field-of-view of 1.4 milliradians yields a HRPT ground resolution of approximately 1.1 km at the satellite nadir from the nominal orbit altitude of 833 km.

LAC are full resolution data that are recorded on an on board tape for subsequent transmission during a station overpass. The average instantaneous field-of-view of 1.4 mill radians yields a LAC ground resolution of approximately 1.1 km at the satellite nadir from the nominal orbit altitude of 833 km.

GAC data are derived from a sample averaging of the full resolution AVHRR data. Four out of every five samples along the scan line are used to compute one average value and the data from only every third scan line are processed, yielding 1.1 km by 4 km resolution at the sub point.

Two global-mapped AVHRR datasets over land have been aggregated by sampling those observations and mapping them into a regular grid, with further reduction of the data volume by temporal compositing that also reduces cloud contamination [71]. They are:

1. National Aeronautics and Space Administration (NASA) Global Inventory Monitoring and Modeling Studies (GIMMS) and
2. NOAA global vegetation index (GVI).

Both are sampled AVHRR global area coverage (GAC) data, mapped into regular grids, with each map cell being represented by a single GAC 4-km pixel.

The GIMMS dataset, with a spatial resolution of about (8 km) 2, was produced on a continent-by-continent rather than globally-uniform basis and does not include all AVHRR channels [74]. Although no complete documentation, such as a user's guide, is available, this research dataset has been very useful for numerous studies (e.g. Tucker et al. 1985; Justice et al. 1985; Tucker et al. 1991; Los et al. 1994; among others).

Between 1982 and April 1985, measurements in only solar wavebands of AVHRR and their combination -- normalized difference vegetation index (NDVI) -- were archived as the first-generation GVI product. Many vegetation studies have been based on NDVI data.

Since April 1985, measurements in thermal IR wavebands and the associated solar zenith and satellite scan angles were added to the GVI dataset, forming the second-generation GVI product. This additional information made the GVI a unique tool for global land studies although a number of challenging remote sensing and data management issues still needed to be properly addressed.

The third generation Global Vegetation Index (GVI) weekly composite data are produced operationally by NOAA/NESDIS and includes conversion of counts to reflectance and brightness temperatures using the post-launch calibration and non-linearity correction coefficients. Cloud flags are generated and appended to each map cell. The GVI dataset represents a sample of Global Area Coverage (GAC) observations mapped into 0.104 degree resolution maps in equal-angle projection (Plate Carree). A 7-day composite is a mosaic of observations produced by retaining data for each map cell corresponding to the maximum difference between AVHRR channels 2 and 1. Normalized Difference Vegetation Index (NDVI) is calculated from AVHRR channel 2 and 1 reflectance using the following formula: NDVI = (CH2 - CH1) / (CH2 + CH1) and the channel 4 radiances were converted to brightness temperature (BT).

In 1989, analysis and re-processing of the GVI dataset became a core project of the NOAA Climate and Global Change Program. The goal of the GVI project was to analyze and improve the GVI dataset to make it more useful for climate change-related applications. A generic processing scheme for AVHRR data over land was worked out. Uniformity of GVI data in time was improved by applying an updated AVHRR calibration and by reducing noise with better cloud screening. The following climate-related GVI products are currently available: monthly 0.15° global maps of the top-of-the-atmosphere reflectance, NDVI, brightness temperatures, a perceptible water index, and associated 5-yr climatology (means and standard deviations) [86, 95].

Chapter 4

Study Area, Bangladesh

4.1 Introduction

Bangladesh is located in the tropical region in Southeast Asia and lies between 20°34' and 26°38' north latitude, and 88°01' and 92°41' east longitude. From the east to the north and the west, Bangladesh has its borders with the Indian states of Mizuram, Tripura, Assam and West Bengal. The southern deltaic region faces the Bay of Bengal. It has a small inter-country border with Myanmar [33].

Bangladesh has 64 districts and 6 administrative divisions: Barisal, Chittagong, Dhaka, Khulna, Rajshahi and Sylhet (**Figure 4.1**). It has a population of 88 million with a population density of 868 persons per square kilometers. Eighty percent of total population lives in rural area. Bangladesh mostly comprises of low, mostly flat alluvial plain; hilly in southeast, intersected by numerous rivers and rivulets, canals, swamps and marshy lands. Nearly two-thirds of Bangladeshis are employed in the agriculture sector, with rice as the single most important product. Natural resources are natural gas, arable land, timber and coal.

4.2 Landscape

Bangladesh mostly comprises of low, flat alluvial plain; hilly in southeast, intersected by numerous rivers and rivulets, canals, swamps and marshy lands. The area of the country is 107,570 square kilometers (land: 93,910 sq km (arable land: 60.7% permanent crops: 2.61%, forest: 8% other: 28.69%) water: 10,090 sq). **Figure 4.2** shows the land distribution of Bangladesh.

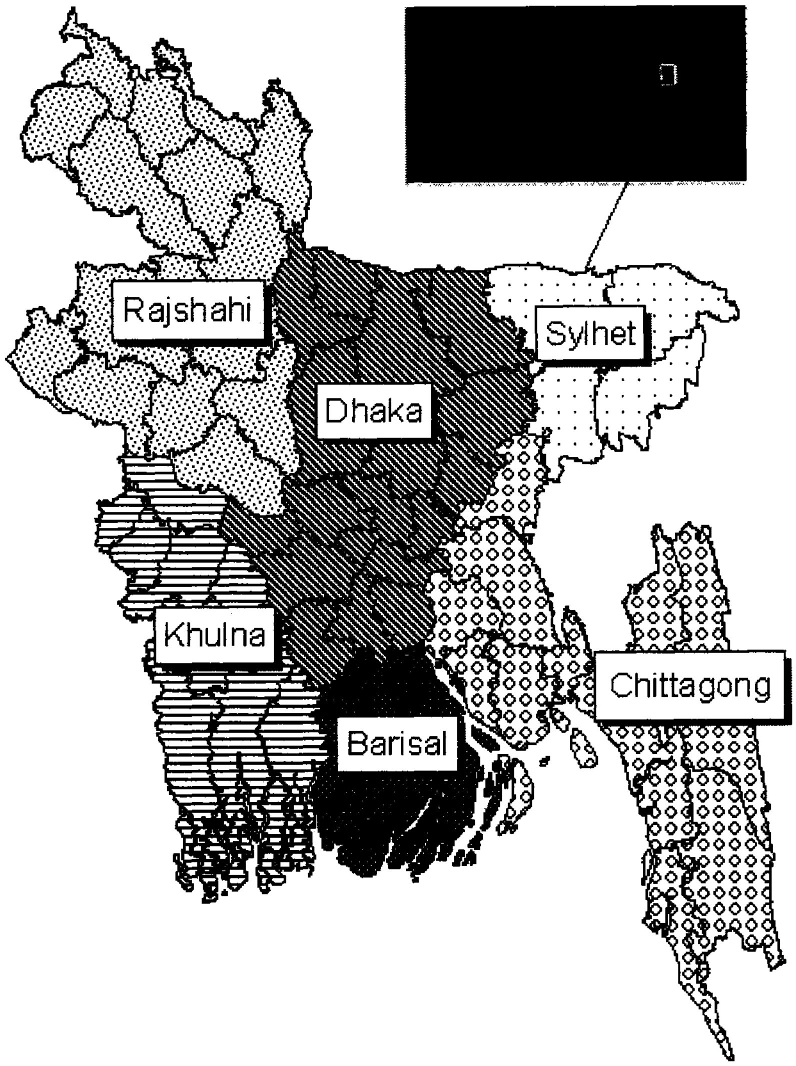


Figure 4.1 Geographical Map of Bangladesh

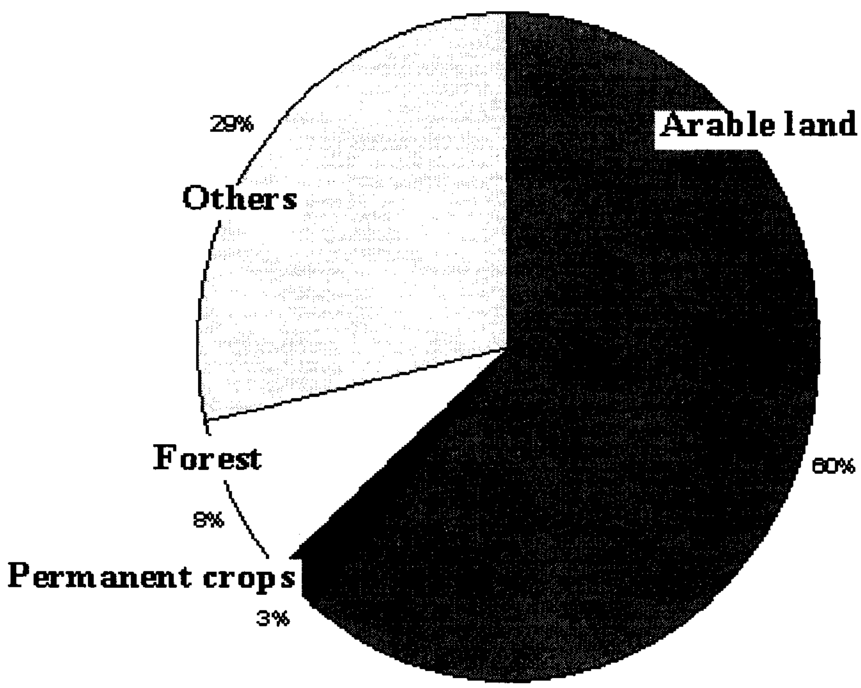


Figure 4.2 Land distribution of Bangladesh

4.3 Climate

The climate of Bangladesh is subtropical and monsoon [28]. There are three major seasons:

1. Hot and wet –From April to October
2. Cool and dry – From November to February
3. Hot and dry – From February to April

The alluvial soil of Bangladesh is continuously enriched by heavy silt deposits during the rainy season. The country is prone to natural disaster, floods droughts, cyclones, and tidal bores, much of the country routinely inundated during the summer monsoon season and faces the consequences of such disasters almost every year. The climatology of Bangladesh is shown in **Table 4.1**.

Bangladesh has 34 meteorological stations; there locations are shown in **Figure 4.3**.

Table 4.1 Climatology of Bangladesh

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Max. Temp (°C)	25.4	28.1	32.3	34.2	33.4	31.7	31.1	31.3	31.6	31.0	28.9	26.1
Min. Temp (°C)	8.3	10.0	19.0	23.1	24.5	25.5	25.7	25.8	25.5	23.5	18.5	9.7
Rainfall (mm)	07.0	19.8	40.7	110.7	257.5	460.9	517.6	431.9	289.9	184.2	35.0	09.4

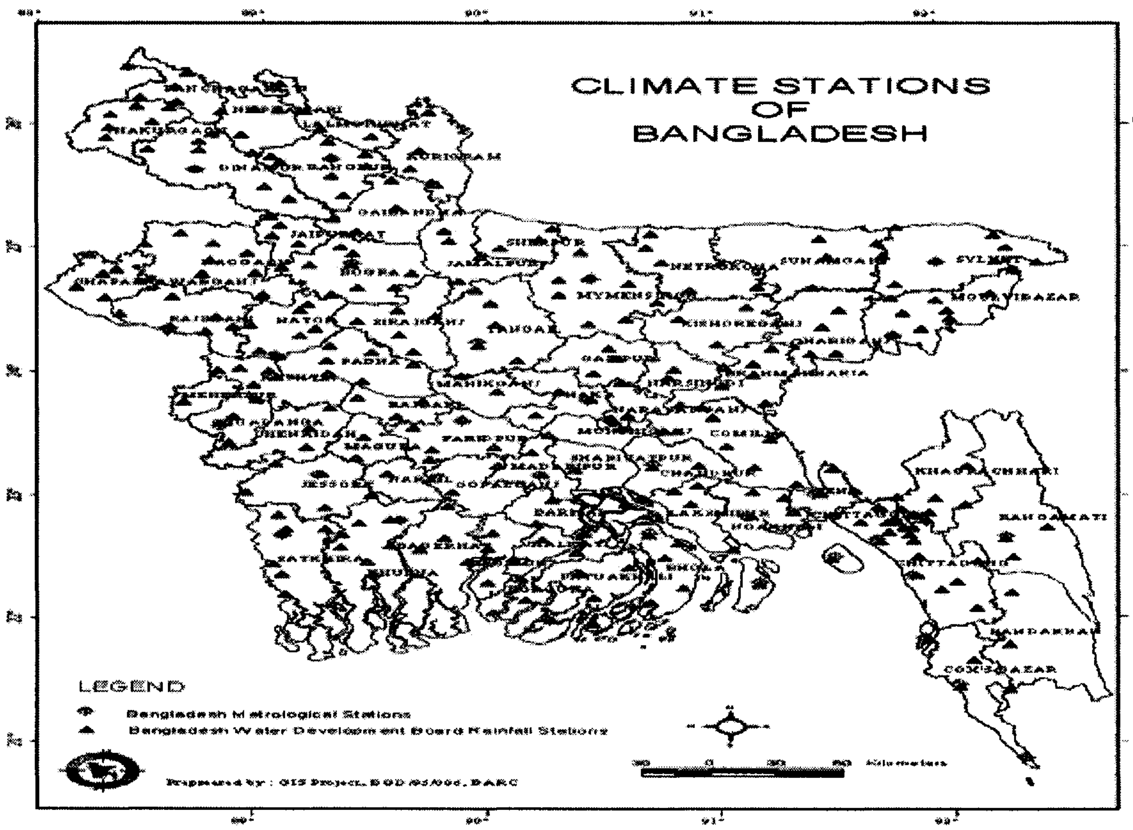


Figure 4.3 Locations of Meteorological stations in Bangladesh

4.4 Malaria

Malaria parasite (plasmodium) in Bangladesh is transmitted by female Anopheles mosquitoes. Out of the 15 species, Anopheles Dirus (AD) is most spread in the Southeast Asia [42, 43]. Breeding habitats of AD are puddles on footpath and turbulence pits at the heads of drainage gullies, which are able to hold water for sometime without supplemental rainfall.

Mosquitoes transmit malaria year around. However during the cooler season (November-March) mosquito are less active and the number of malaria cases is small. This number increases considerably during warm and wet. Malaria is transmitted by adult infected female which bites in order to get human blood for laying eggs. Mosquito hatching period from laying eggs to an adult stage is 7-15 days and incubation period for development of malaria after infected mosquito bites is 8-35 days. An entire cycle, when AD is able to bite and transmit malaria is 15-50 days. Therefore, during April-October, four-five cycles might occur. After laying eggs, larva appears in 4-10 days the following pupae stage requires 1-4 days and then after a couple of days, depending on water temperature the adult mosquito is ready to bite.

Distribution of malaria cases in Bangladesh for 1994 is shown in **Figure 4.4**.

Percent of Malaria cases for Bangladesh per division for 1992-2001 from DG Health of Bangladesh are shown in **Table 4.2**.

Table 4.2 shows that Countrywide, between 1998 and 2001 a general increase in the number of reported cases by 4 -5%. This increase can be explained in two ways, one is, the government adopt a new program "Essential Services Package" for fighting malaria and vector-borne diseases, second most important one is reoccurrence of malaria outbreaks along the border area [26].The positive cases increased in the Chittagong, Khulna and Rajshahi division, which are the border area and mostly forest covered.

4.5 Dengue

Dengue fever (DF) and dengue hemorrhagic fever (DHF) are caused by four antigenically distinct but related dengue virus (official name: Dengue virus [DENV]) serotypes transmitted primarily by Aedes aegypti (yellow fever mosquito). DHF, the severe form of the disease, is endemic and frequently intensifies into epidemics in Southeast Asia, resulting in frequent hospitalizations and deaths. Recently, dengue has emerged as a substantial global health problem with increased incidence in new countries and tropical areas. DF was documented in Bangladesh from the mid-1960s to the mid-1990s, but an outbreak of DHF has not been previously reported. During late June 2000, a 28-year-old patient was admitted to a hospital in Dhaka, Bangladesh, with hemorrhagic fever, ascites, pleural effusion, and thrombocytopenia. An enzyme-linked immunosorbent assay (ELISA) for anti-dengue antibodies confirmed the case as DHF. That summer, an outbreak of DF (>5,000 hospitalized cases reported) and DHF occurred in Dhaka and other major cities of Bangladesh.

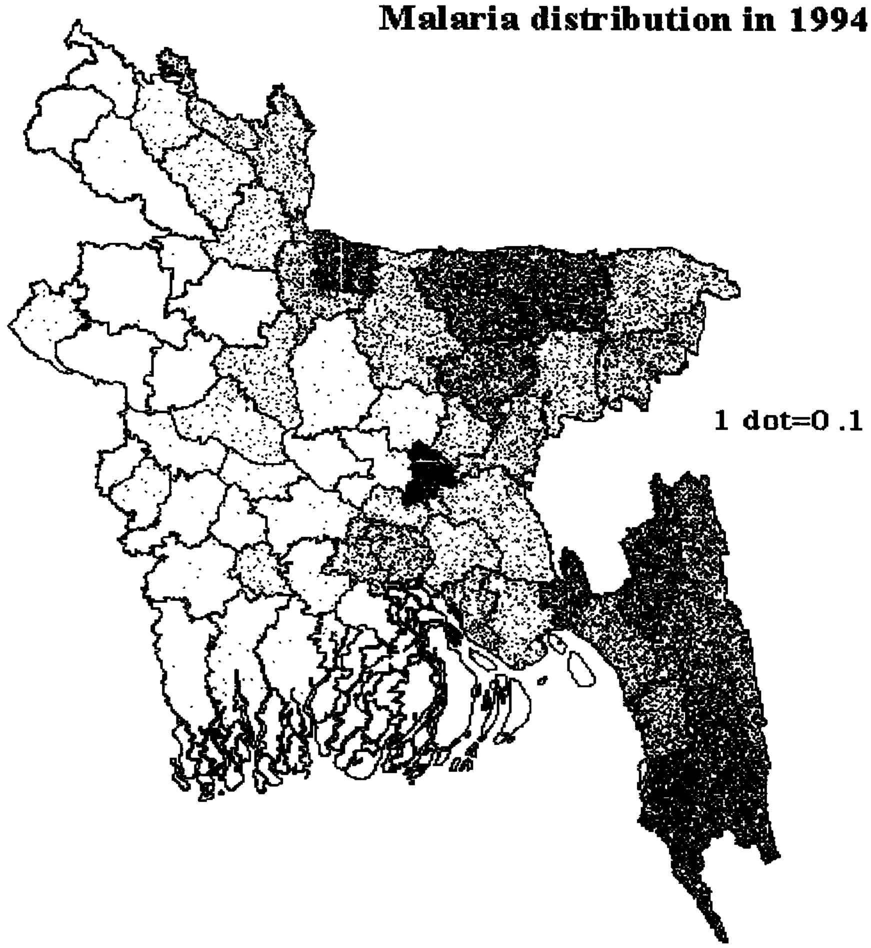


Figure 4.4 Distributions of malaria cases in Bangladesh in 1994

Table 4.2 Percent of malaria cases for Bangladesh per division for 1992-2001

Y\N	Bangladesh	Rajshahi	Khulna	Braishal	Dhaka	Chittagong	Sylhet
1992	6.02	0.72	0.067	0	5.4	16.6	9.6
1993	7.6	0.57	0.057	0.086	7.6	17.55	8.76
1994	10.24	0.69	0.07	0.07	7.7	21.76	21.25
1995	10.45	0.7	0.08	0.07	6.9	21.63	20.67
1996	8.7	0.34	0.19	0.10	3	20.53	8.8
1997	7.17	0.2	0.16	0.11	2.03	17.10	7.4
1998	9.7	0.46	0.4	0.58	2.5	22.21	7.03
1999	16.5	0.56	0.78	0.72	2.4	24.3	5.85
2000	15.53	0.29	0.8	0.68	1.7	21.47	8
2001	15.39	0.39	1.52	0.65	1.7	21.47	8

Clinical malaria data (100*positive Case/Total blood sample) for Bangladesh (1992-2001)

Dengue out break history in Bangladesh:

1964: First documented out break of dengue in Bangladesh.

1977 - 78: Few cases of DF were found in a Clandestine Survey by IEDCR.

1982 - 83: of 2456 blood samples taken, 278 found DEN - 1.

1984 - 86: 21 samples collected, 3 found positive by HI Test.

Up to 1986: Major cities were free to DHF.

1997: Cross sectional serological survey at CMCH tested 255

paired sera in which 35 were positive cases .

1999: Few death cases were reported in DHF.

2000: Currently an epidemic has been reported in this country.

2001: Epidemic has been reported in this country.

2002: Epidemic has been reported in this country.

Chapter 5

Methodology

5.1 Introduction

Three data types were used in this study: malaria statistics, satellite data, and meteorological data.

5.2 Malaria statistics

Malaria statistics were represented by annual total clinical malaria cases for 1992-2001. The data were collected from the Directorate General of Health, Bangladesh's Ministry of Health. These data provided the number of malaria cases from all patients with fever, who came to the hospitals of Bangladesh. The data were aggregated to local administrative unit health centers and to district level. These data included the number of persons tested and the number of positive malaria cases. In this study, the latter was expressed in percentage of the former.

5.3 Satellite data

Satellite data included radiances measured by the Advanced Very High Resolution Radiometer (AVHRR) flown on NOAA afternoon polar orbiting satellites. They were collected from the NOAA/NESDIS Global Vegetation Index (GVI) data set from 1992 through 2001. The GVI has spatial resolution of 4 km (sampled to 16 km) and daily temporal resolution sampled to 7-day composite. The radiances in the visible (Ch1), near infrared (Ch2) and infrared (Ch4) were used in this study. Post lunch-calibration was applied to Ch1 and Ch2 radiances and normalized difference vegetation index (NDVI) was calculated (NDVI= (Ch2-Ch1)/ (Ch2+Ch1)); the Ch4 radiances were converted to brightness temperature (BT).

The method for processing NDVI and BT included removal of high frequency noise from the annual time series, approximation of annual cycle, calculation of multi-year climatology, and derivation of medium frequency variations associated with weather fluctuations.

High frequency noise (related to fluctuating transmission of atmosphere, sun/sensor geometry, bi-directional reflectance, random noise and etc) was removed by statistical smoothing of NDVI and BT annual time series using a combination of median filter and least square technique. After removal of high frequency noise, seasonal cycle in NDVI and BT become evident. Climatology of NVDI and BT was approximated by multi-year maximum (MAX) and minimum (MIN) values taken from smoothed data [63, 67]. The MAX and MIN for each pixel and week were calculated from twelve years of historical data described in Kogan (2001). Difference between MAX and MIN (MAX-MIN) represents those extreme fluctuations in NDVI and BT associated with weather fluctuations. The (MAX-MIN) criteria were used to describe and classify weather-related ecosystem's "carrying capacity" [76, 80]. Following Kogan (2001) the MAX, MIN and MAX-MIN values were used to approximate vegetation health indices: Vegetation Condition Index (VCI), Temperature Condition Index (TCI) and Vegetation Health Index (VHI) [10, 85, 92].

$$VCI=100*(NDVI - NDVI\ min)/\ (NDVI\ max - NDVI\ min) \qquad (3)$$

$$TCI=100*(BT\ max - BT)/\ (BT\ max - BT\ min) \qquad (4)$$

$$VHI=a*\ VCI + (1 - a)*\ TCI \qquad (5)$$

Where NDVI, NDVImax, and NDVImin (BT, BTmax, and BTmin) are smoothed weekly NDVI (BT), their multi year absolute maximum and minimum respectively; a is a coefficient quantifying a share of VCI and TCI contribution in the VHI (Kogan 2001). The VCI, TCI and VHI change from 0 to 100, reflecting changes in vegetation conditions from extremely unfavorable (vegetation stress) to optimal (favorable), respectively. These indices estimate moisture (VCI), thermal (TCI) and combination of both (VHI) conditions. The VCI, TCI and VHI values around 50 estimates near normal conditions. If these indices approach to 0 then condition deteriorate indicating vegetation stress. On the opposite side of the scale, the conditions are estimated as favorable.

5.4 Meteorological data

Ten-day average temperature (T°C) and humidity (H %) and 10-day total rainfall (R, mm) data were collected from 34 meteorological stations in Bangladesh during 1992-1999. Meteorological parameters (T, R and H) were expressed as a deviation from mean value during 1992-1999 (percent of mean for R, difference from mean for T and H) in order to evaluate weather anomalies during the annual cycle. Regional average T, H and R were calculated as average values from weather stations, in the divisions.

Chapter 6

Analysis for coastal divisions

6.1 Introduction

Coastal divisions include Chittagong, Khulna and Barisal division (**Figure 6.1**) (http://www.bangladeshgov.org/bdmaps).

Chittagong (21°34' to 23°38' N and 91°80' to 92°70' E) division is located in the south-eastern part of Bangladesh Ecosystem type here is highland covered with the evergreen forest. The western one third of the region is the most populated and is subject to all malaria cases. Similar to the rest of the country, Chittagong division has sub-tropical warm, wet and humid climate. Total annual rainfall amount is large, around 3000 mm per year, average temperature 21-22° C, and relatively humidity around 80%.

Khulna (22° 15'to 22°65' N and 92°15' to 92°55' E) division is located in south-western part of Bangladesh. Khulna division is principally marshland and jungle. The principal place of interest in this area of the country is the Sundarban National Park, a supreme example of lush coastal vegetation.

Barisal (22° to 23° N and 90° to 91° E) division is located in south-central part of Bangladesh, bounded by Dhaka division on the north, bay of bengal on the south, Chittagong division on the east and Khulna division on the west. Barisal division situated in an area dissected by rivers, it is the most important river port in the south of the country. Barisal Division is principally lowland and with coastal vegetation.

All three divisions have also sub-tropical climate like all over Bangladesh.

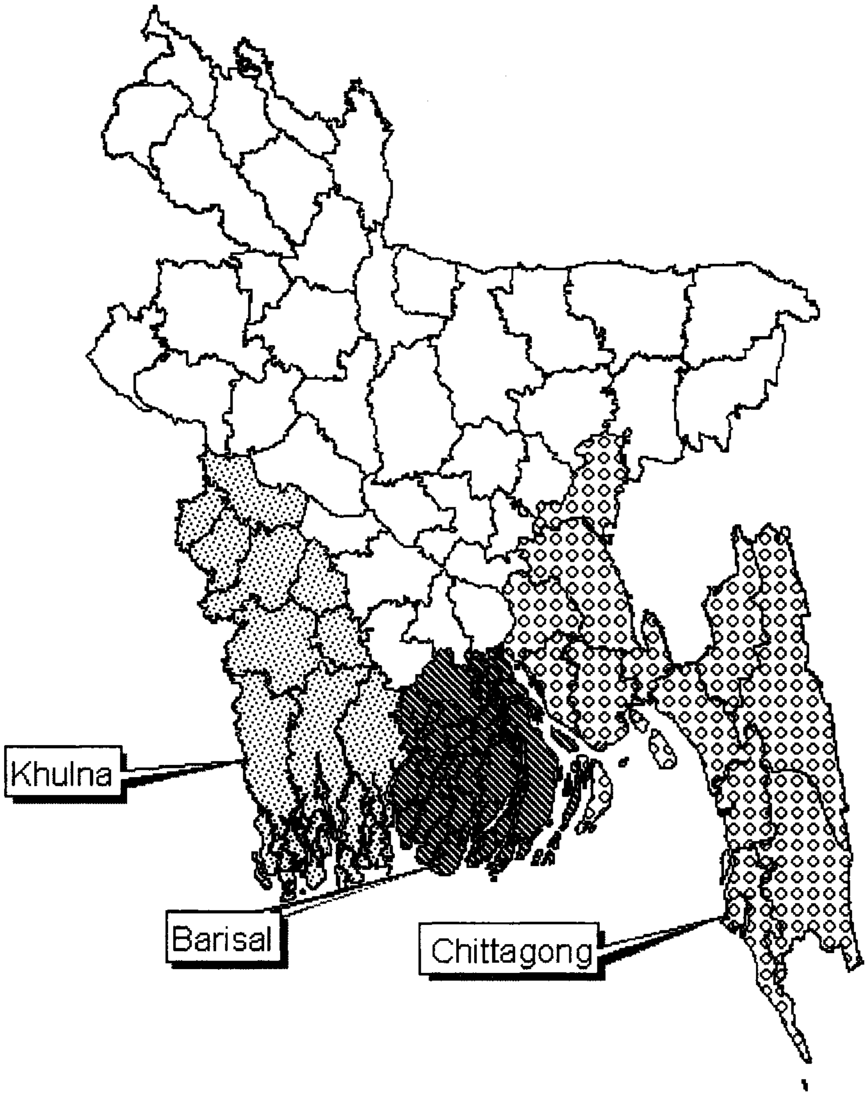


Figure 6.1 Coastal divisions geological map

6.2. Malaria

Malaria parasite (plasmodium) in coastal divisions is transmitted by female Anopheles mosquitoes. Chittagong division has 60-80 percent of all malaria cases in Bangladesh. Breeding habitats of AD are puddles on footpath and turbulence pits at the heads of drainage gullies, which are able to hold water for sometime without supplemental rainfall. Mosquitoes in coastal divisions transmit malaria year around. However during the cooler season (November-March) mosquito are less active and the number of malaria cases is small. This number increases considerably during warm and wet season. Malaria cases of coastal divisions are shown in **Table 6.1**.

Table 6.1 Malaria statistics of coastal divisions 1992-2001

Year	Chittagong	Khulna	Braishal
1992	16.6	0.067	0
1993	17.55	0.057	0.086
1994	21.76	0.07	0.07
1995	21.63	0.08	0.07
1996	20.53	0.19	0.14
1997	17.14	0.16	0.11
1998	22.21	0.4	0.58
1999	24.3	0.78	0.72
2000	21.47	0.8	0.68
2001	21.47	1.52	0.65

6.3 Environment

Three principal environmental factors for mosquito activity and malaria epidemiology are important: temperature, humidity, and rainfall. The optimum temperatures for intensive mosquitoes' development and activity are 25°-27° C [28]. If daytime temperature exceeds 40° C mosquitoes are less active and parasite transmission is limited. In general, larger amount of rainfall stimulates mosquitoes' activity. However, frequent rainfall during monsoon period might produce stagnation in malaria transmission since they wash out eggs and reduce chances for development of adult mosquitoes. AD females stay active during the period when precipitation exceeds 50 mm per month. However, a combination of large rainfall and hot weather during June-August might reduce mosquito's activity. Malaria transmission is also reduced if the humidity drops below 60%. In general, two seasons are defined in the annual cycle: wet and warm during April-October and cool and dry during December-February. Most precipitation falls during April-October, when average daily temperature is around 25° C with maximum temperature reaching 30° C during daytime.

Monthly temperature and humidity are stable from year-to-year (variation are 1° C and 1%, respectively), in Chittagong but variation in total annual rainfall could be large for Chittagong is 1000 mm and for Khulna and Barisal is 200 mm. Variation in monthly rainfall between dry and wet years as seen in **Table 6.2**

Table 6.2 Total precipitation and mean temperature coastal divisions, (a) Chittagong; (b) Khulna

Month	Precipitation(mm)		Temperature (°C)	
	Dry	Wet	Hot	Cool
January	0	15	14	14
February	0	61	17	15
March	0	120	25	21
April	3	207	23	22
May	64	267	25	24
June	218	511	26	25
July	271	619	25	25
August	278	489	26	25
September	152	411	25	23
October	49	232	25	24
November	57	142	23	20
December	0	53	18	16

(a)

Month	Precipitation(mm)		Temperature (°C)	
	Dry	Wet	Hot	Cool
January	0	21	20	18
February	0	42	23	21
March	0	65	28	25
April	6	57	31	27
May	44	81	31	29
June	79	196	32	29
July	133	184	30	29
August	115	165	30	29
September	93	191	30	29
October	44	117	30	28
November	3	65	27	25
December	0	24	22	20

(b)

Table 6.2 c. Total precipitation and mean temperature coastal divisions for Barisal

Month	Precipitation(mm)		Temperature (°C)	
	Dry	Wet	Hot	Cool
January	0	21	20	19
February	0	45	23	21
March	0	98	28	25
April	7	77	30	26
May	53	132	30	28
June	85	253	30	29
July	139	286	29	28
August	114	229	29	28
September	47	199	29	28
October	8	114	29	28
November	1	109	27	25
December	0	4	22	20

6.4 Trend and statistical analysis

Figure 6.2 shows annual percent of malaria cases in coastal division during 1992-2001. As seen, malaria is on a rise during the 1990s. Although the Government of Bangladesh made efforts to eradicate malaria, the number of cases in Chittagong division was growing which is associated with poverty in this region. Variations in the number of cases around the trend are associated with weather changes from year to year. The long-term tendency in malaria cases dynamics was approximated by linear equation (1) and weather-related variations around the trend were expressed as a ration (equation 2) of actual cases to the estimated from the trend.

$$Y_{trend} = a + b*Year \quad (1)$$

$$DY = (Y / Y_{trend})*100 \quad (2)$$

Where, Y_{trend} is percent of malaria cases for weather conditions near normal; Y is % of malaria cases; Year is year number; a is intercept; b is slope; DY is deviation from trend expressed in percentage.

Intercepts and slopes for these divisions are shown in **Table 6.3**.

The DY for Chittagong division can be explained by comparing two neighboring years 1997 and 1998. In 1997, DY was 86% or 14% below the trend, while in 1998 DY was 108% or 8% above the trend. These estimates indicate that the 1997 was an unfavorable year for mosquito development, while 1998 was favorable.

The DY for Khulna division can be explained by comparing two extreme years 1997 and 1999. In 1997, DY was 33% or 67% below the trend, while in 1997 DY was 103% or 3% above the trend. These estimates indicate that the 1997 was an unfavorable year for mosquito development, while 1999 was favorable.

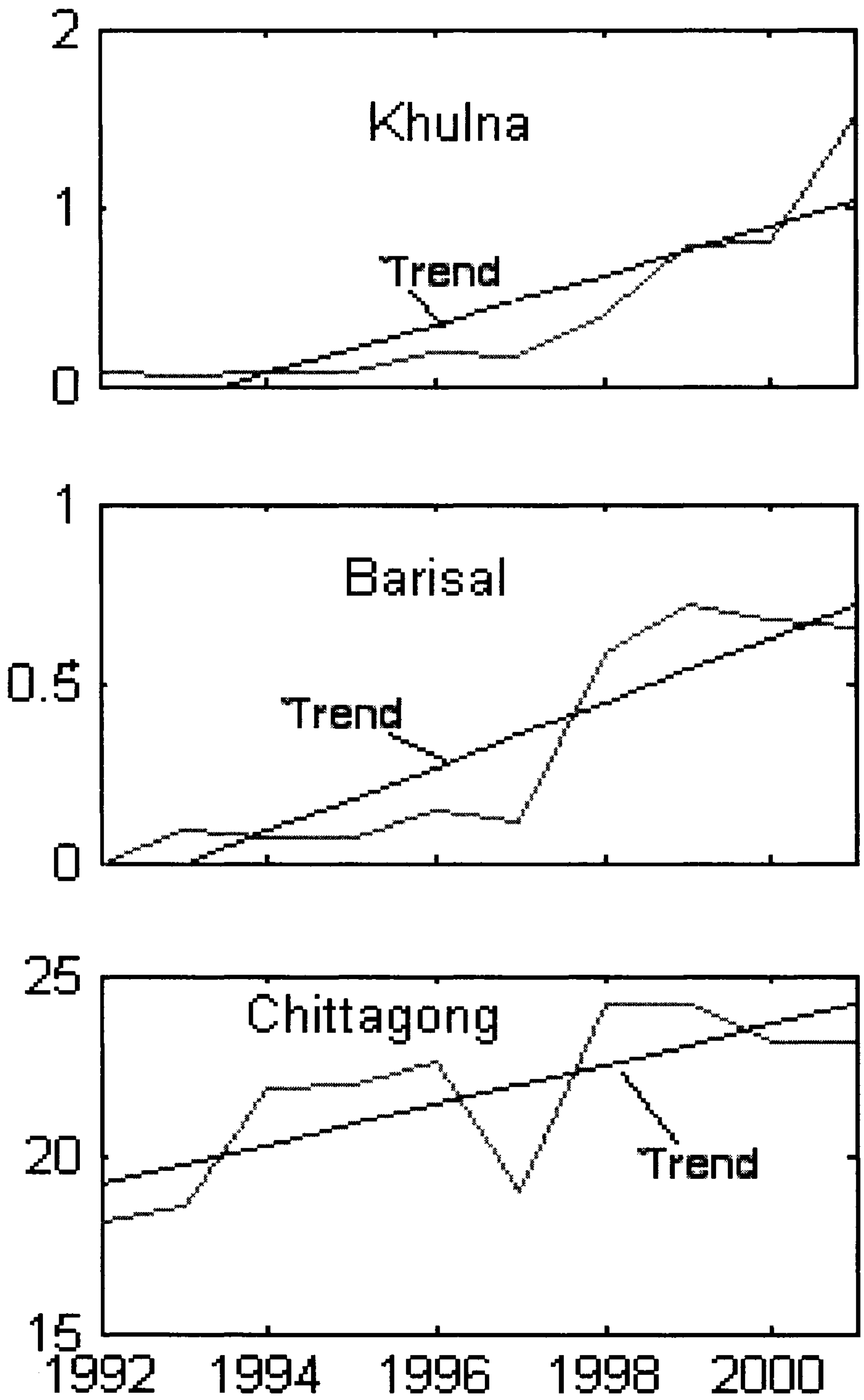


Figure 6.2 Annual malaria cases in coastal divisions and trend line, 1992-2001

Table 6.3 Intercepts and slopes for coastal divisions

Division	Intercept(a)	Slop(b)
Chittagong	18.65	0.55
Khulna	-0.35	0.14
Barisal	-0.18	0.09

The DY for Barisal division can be explained by comparing two years 1994 and 1999. In 1994, DY was 10% or 90% below the trend, while in 1999 DY was 101% or 1% above the trend. These estimates indicate that the 1994 was an unfavorable year for mosquito's development, while 1999 was favorable.

Malaria distributions of coastal divisions for the extreme years are shown in **Figure 6.3**.

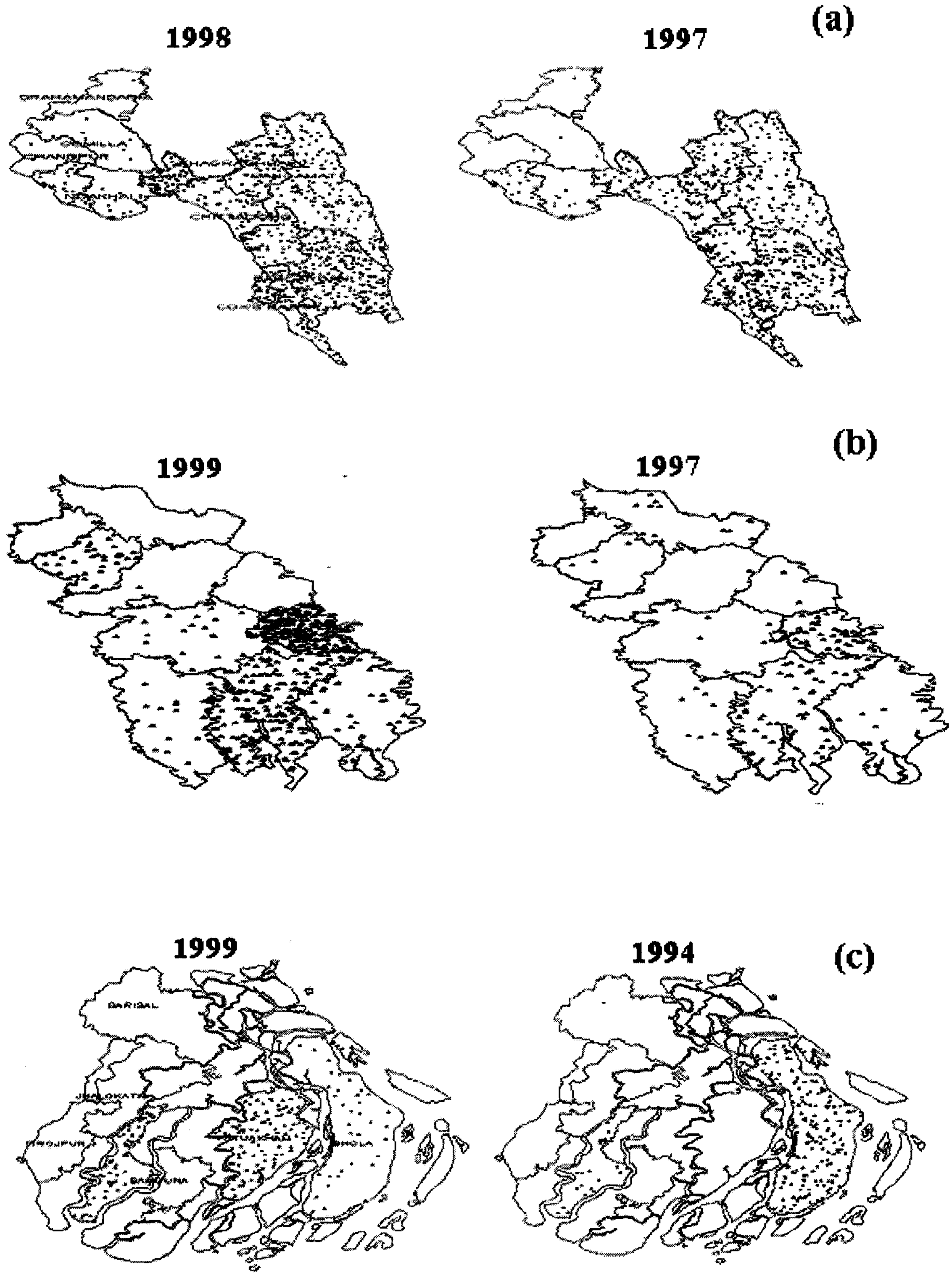


Figure 6.3 Malaria distributions for years with highest and lowest number of malaria cases. (a) Chittagong; (b) Khulna; (c) Barisal division

6.5 Correlation Analysis for satellite data

6.5.1 TCI and VCI for two extreme years (highest and lowest number of malaria cases)

First, the differences, in VCI and TCI dynamics were investigated during the years with the extreme differences in the percent of DY (below and above trend).The assumption was that the environmental conditions of these years were quite different and they would be reflected in VCI and TCI values.

For Chittagong division 1997 and 1998 VCI and TCI time series shown in **Figure 6.4.a** indicate that if TCI is above 60 (indicating cooler temperature) during spring/early summer (weeks 16-26), than larger number of malaria cases (DY above trend) occurs as it was in 1998.

However, when TCI is below 40 (indicating thermal stress), the number of malaria cases is much smaller as it was in 1997. In late summer and during fall (weeks 27-40), TCI differences between two extreme years were smaller. Similarly, smaller differences were observed during the entire rainy season (May-September). This preliminary analysis has already indicated that in the environment of Chittagong division, thermal conditions are more important factor for controlling malaria epidemics.

For Khulna division 1997 and 1999 VCI and TCI time series shown in **Figure 6.4.b** indicate that if TCI is above 60 (indicating cooler temperature) during weeks 22-40 of 1997, than larger number of malaria cases (DY above trend) occurs as it was in 1999.

However, when TCI is below 40 (indicating thermal stress), the number of malaria cases is much smaller as it was in 1997. In late summer and during fall (weeks 27-40), TCI differences between two extreme years were smaller. Similarly, smaller differences were observed during the entire rainy season (May-September). This preliminary analysis has already indicated that in the environment of Khulna division, thermal conditions are more important factor for controlling malaria epidemics.

For Barisal 1994 and 1999 VCI and TCI time series shown in **Figure 6.4.c** indicate that if TCI is above 40 (indicating cooler temperature) during weeks 22-40 of 1997, than larger number of malaria cases (DY above trend) occurs as it was in 1999.

However, when TCI is below 40 (indicating thermal stress), the number of malaria cases is much smaller as it was in 1997. In late summer (weeks 17-25), TCI differences between two extreme years were smaller. Similarly, smaller differences were observed during the entire rainy season (May-September).

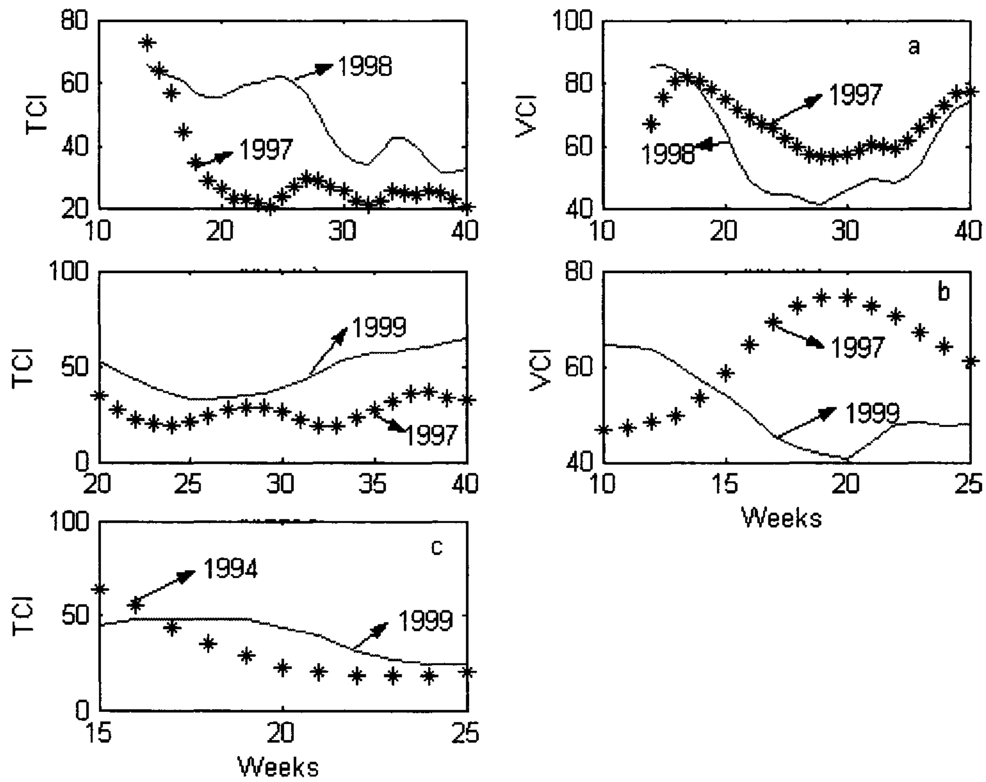


Figure 6.4 Temperature Condition Index (TCI) and Vegetation Condition Index (VCI) dynamics for years with highest and lowest number of malaria cases for coastal divisions, (a) Chittagong; (b) Khulna; (c) Barisal division

6.5.2 Correlation between malaria cases and TCI and VCI

Investigation included correlation analysis of detrended malaria cases (DY) versus VCI and TCI, shown in **Figure 6.5.**

In Chittagong division during cooler month (spring and fall) when mosquitoes are less active; correlation is low for both indices. In spring (week 16) when mosquito activity season starts, correlation increases reaching maximum (0.6 for TCI and 0.5 for VCI) at the end of June (week 25-26); by fall, the correlation is gradually decreasing. These results are compatible with mosquito's activity. After laying eggs in April-May, new mosquitoes female reach adult stage in 7-15 days. After that their biting activity increases, leading to enhanced malaria transmission.

In Khulna division in spring (week 16) when mosquito activity season starts, correlation increases reaching maximum (0.6 for TCI) at the middle of June (week 20-26); by fall, the correlation is gradually decreasing. In week 30 correlations starts increase and reaches maximum (0.5 for TCI) at middle of October; by late fall it gradually decreases.

In Barisal division in week 16 when mosquito activity season starts, correlation increases reaching maximum (0.6 for TCI) at the middle of June (week 20-26); by fall, the correlation is gradually decreasing. These results are compatible with mosquito's activity. After laying eggs in April-May, new mosquitoes female reach adult stage in 7-15 days. After that their biting activity increases, leading to enhanced malaria transmission.

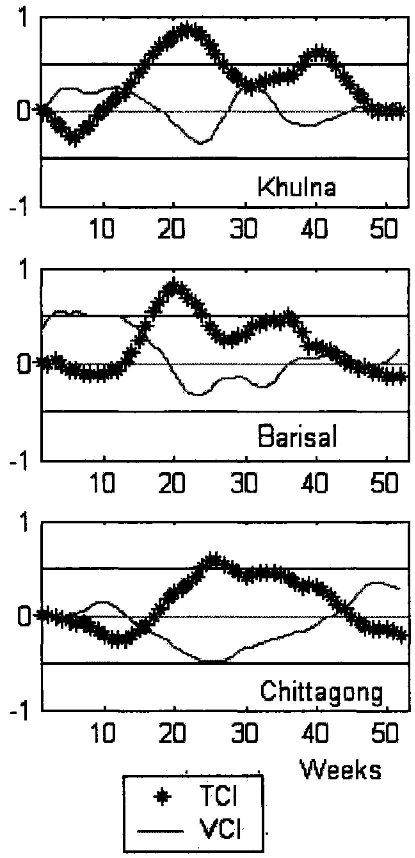


Figure 6.5 Correlation coefficient dynamics of DY (deviation of malaria cases) versus Temperature Condition Index (TCI) and Vegetation Condition Index (VCI) for coastal divisions

Although the correlation of DY with VCI during the same wet period is weaker than with TCI, the dynamics of correlation coefficient (CC) in **Figure 6.5** rightly emphasize seasonal cycle (increase of CC at the beginning of the warm season, maximum CC, during the critical period and decrease of CC during the end of the warm season). Correlation analysis was also performed for DY versus VHI. However CC was smaller than the correlation of DY with VCI and TCI because the correlation of DY with VCI has opposite sign to TCI.

Vegetation map of extreme two years for coastal divisions are shown in **Figure 6.6.**

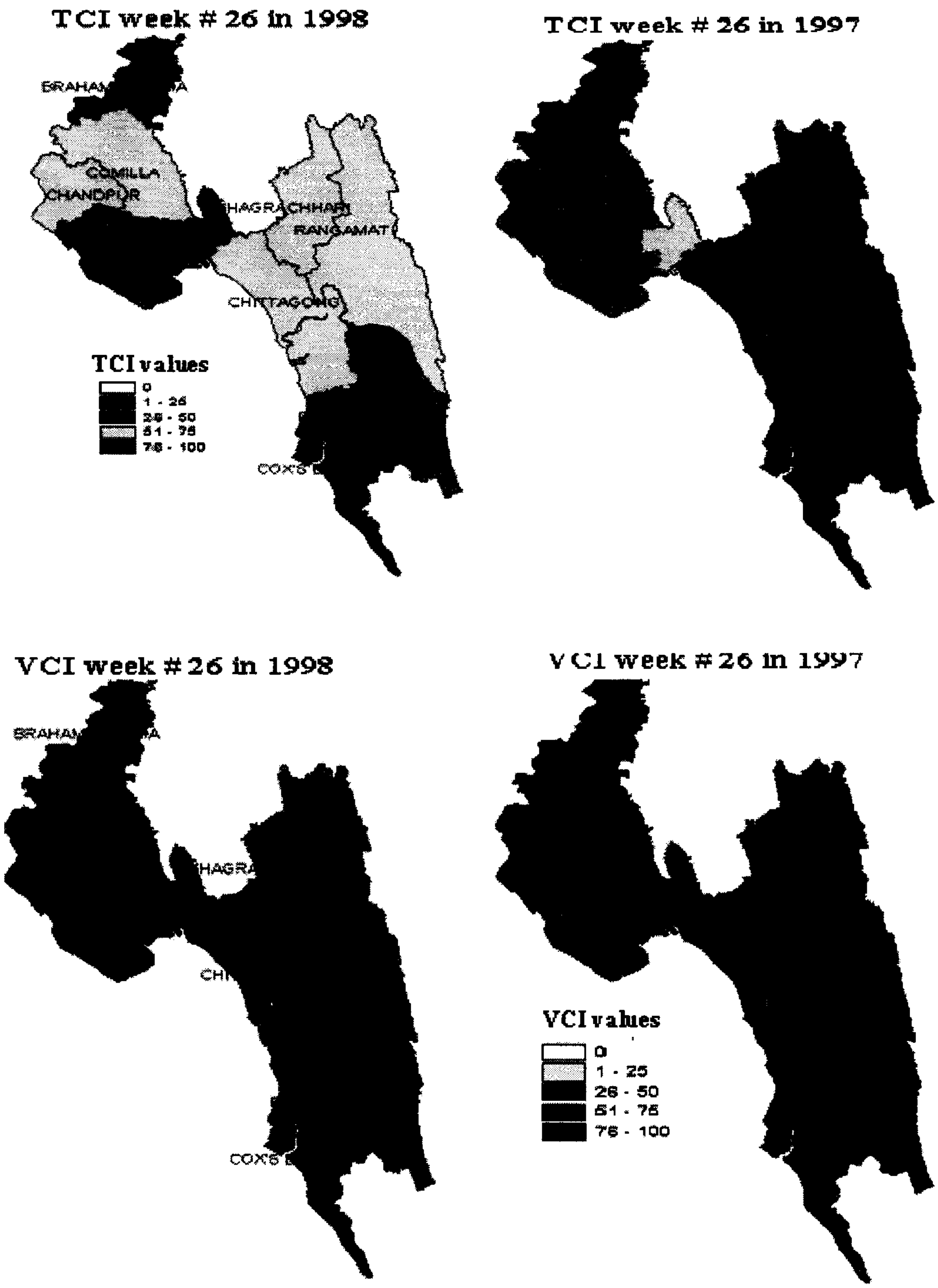


Figure 6.6 a. Vegetation maps of Temperature Condition Index (TCI) and Vegetation Condition Index (VCI) for Chittagong division

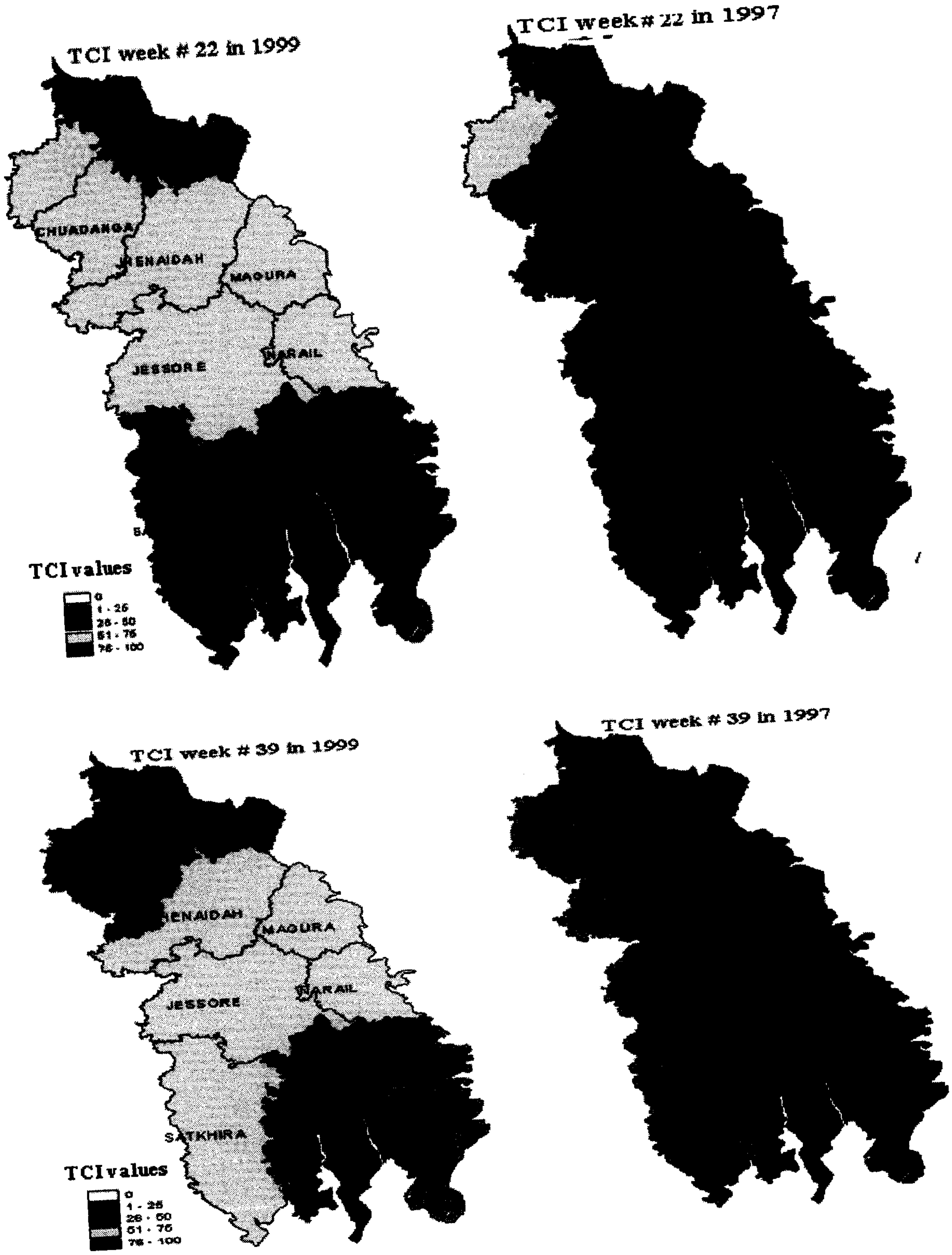


Figure 6.6 b. Vegetation maps of Temperature Condition Index (TCI) and Vegetation Condition Index (VCI) for Khulna

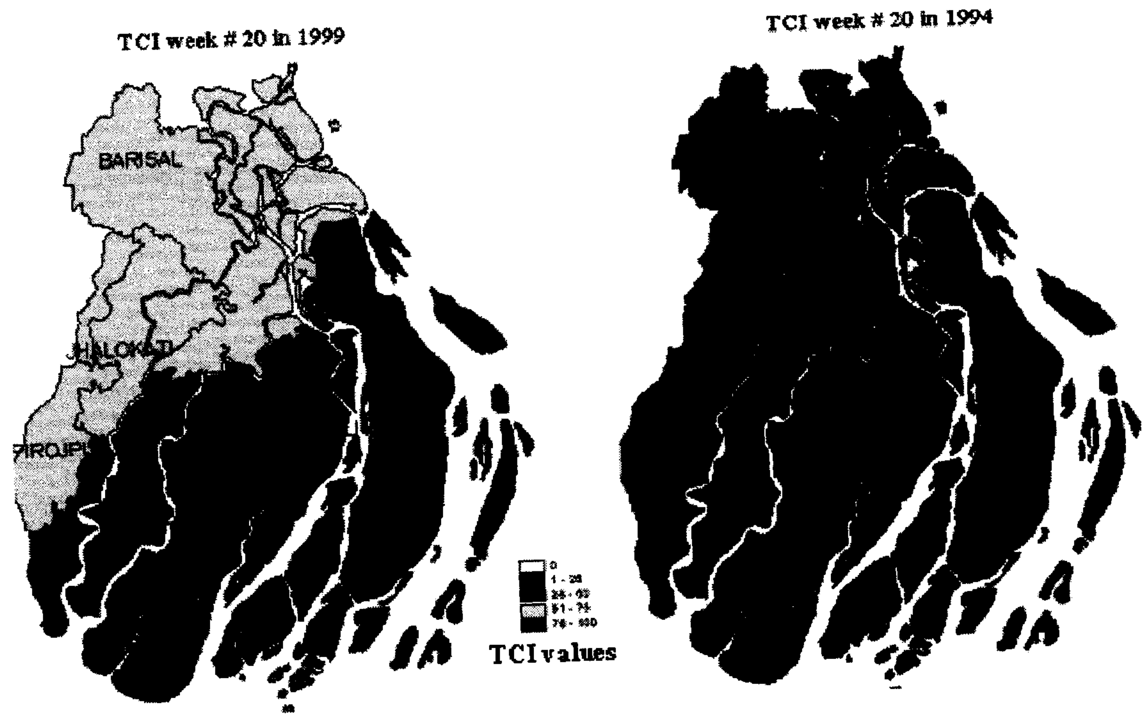


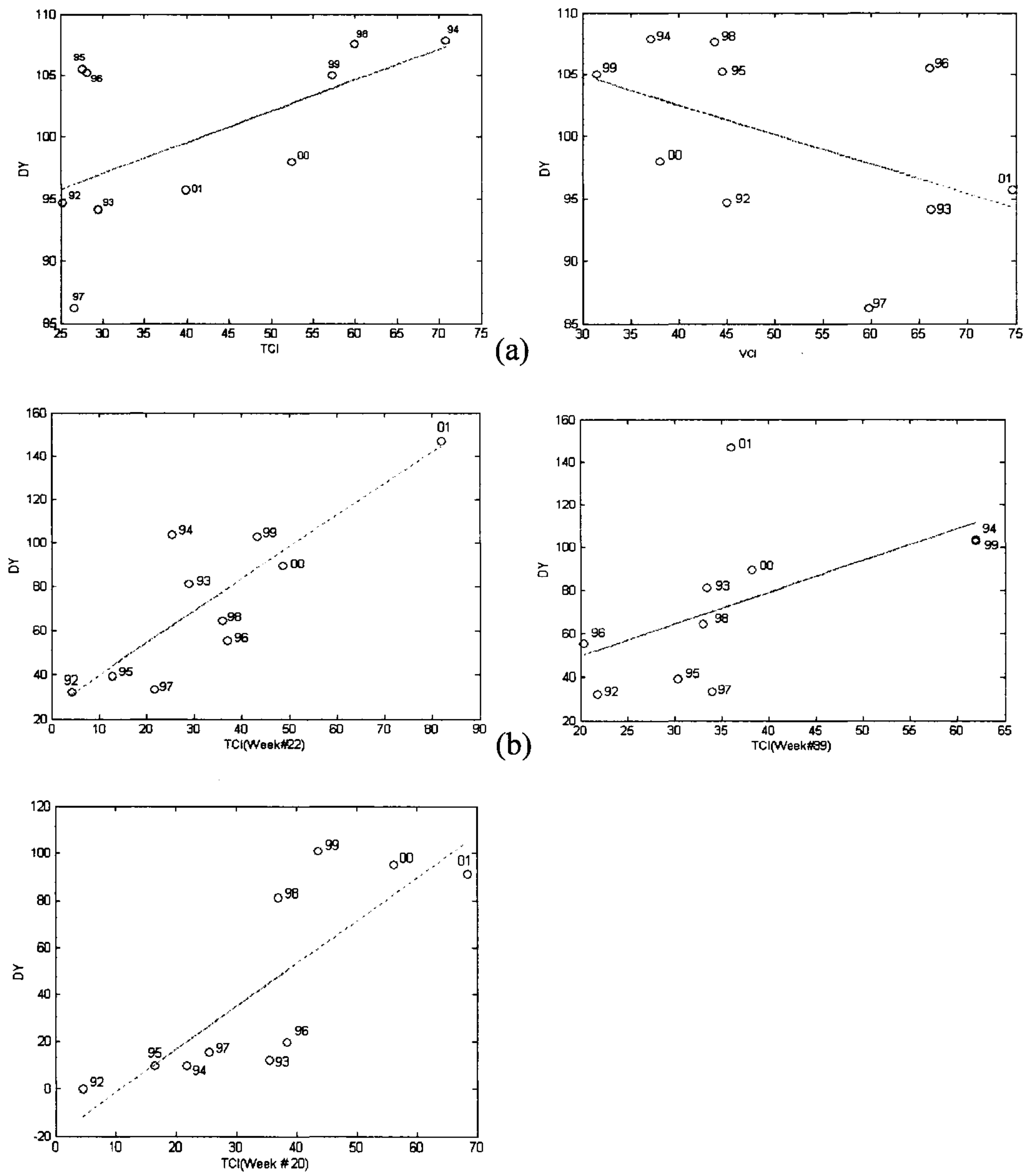
Figure 6.6 c. Vegetation maps of Temperature Condition Index (TCI) and Vegetation Condition Index (VCI) for Barisal

6.5.3 Scatter Plot for TCI and VCI

For Chittagong division, it is important to emphasize that correlation of DY with TCI is positive (**Figure 6.7**) indicating that DY increases from below trend values (fewer malaria cases) for smaller TCI (hotter conditions) to above trend (larger number of malaria cases) for larger TCI (cooler conditions). These results are in line with climate impact analysis literature indicating that hot weather depresses mosquito activity and malaria transmission [3, 41].

For Khulna division correlation of DY with TCI for week 22 and 39 is positive (**Figure 6.7**) indicating that DY increases from below trend values (fewer malaria cases) for smaller TCI (hotter conditions) to above trend (larger number of malaria cases) for larger TCI (cooler conditions). These results are in line with climate impact analysis literature indicating that hot weather depresses mosquito activity and malaria transmission.

For Barisal division It is important to emphasize that correlation of DY with TCI for week 20 is positive (**Figure 6.7**) indicating that DY increases from below trend values (fewer malaria cases) for smaller TCI (hotter conditions) to above trend (larger number of malaria cases) for larger TCI (cooler conditions). These results are in line with climate impact analysis literature indicating that hot weather depresses mosquito activity and malaria transmission



(c)

Figure 6.7 Scatter plot of DY (deviation of malaria cases) versus Temperature Condition Index (TCI) and Vegetation Condition Index (VCI), (a) Chittagong; (b) Khulna; (c) Barisal

6.6 Regression analysis for satellite data

The result of correlation analysis in **Figure 6.5** was used to develop regression equation. For Chittagong division two options were investigated: using TCI only and both TCI and VCI for the week of the highest correlation. The equations are shown below

$DY=89.96 + 0.24\ TCI_{26}$ (3)

$MCC=0.56; E=6.7\ \%$ (4)

$DY=96.49 + 0.201\ TCI_{26} - 0.096\ VCI_{26}$ (5)

$MCC=0.60; E=6.5\%$ (6)

Where MCC is multiple correlation coefficient and E is the error of estimation;

TCI_n is TCI value for week number n and VCI_n is VCI value for week number n.

The results of regression show that MCC increases slightly when both TCI and VCI are used, however regression coefficients indicate larger contribution of TCI (0.201) versus VCI (0.096).

These regressions reflect relationship of DY versus VCI and TCI for one week only. However as seen in **Figure 6.5**, other weeks around the peak of the correlation influence DY as well. Therefore, another equation was constructed, which combined five weeks (23-27). However, since the data sample was small (10 years) to build regression with five independent variables, the weekly indices were combined into one variable, using CC as a weighting measure. The weekly weights (W) were calculated as

$W_i = CC^2_i / (CC^2_{23} + CC^2_{24} + CC^2_{25} + CC^2_{26} + CC^2_{27})$ (7)

Where *i*, is week number.

Total weighted TCI for weeks 23 to 27 ($TCI_{23\text{-}27}$) was composed as

$TCI_{23\text{-}27} = 0.12^*\ TCI_{23} + 0.19^*TCI_{24} + 0.24^*\ TCI_{25} + 0.24^*\ TCI_{26} + 0.21^*\ TCI_{27}$ (8)

The regression equation for DY versus weighted TCI_{23-27} is written below:

$$DY = 90.63 + 0.23*TCI_{23-27} \qquad (9)$$

$$MCC = 0.51;\ E = 6.9\%. \qquad (10)$$

Based on this regression estimates no improvement was found therefore, the equation for VCI and TCI parameters for week 26 was accepted as the best estimation of DY.

For Khulna division two options were investigated: using TCI only for the week 22 and 39 of the highest correlation. The equations are shown below

$$DY= -19.4+ 2.11\ TCI_{22} \qquad (11)$$

$$MCC=0.67;\ E=53\% \qquad (12)$$

$$DY= -34.7 + 2.34\ TCI_{39} \qquad (13)$$

$$MCC=0.49;\ E=62\% \qquad (14)$$

Where MCC is multiple correlation coefficient and E is the error of estimation.

The equations for TCI parameters for weeks 22 and 39 were accepted as the best for estimation of DY.

For Barisal division two options were investigated: using TCI only and both TCI for the week of the highest correlation. The equations are shown below

$$DY= -19.9+ 1.82\ TCI_{20} \qquad (15)$$

$$MCC=0.8;\ E=26.46\% \qquad (16)$$

Where MCC is multiple correlation coefficient and E is the error of estimation.

The results of regression shows that MCC increases slightly when both TCI and VCI are used, however regression coefficients indicate larger contribution of TCI (0.8).

The regression equation for DY versus weighted TCI_{18-22} is written below:

$$DY = -20+ 1.84*TCI_{18-22} \qquad (17)$$

MCC = 0.78; E =28.30%. (18)

The equation for TCI parameters for week 20 was accepted as the best for estimation of DY.

6.7 Correlation Analysis for Meteorological data

6.7.1 Correlation between malaria cases and temperature

Correlation between DY (percent of malaria cases) and deviation from mean temperature DT is shown in **Figure 6.8**.

For Chittagong division 10 days time series period 15-16 (weeks 20-22, April-May), period 28 (week 40-41, October) and period 30-31 (week 43-45, November) are positively correlated and correlation coefficient is more than 0.6. Transmission of malaria by Anopheles Dirus occurs only during 7 month monsoon (April to October).We will consider period 15-16 (weeks 20-22, April-May) and period 28 (week 40-41, October).

For Khulna and Barisal division correlation is positively and negatively correlated and correlation coefficient is more than 0.5 and it is not stable correlation. So we can not predict malaria cases based on this correlation.

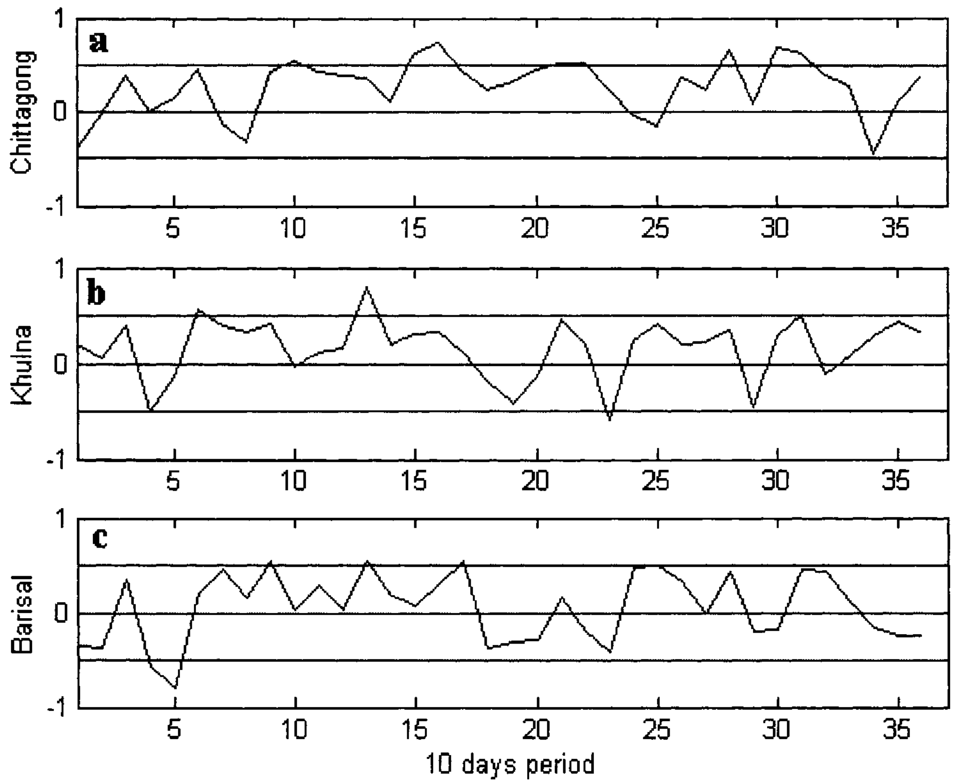
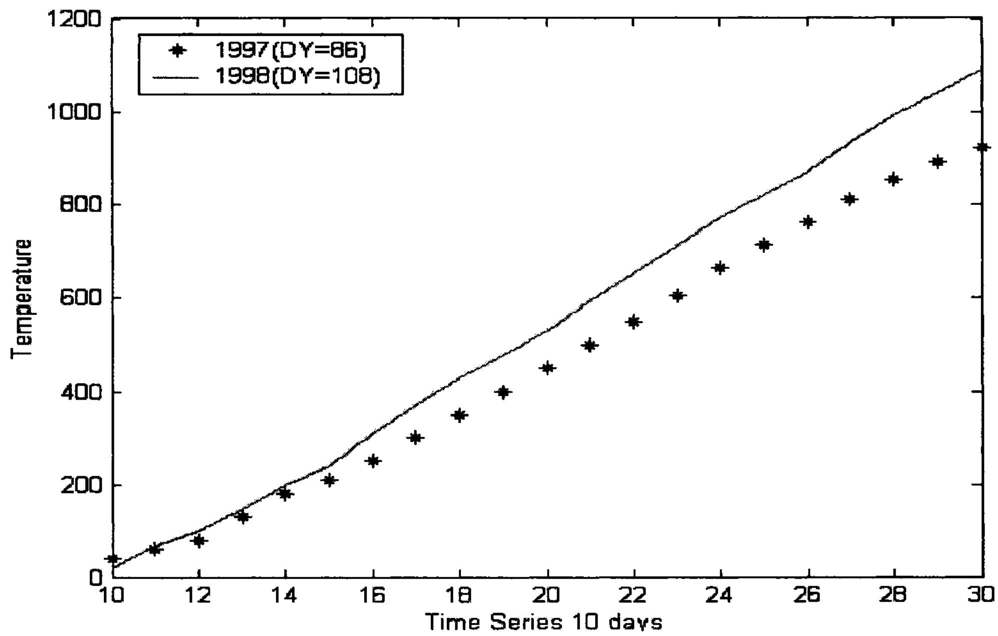


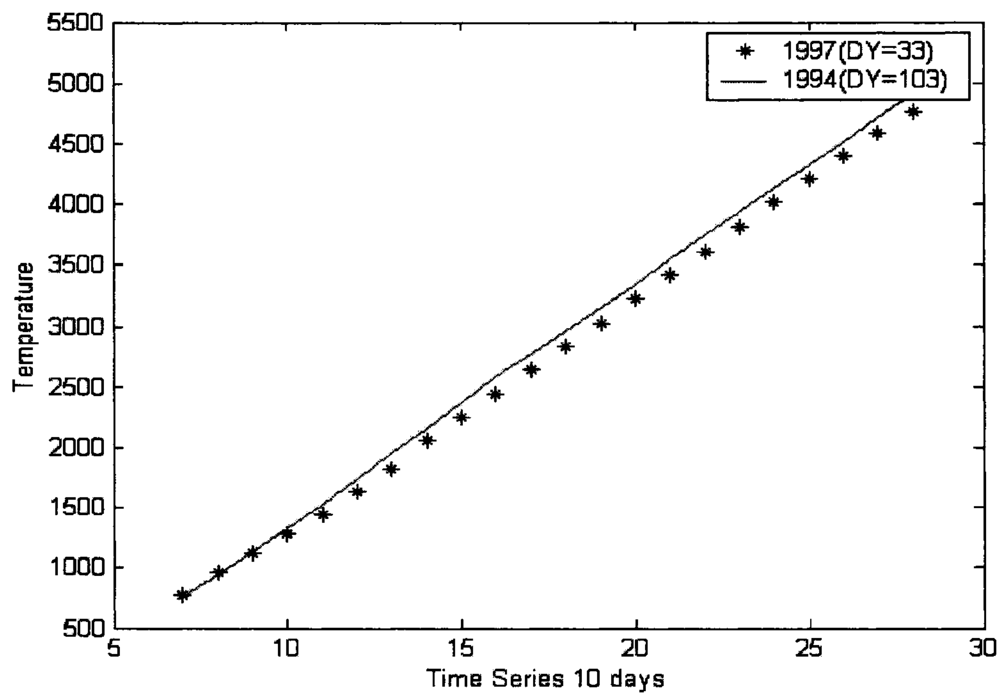
Figure 6.8 Correlation between DY (deviation of malaria cases) and DT (deviation from mean temperature), (a) Chittagong; (b) Khulna; (c) Barisal

Figure 6.9 shows that temperature of Chittagong division for period 15-16 (weeks 20-22, April-May) and period 28 (weeks 40-41, October) of 1998 is higher than Temperature in same period of 1997. We can conclude that Temperature of period 15-16 (weeks 20-22, April-May) and period 28 (W#40-41, October) has influence to malaria cases

Figure 6.9 shows that accumulative temperature of Khulna division for 1994 higher than temperature in same period of 1997. Temperature of Barisal division for 1999 higher than temperature in same period for 1994. We can conclude that temperature of time Series (10 days) has influence to malaria cases. The number of malaria cases is larger for higher temperature.



(a)



(b)

Figure 6.9 Cumulative temperatures for highest and lowest number of malaria cases, (a) Chittagong; (b) Khulna

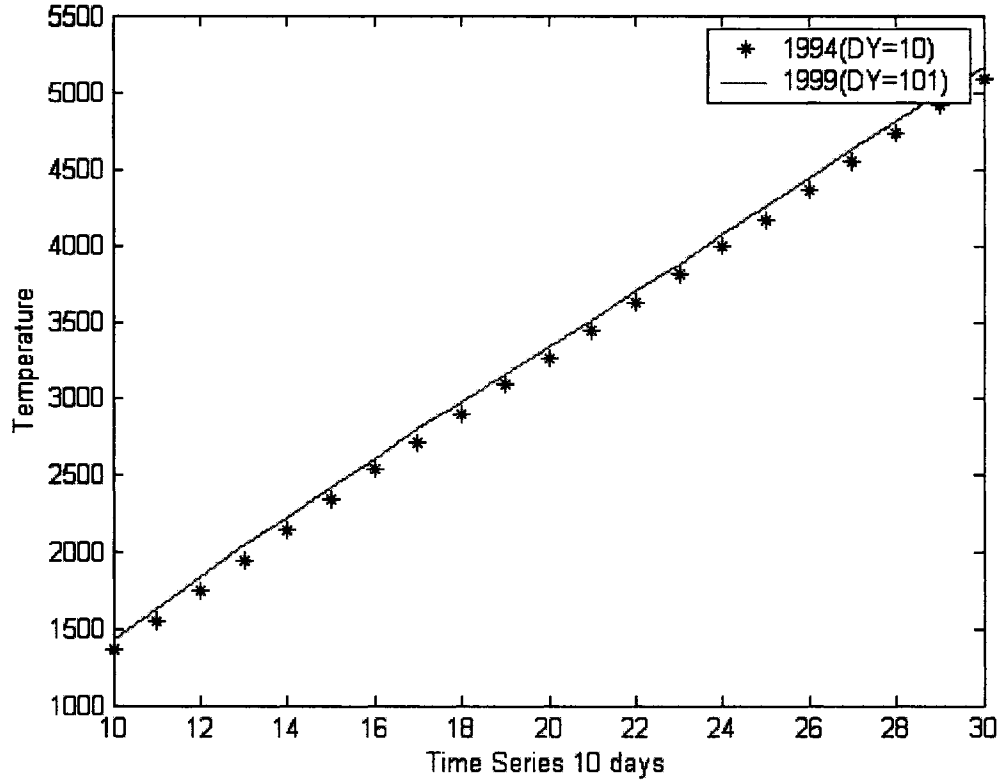


Figure 6.9 c. Cumulative temperatures for highest and lowest number of malaria cases for Barisal

6.7.2 Correlation between malaria cases and rainfall

Correlation between DY (percent of malaria cases) and cumulative deviation from rainfall DR. are shown **Figure 6.10**.

For Chittagong division period 4, 8, 11, 26 and 28 are negatively correlated and correlation coefficient is more than -0.6. Mosquito observed throughout the year but the main season was during the rains between April and October with single peak. So we will consider period 26 (week #38-39, September) and period 28 (week #40-41, October).

Correlation for Khulna division is several times positively correlated and correlation coefficient is more than 0.5 and it is not stable correlation. So we can not predict malaria cases based on this correlation. For Barisal correlation is several times positively and negatively correlated and correlation coefficient is more than 0.5 and it is not stable correlation. So we can not predict malaria cases based on this correlation.

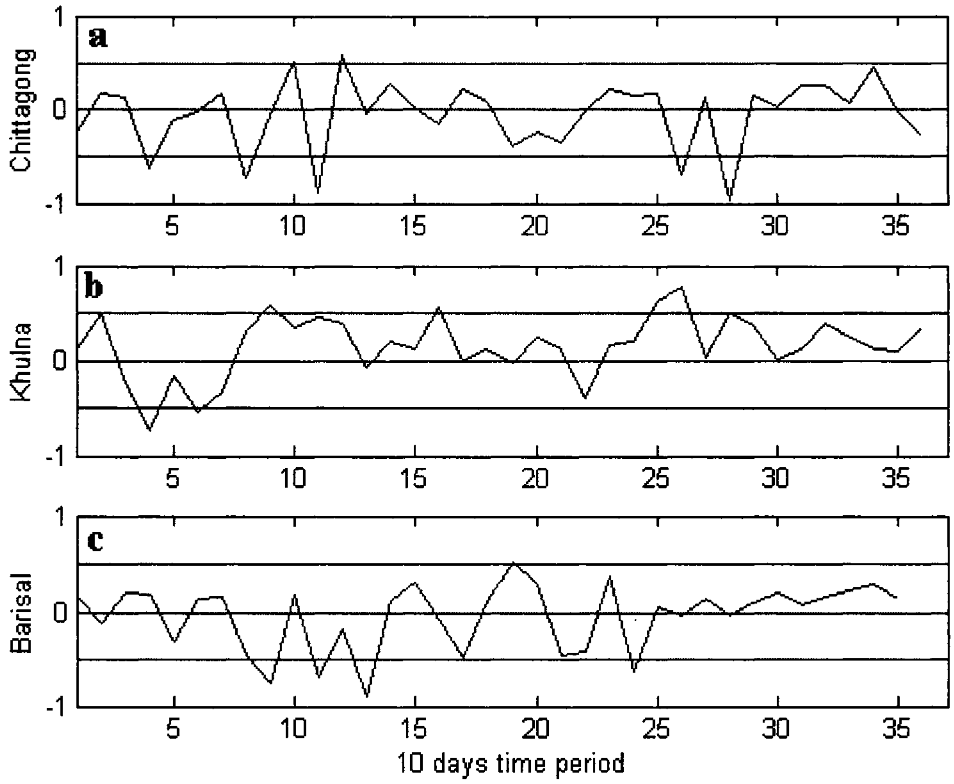
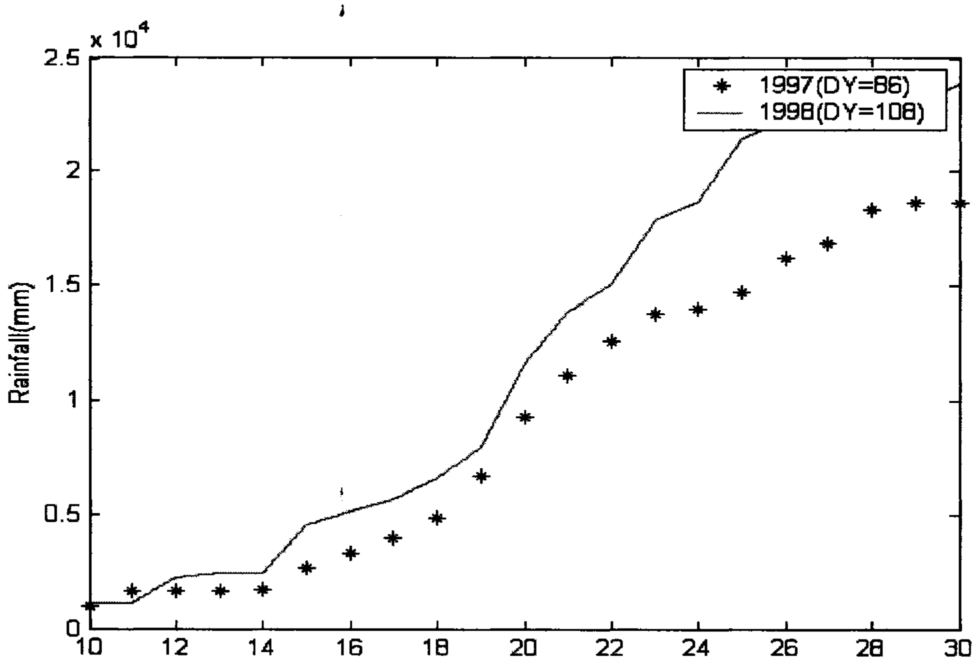


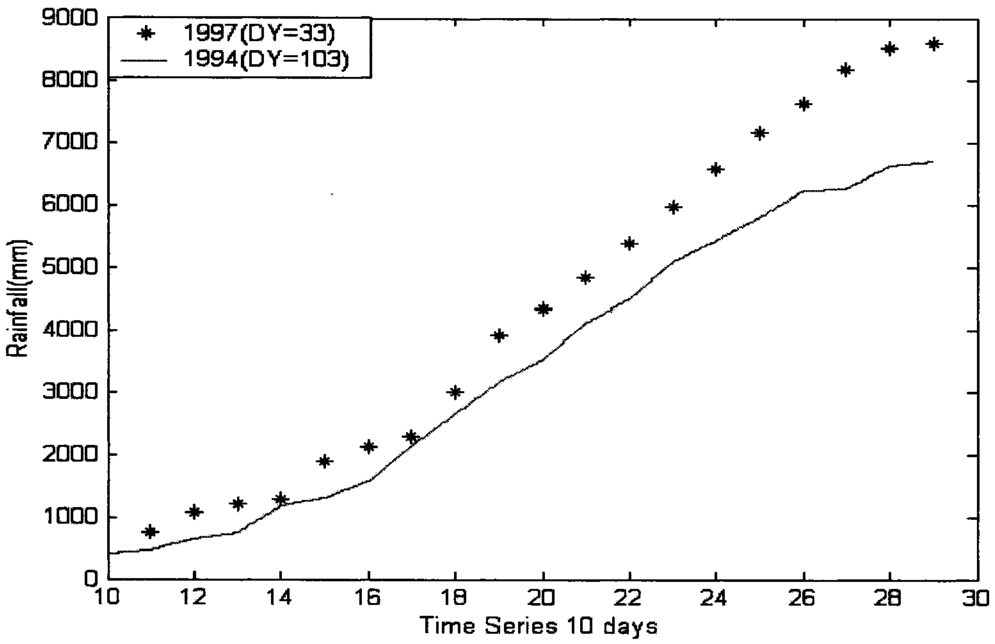
Figure 6.10 Correlations between DY (deviation of malaria cases) and DR (deviation from cumulative rainfall), (a) Chittagong; (b) Khulna; (c) Barisal

Rainfall graphs for two extreme years for coastal division are shown in **Figure 6.11**. Rainfall of Chittagong division in period 26 (week #38-39, September) and period 28 (weeks 40-41, October) of year 1998 is higher than same of year 1997. So higher rainfall relates to higher malaria cases.

For Khulna division in period 10-30 rainfall for1997 is higher than rainfall in the same period of 1994 and indicates that higher rainfall associates with fewer malaria cases. But for Barisal division in period 10-30 for two years 1994 and 1999 are not stable and we can not predict malaria cases based on it.



(a)



(b)

Figure 6.11 Rainfalls for highest and lowest number of malaria cases (a) Chittagong; (b) Khulna

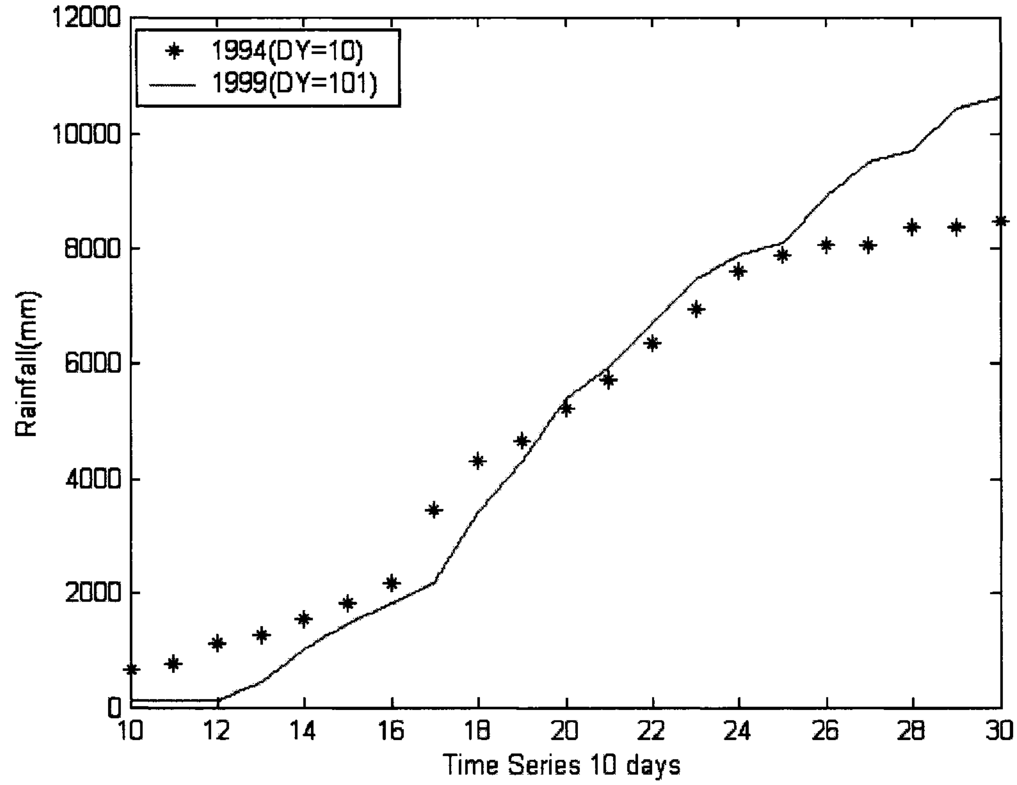


Figure 6.11 c. Rainfalls for highest and lowest number of malaria cases for Barisal

6.7.3 Correlation between malaria cases and relative humidity

Correlation between DY (percent of malaria cases) and deviation from mean relatively humidity DH shown in **Figure 6.12.**

Correlation for Chittagong division in period 24 (weeks 35-36, August) is only positively correlated and correlation coefficient is more than 0.6. It has very poor correlation. So humidity does not have impact on mosquito and vector development.

Correlation for Khulna and Barisal division are not stable correlation. So we can not predict malaria cases based on this correlation.

Humidity graph for two extreme years 1998 and 1997 for Chittagong division, 1994 and 1997 for Khulna division and 1994 and 1999 for Barisal division are shown in **Figure 6.13**. Humidity is always higher than 60% and it is favorable for mosquitoes' development.

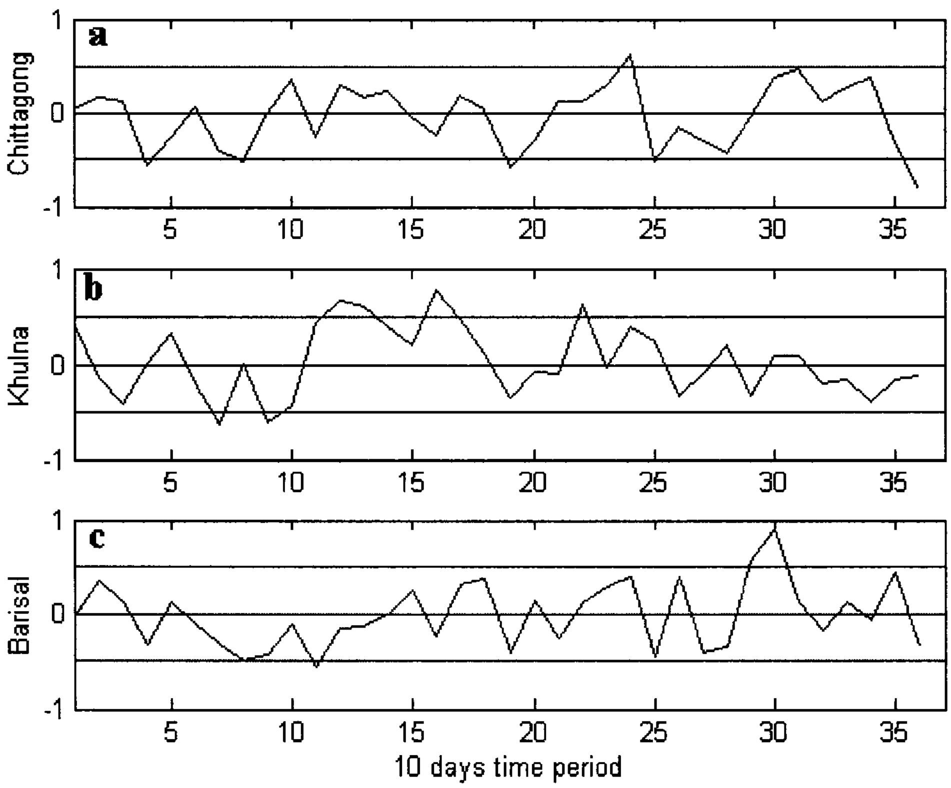


Figure 6.12 Correlations between DY (deviation of malaria cases) and DH (deviation from mean relatively humidity), (a) Chittagong; (b) Khulna; (c) Barisal

6.8 Summary

Trend and statistical analyses shows that number of malaria cases in coastal division are raising and number of malaria cases is correlated with TCI and VCI. Correlation analysis was used to develop regression equations.

The result of this study showed that AVHRR-based vegetation health indices (VCI and TCI) can be used as a proxy for numerical estimation of number of malaria cases in coastal division of Bangladesh.

The number of malaria cases is larger for higher temperature for coastal divisions. Larger number of malaria cases associated with larger rainfall for Chittagong division but for Khulna division it is opposite and for Barisal division it does not have any effect.

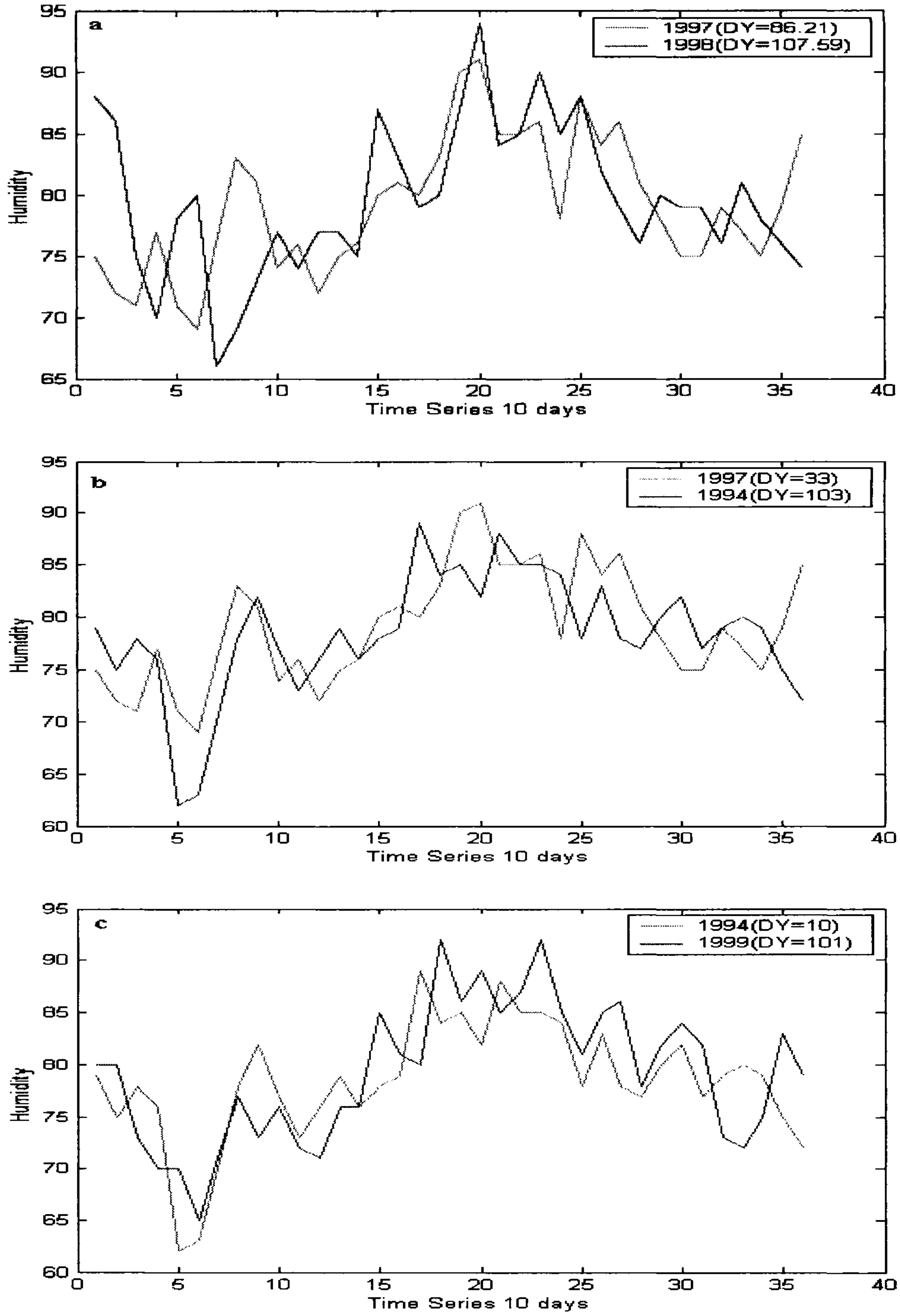


Figure 6.13 Relative humidity for years with highest and lowest number of malaria cases (a) Chittagong; (b) Khulna; (c) Barisal

Chapter 7

Analysis for highland and forest cover divisions

7.1 Introduction

Coastal divisions include Sylhet, Dhaka and Rajsahi division (**Figure 7.1**) (http://www.bangladeshgov.org/bdmaps). . Similar to coastal divisions, these divisions have sub-tropical warm and humid climate.

Sylhet (24° to 25°10' N and 91°25' to 92°60' E) division is located in north-eastern portion of Bangladesh. Ecosystem type here is high and low land covered with the tropical forest with numerous tea plantations

Dhaka (23°25' to 25°1' N and 89° to 91° E) division is located in the south-eastern part of Bangladesh and has border with India. Ecosystem type here is highland part covered with evergreen forest and agricultural land (mostly rice field).

Rajshahi (24° to 26° N and 89° to 89° 90' E) division is located in north-western part of of Bangladesh and has border with India. Rajshahi division is principally highland, jungle and agricultural land (mostly rice field).

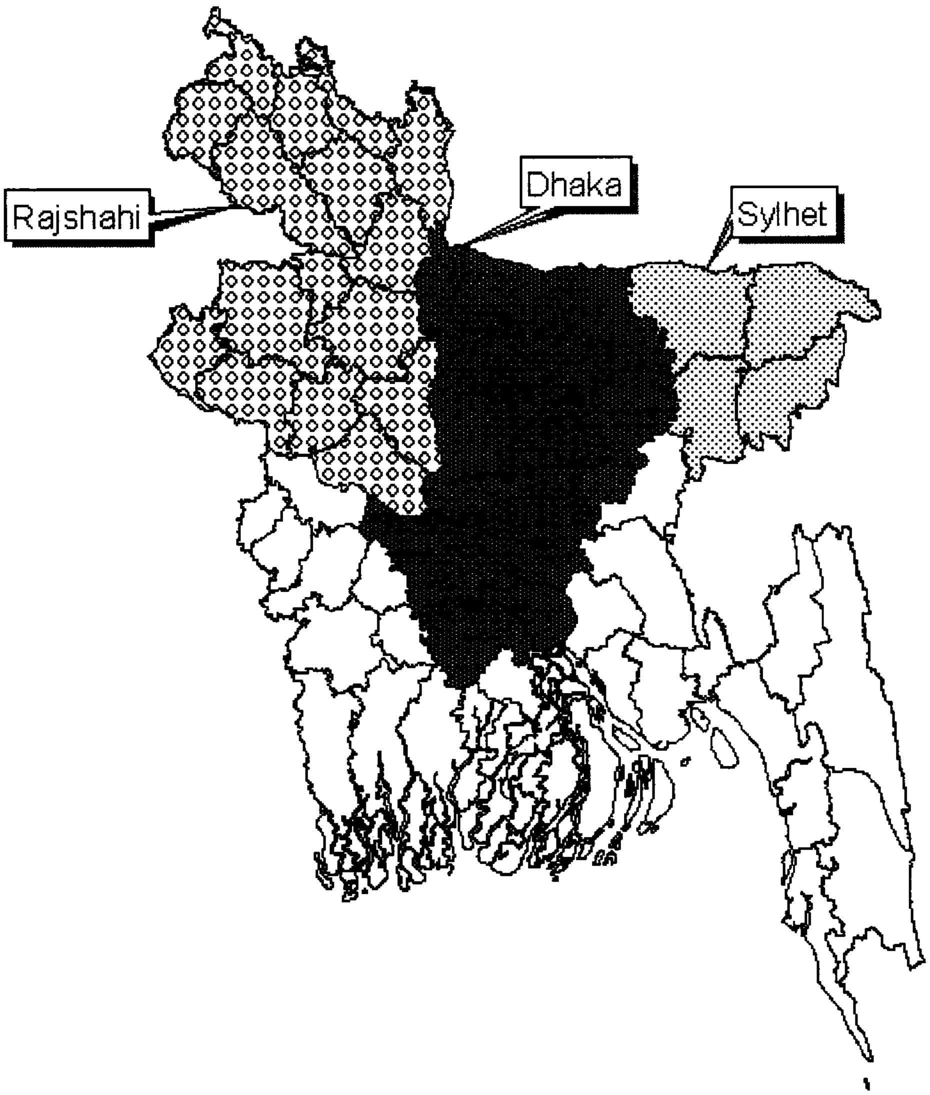


Figure 7.1 Geological Map of highland and forest cover divisions

7.2 Malaria

Malaria parasite (plasmodium) in Bangladesh as well as in highland forest covered divisions is transmitted by female Anopheles mosquitoes. Out of 15 species, Anopheles Dirus (AD) is the most spread in the Southeast Asia. Breeding habitats of AD are puddles on footpath and turbulence pits at the heads of drainage gullies, which are able to hold water for some times without supplemental rainfall. Among these divisions Sylhet division has highest number of malaria cases and Rajshahi division lowest number of malaria cases.

Mosquitoes in highland forest covered divisions transmit malaria year around. However during the November-March mosquito are less active and the number of malaria cases is small. This number increases considerably during warm and wet season. Malaria is transmitted by adult infected female which bites in order to get human blood for laying eggs. Malaria statistics for highland forest covered divisions is shown in **Table 7.1**.

7.3 Environment

Temperature, humidity, and rainfall are environmental factors for mosquito activity and malaria epidemiology. Variation in monthly rainfall between dry and wet years as seen in **Table 7.2**

Table7.1 Malaria statistics of highland forest covered divisions 1992-2001

Year	Sylhet	Dhaka	Rajshahi
1992	9.6	5.4	0.72
1993	12.76	7.6	0.57
1994	21.25	7.7	0.69
1995	20.67	6.9	0.7
1996	12.12	3	0.34
1997	7.4	2.03	0.2
1998	7.03	2.5	0.46
1999	5.85	2.4	0.56
2000	8	1.7	0.29
2001	8	1.7	0.39

Table 7.2 Total precipitations and mean temperature in highland and forest covered divisions, (a) Sylhet; (b) Dhaka;

Month	Precipitation (mm)		Temperature (°C)	
	Dry	Wet	Hot	Cool
January	0	4	17	11
February	0	23	15	13
March	0	72	20	17
April	1	75	24	20
May	5	92	24	22
June	4	169	25	24
July	6	180	26	25
August	5	127	25	26
September	3	110	23	26
October	4	67	24	21
November	0	26	21	18
December	0	11	15	12

(a)

Month	Precipitation (mm)		Temperature (°C)	
	Dry	Wet	Hot	Cool
January	0	7	13	11
February	0	17	16	14
March	0	22	21	17
April	6	55	25	20
May	35	120	25	23
June	70	176	27	25
July	60	177	27	26
August	58	154	27	26
September	53	129	27	25
October	20	115	26	22
November	0	60	21	19
December	0	15	15	13

(b)

Table 7.2 c. Total precipitations and mean temperature in Rajshahi division

Month	Precipitation (mm)		Temperature (°C)	
	Dry	Wet	Hot	Cool
January	0	20	19	16
February	0	19	22	19
March	0	24	26	23
April	1	56	30	27
May	57	176	31	28
June	115	330	30	29
July	91	331	29	29
August	86	340	30	29
September	116	391	30	28
October	13	177	29	27
November	0	44	25	24
December	0	16	22	19

7.4 Trend and statistical analysis

Figure 7.2 shows annual percent of malaria cases in highland and forest covered divisions during 1992-2001. The Government of Bangladesh makes effort to eradicate malaria; the number of cases in highland and forest covered divisions is decreasing. Variations in the number of cases around the trend are associated with change of weather from year to year. The long-term tendency in malaria cases dynamics was approximated like coastal divisions by linear equation (1) and weather-related variations around the trend were expressed as a ration (equation 2) of actual cases to the estimated from the trend.

Intercepts and slopes for these divisions are shown in **Table 7.3**.

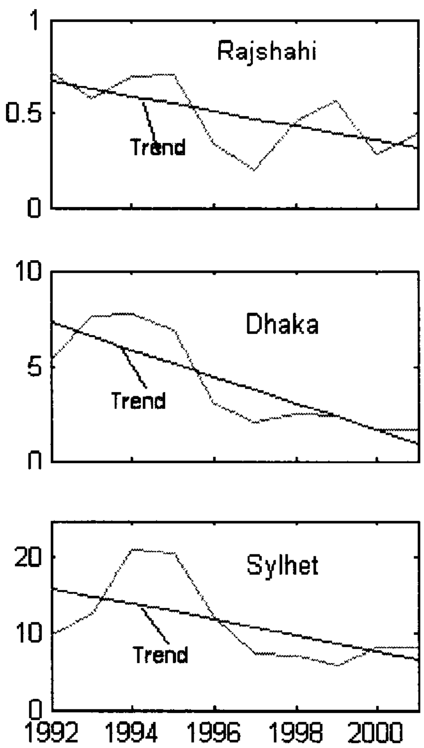


Figure 7.2 Annual malaria cases in highland and forest covered divisions and trend line, 1992-2001

Table 7.3 Intercepts and slopes for highland and forest covered divisions

Divisions	Intercept (a)	Slop (b)
Sylhet	16.95	-1.03
Dhaka	7.94	-0.7
Rajshahi	0.71	-0.04

The DY for Sylhet division can be explained comparing years 1992 and 1995. In 1992, DY was 60% or 40% below the trend, while in 1995 DY was 160% or 60% above the trend. These estimates indicate that the 1992 was unfavorable year for mosquito development, while 1995 was favorable.

The DY for Dhaka division can be explained comparing years 1995 and 1997. In 1997, DY was 54% or 46% below the trend, while in 1995 DY was 134% or 66% above the trend. These estimates indicate that the 1997 was unfavorable year for mosquito development, while 1995 was favorable.

The DY for Rajshahi division can be explained comparing years 1997 and 1999. In 1997, DY was 42% or 58% below the trend, while in 1999 DY was 142% or 42% above the trend. These estimates indicate that the 1997 was unfavorable year for mosquito development, while 1999 was favorable.

Malaria distributions of highland and forest covered divisions for the extreme years are shown in **Figure 7.3**.

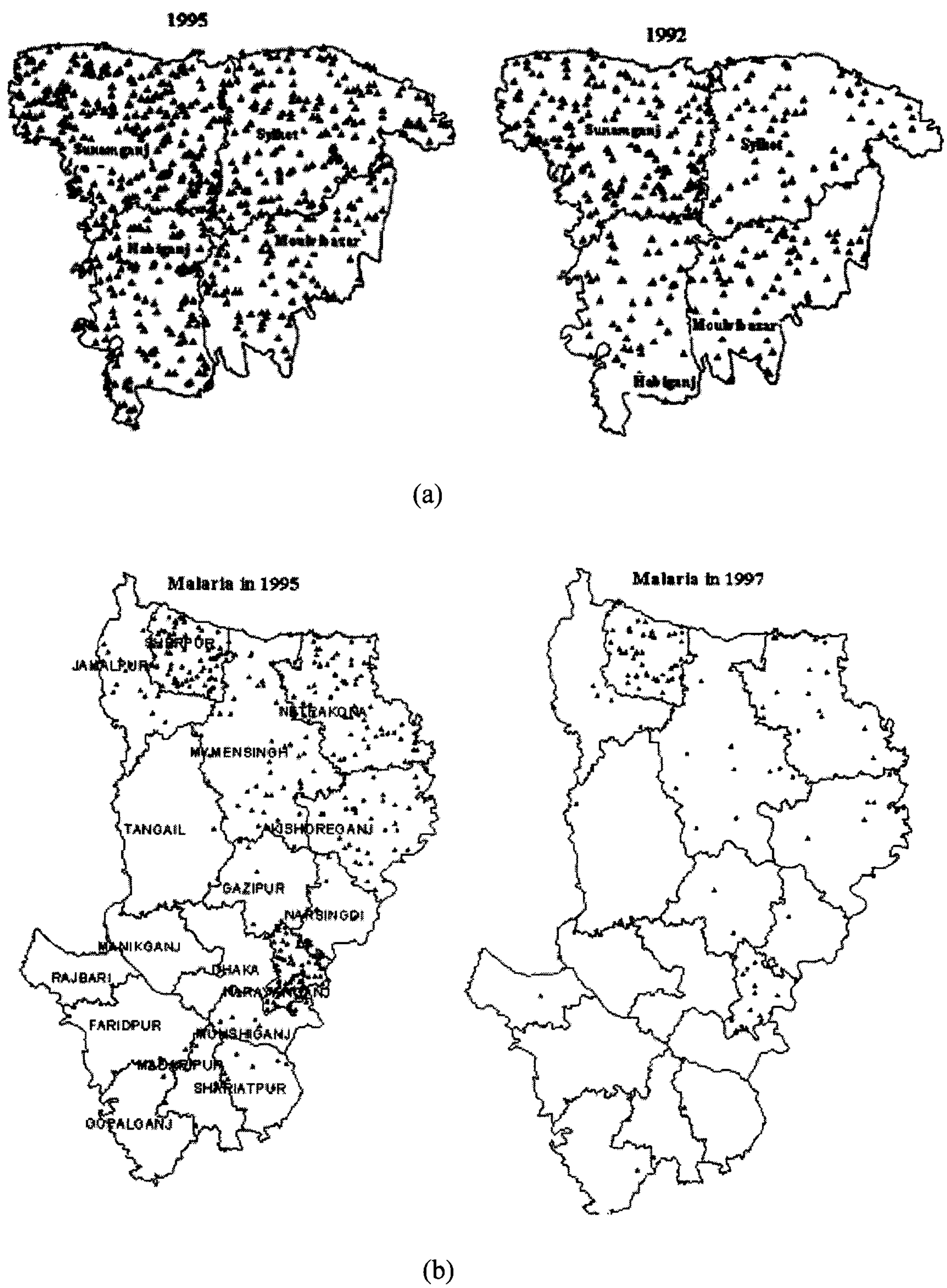


Figure 7.3 Malaria distributions for years with highest and lowest number of malaria cases, (a) Sylhet; (b) Dhaka

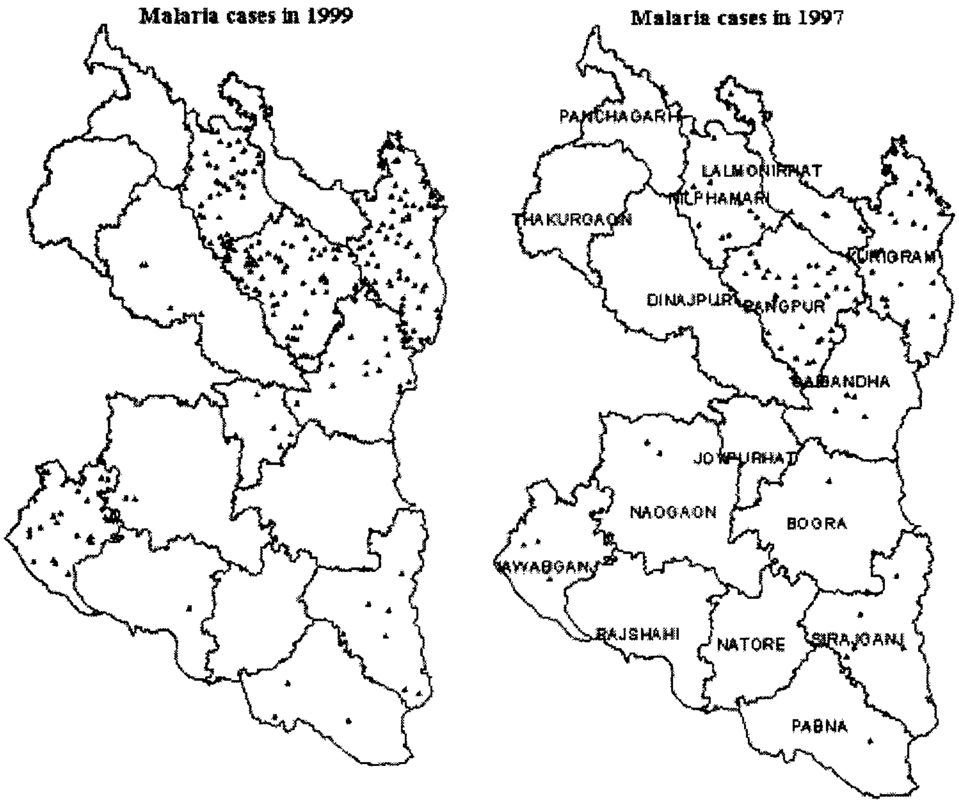


Figure 7.3 c. Malaria distributions for years with highest and lowest number of malaria cases for Rajshahi

7.5 Correlation Analysis for satellite data

7.5.1 TCI and VCI for two extreme years (highest and lowest number of malaria cases)

First, the differences, in VCI and TCI dynamics were investigated during the years with the extreme differences in the percent of DY (below and above trend).

Two years for Sylhet division were selected 1992 (DY=60% de-trended malaria cases or 40% less cases than in the average weather year) and 1995 (DY=160% or 60% more cases than in the average weather year). The assumption was that the environmental conditions of these years were quite different and they would be reflected in VCI and TCI values. The 1992 and 1995 VCI and TCI time series shown in **Figure 7.4.a** indicate that if TCI is higher (indicating cooler temperature) during fall (weeks 35-40), than larger number of malaria cases (DY above trend) occurs as it was in 1995. However, when TCI is lower (indicating thermal stress), the number of malaria cases is much smaller as it was in 1992. In spring and during early summer (weeks 16-30), TCI differences between two extreme years were smaller.

Two years for Dhaka division were selected 1997 (DY=54% de-trended malaria cases or 64% less cases than in the average weather year) and 1995 (DY=134% or 34% more cases than in the average weather year). The assumption was that the environmental conditions of these years were quite different and they would be reflected in TCI values. The 1995 and 1997 TCI time series shown in **Figure 7.4.b** indicate that if TCI is lower (indicating hotter temperature) during weeks 26-30), than larger number of malaria cases (DY above trend) and if TCI is higher (indicating cooler temperature) during fall (weeks 39-43), than larger number of malaria cases (DY above trend) occurs as it was in 1995.

Two years for Rajshahi division were selected 1997 (DY=42% de-trended malaria cases or 58% less cases than in the average weather year) and 1999 (DY=142% or 42% more cases than in the average weather year).

The assumption was that the environmental conditions of these years were quite different and they would be reflected in TCI values. The 1997 and 1999 TCI time series shown in **Figure 7.4.c** indicate that if TCI is above 40 (indicating cooler temperature) during weeks 35-45 of 1997, than larger number of malaria cases (DY above trend) occurs as it was in 1999.

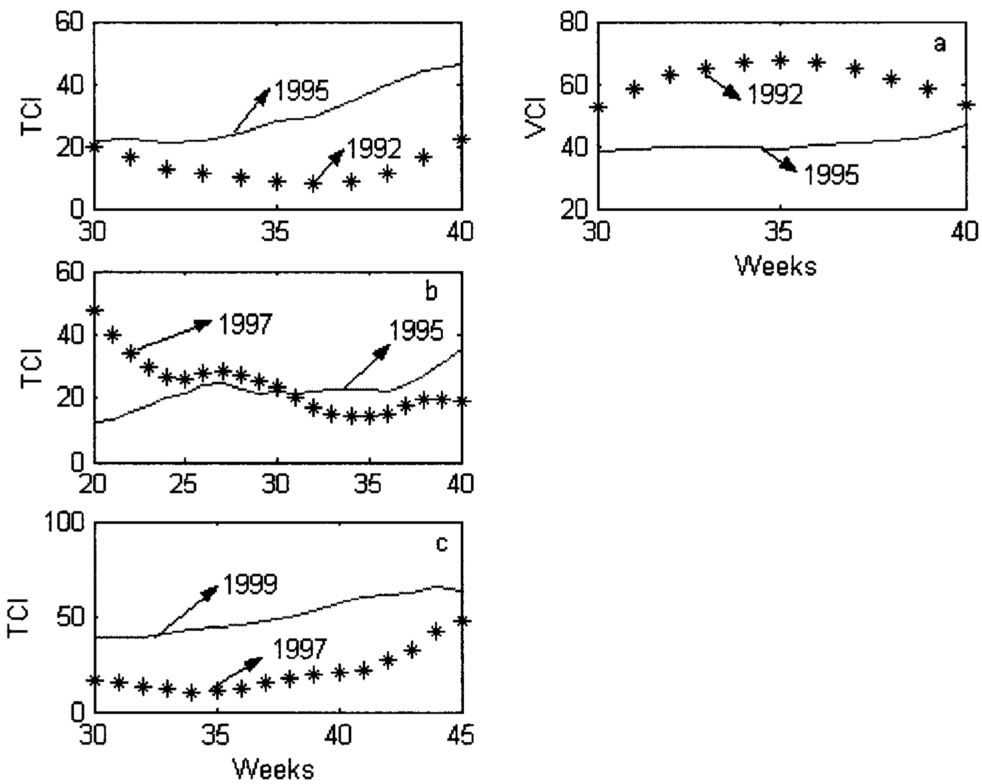


Figure 7.4 Temperature Condition Index (TCI) and Vegetation Condition Index (VCI) dynamics for years with highest and lowest number of malaria cases, (a) Sylhet; (b) Dhaka; (c) Rajshahi

7.5.2 Correlation between malaria cases and TCI and VCI

Correlation analysis of detrended malaria cases (DY) versus VCI and TCI are shown in **Figure 7.5**.

In Sylhet division during fall (week 35) when mosquito activity season starts, correlation increases reaching maximum (0.5 for TCI and 0.4 for VCI) at the end of September (week 38-39); by late fall, the correlation is gradually decreasing. After that their biting activity increases, leading to enhanced malaria transmission.

In Dhaka division during spring and summer when mosquitoes are less active; correlation is low for TCI. In week 26 when mosquito activity season starts, correlation negatively increases reaching maximum (-0.5 for TCI) at the beginning of July (week 26-30); by late July, the correlation is gradually decreasing. In week 39 correlations starts increase and reaches maximum (0.6 for TCI) at end of September; by late fall it gradually decreases.

For Rajshahi division **Figure 7.5** show that VCI does not have any correlation. It should be emphasized that during spring and summer when mosquitoes are less active; correlation is low for TCI. In week 26 when mosquito activity season starts, correlation increases reaching maximum (0.6 for TCI) at the middle of October (week 40-41); by late October, the correlation is gradually decreasing.

Although the correlation of DY with VCI during the same wet period is weaker than with TCI, the dynamics of correlation coefficient (CC) in **Figure 7.5** rightly emphasize seasonal cycle (increase of CC at the beginning of fall, maximum CC, during the critical period and decrease of CC during the end of the fall). Correlation analysis was also

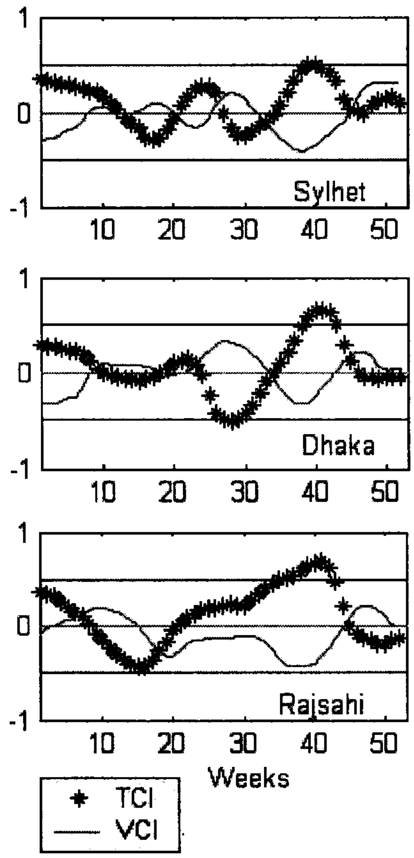


Figure 7.5 Correlations of DY versus Temperature Condition Index (TCI) and Vegetation Condition Index (VCI). (a) Sylhet; (b) Dhaka; (c) Rajshahi

performed for DY versus VHI. However CC was smaller than the correlation of DY with VCI and TCI because the correlation of DY with VCI has opposite sign to TCI. Vegetation map of these divisions for two extreme years are shown in **Figure 7.6**.

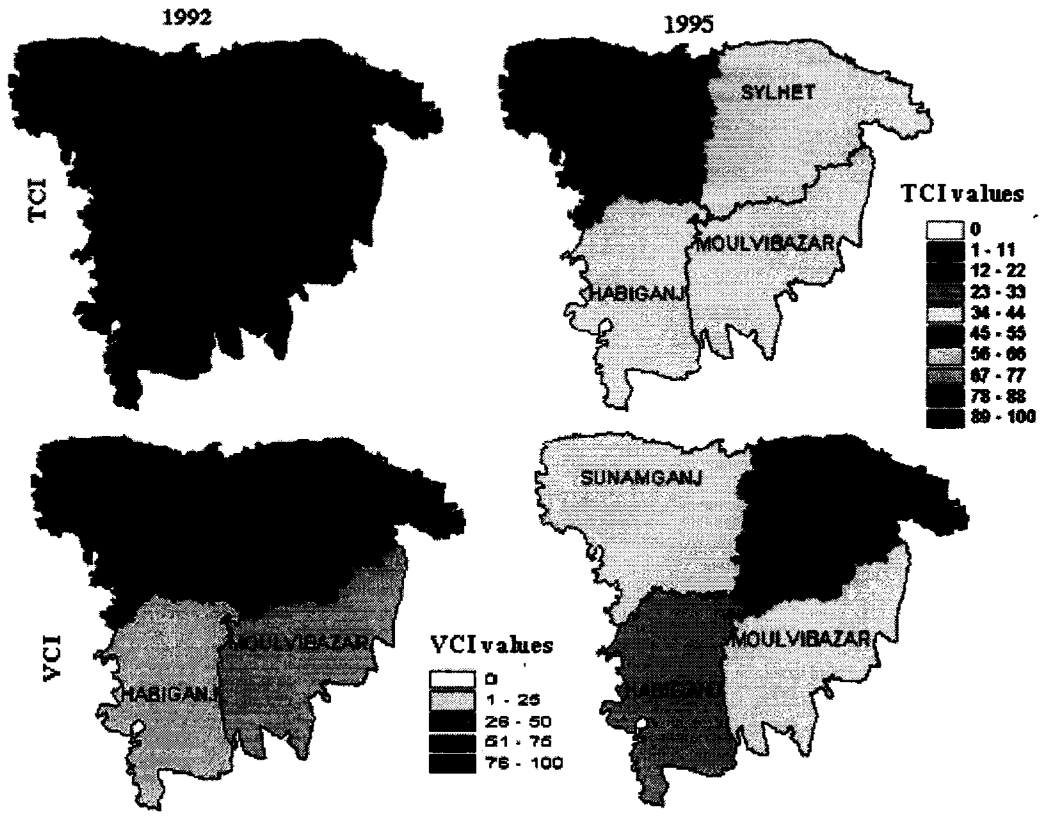


Figure 7.6 a. Vegetation maps of Temperature Condition Index (TCI) and Vegetation Condition Index (VCI) of Sylhet division for week 38, 1992 and 1995

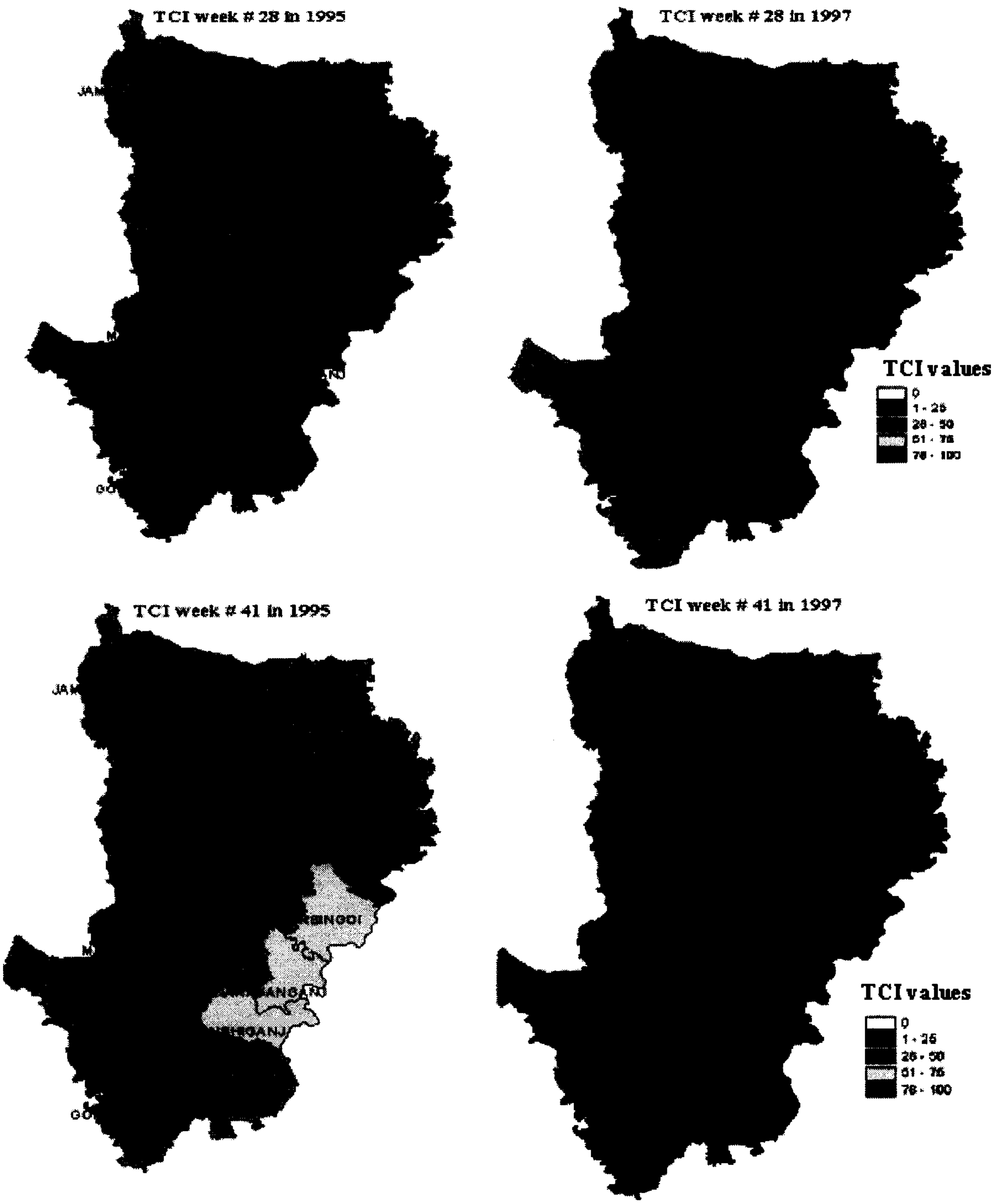


Figure 7.6 b. Vegetation maps of Temperature Condition Index (TCI) of Dhaka division for week 28 and week 41 of 1997 and 1995

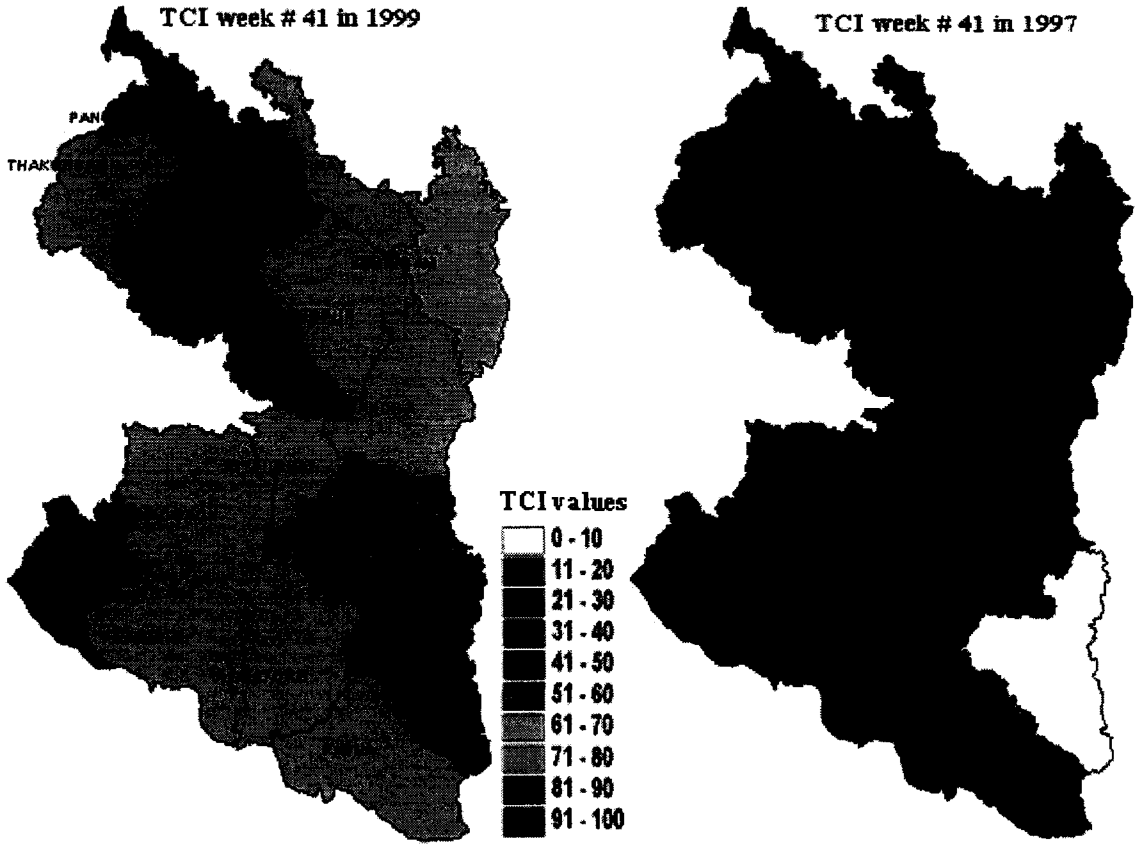


Figure 7.6 c. Vegetation maps Temperature Condition Index (TCI) of Rajshahi division for week 41 for 1997 and 1999

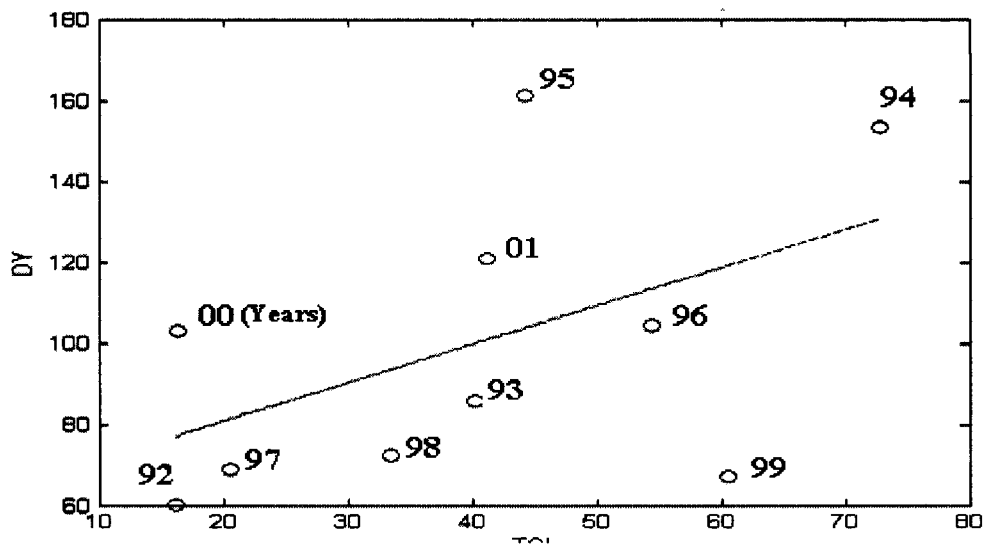
7.5.3 Scatter Plot for TCI and VCI

Correlation of DY with TCI of Sylhet division for week 39 is positive (**Figure7.7**) indicating that DY increases from below trend values (fewer malaria cases) for smaller TCI (hotter conditions) to above trend (larger number of malaria cases) for larger TCI (cooler conditions).

Correlation of DY with TCI of Dhaka division for week 28 is negative (**Figure7.7**) indicating that DY decreases from above trend values (larger malaria cases) for smaller TCI (hotter conditions) to below trend (fewer number of malaria cases) for larger TCI (cooler conditions) and correlation of DY with TCI for week 41 positive indicating that DY increases from below trend values (fewer malaria cases) for smaller TCI (hotter conditions) to above trend (larger number of malaria cases) for larger TCI (cooler conditions).

Correlation of DY with TCI of Rajshahi division for week 41 positive (**Figure7.7**) indicating that DY increases from below trend values (fewer malaria cases) for smaller TCI (hotter conditions) to above trend (larger number of malaria cases) for larger TCI (cooler conditions).

These results are in line with climate impact analysis literature indicating that hot weather depresses mosquito activity and malaria transmission.



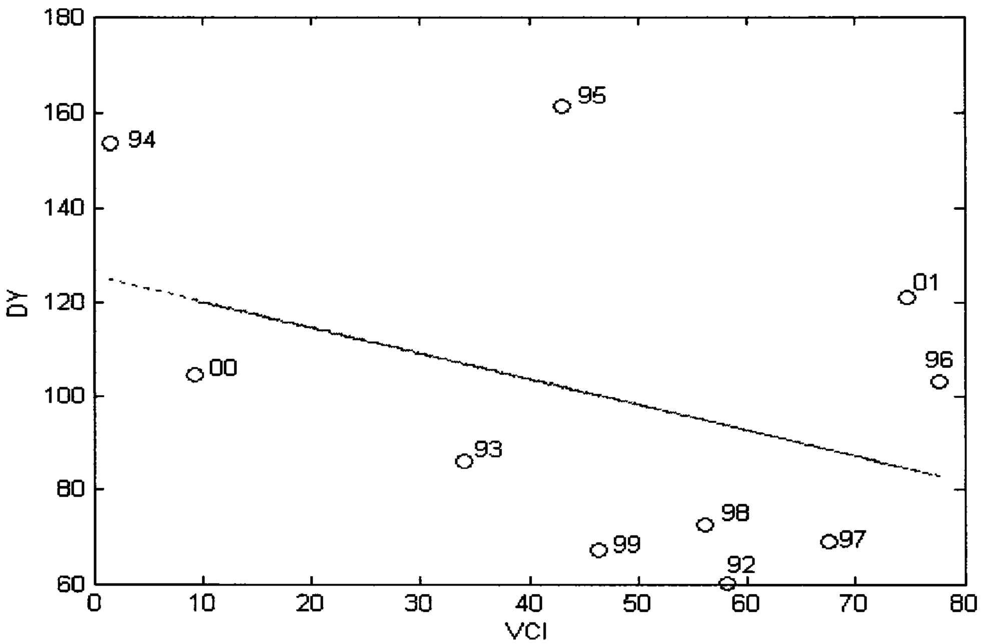


Figure 7.7 a. Scatter plot of DY (deviation of malaria cases) versus Temperature Condition Index (TCI) and Vegetation Condition Index (VCI) for week 39 for Sylhet

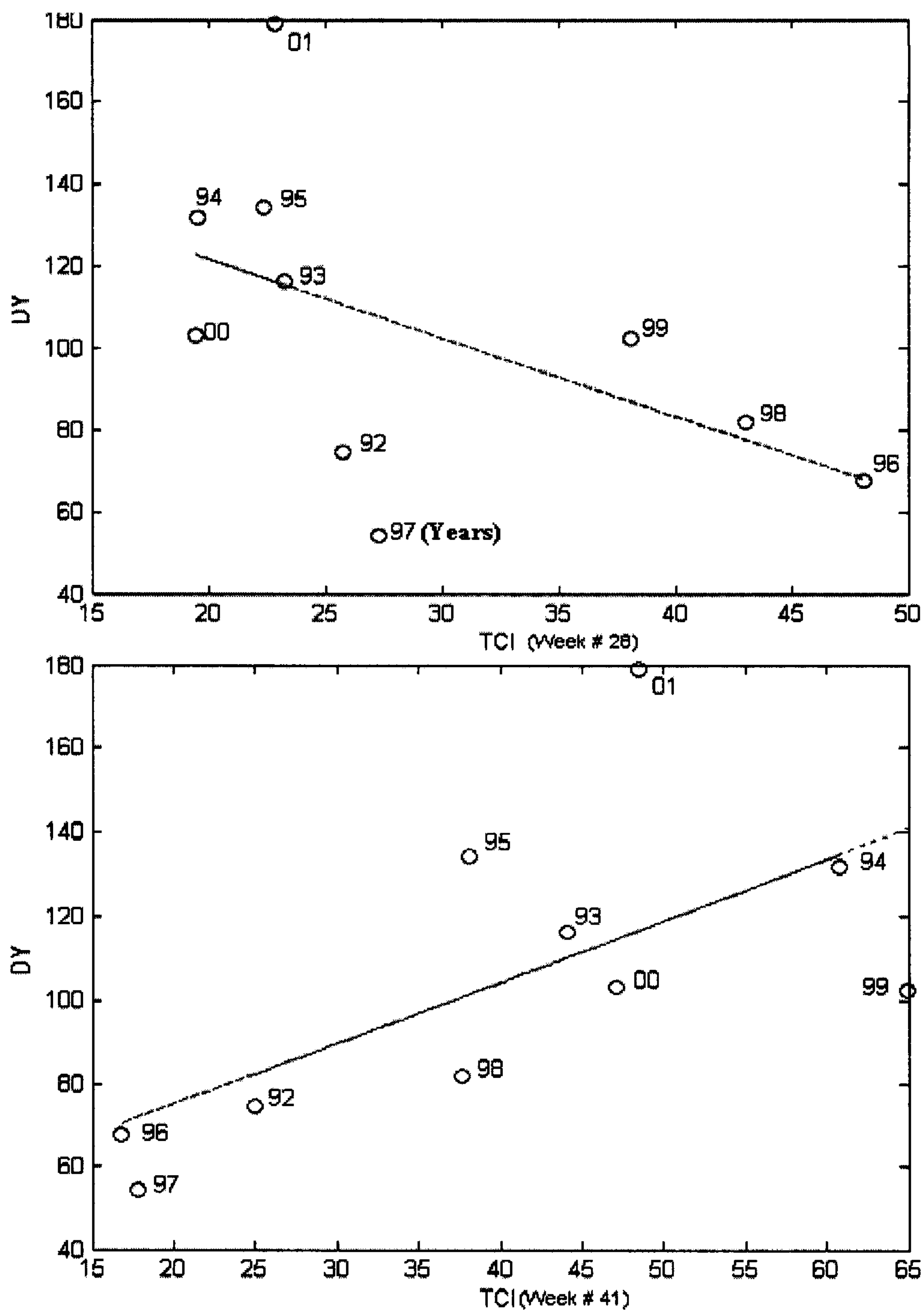


Figure 7.7 b. Scatter plot of DY (deviation of malaria cases) versus Temperature Condition Index (TCI) for week 28 and 41 for Dhaka

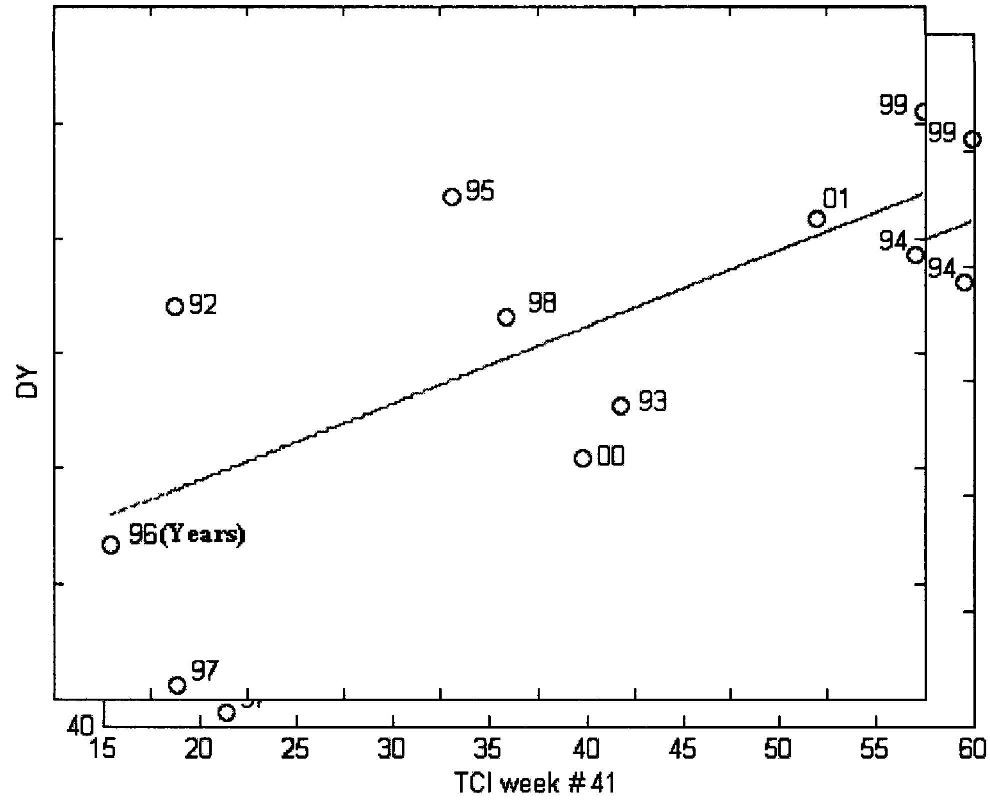


Figure 7.7 c. Scatter plot of DY (deviation of malaria cases) versus Temperature Condition Index (TCI) for week 41 for Rajshahi

7.6 Regression analysis for satellite data

The result of correlation analysis in **Figure 7.5** was used to develop regression equation. For Sylhet division two options were investigated: using TCI only and both TCI and VCI for the week of the highest correlation. The equations are shown below

$$DY=61.88+ 0.95\ TCI_{39} \quad (19)$$

$$MCC=0.50;\ E=33.02\% \quad (20)$$

$$DY=62 + 0.94\ TCI_{39} - 0.002\ VCI_{39} \quad (21)$$

$$MCC=0.50;\ E=35.30\% \quad (22)$$

Where MCC is multiple correlation coefficient and E is the error of estimation.

TCI_n is TCI value for week number n and VCI_n is VCI value for week number n.

The results of regression shows that MCC increases slightly when both TCI and VCI were used, however regression coefficients indicated larger contribution of TCI (0.94) versus VCI (0.002).

The regression equation for DY versus weighted TCI_{23-27} is written below:

$$DY = 90.63 + 0.23*TCI_{23-27} \quad (23)$$

$$R = 0.51;\ E = 6.9\%. \quad (24)$$

The equation for VCI and TCI parameters for week 39 was accepted as the best for estimation of DY.

For Dhaka division two options were investigated: using TCI only for the weeks of the highest correlation. The equations are shown below

$$DY1=160 - 1.92\ TCI_{28} \quad (25)$$

$$MCC=0.53;\ E=33.78\% \quad (26)$$

$$DY2=45.86 + 1.46\ TCI_{41} \quad (27)$$

$MCC=0.66; E=30.33\%$ (28)

Where MCC is multiple correlation coefficient and E is the error of estimation.

The equations for TCI parameters for weeks 28 and 41 were accepted as the best for estimation of DY.

For Rajshahi division two options were investigated: using TCI only for the week 41 of the highest correlation. The equations are shown below

$DY=47.59+ 1.34\ TCI_{41}$ (29)

$MCC=0.69; E=23.29\%$ (30)

Where MCC is multiple correlation coefficient and E is the error of estimation.

The equations for TCI parameters for week 41 were accepted as the best for estimation of DY.

7.7 Correlation Analysis for Meteorological data

7.7.1 Correlation between malaria cases and temperature

Correlation between DY (percent of malaria cases) and deviation from mean temperature DT is shown in **Figure 7.8.**

For Sylhet division 10 days time series period 20 (weeks 28-29, July), 25-26 (weeks 36-38, September) and period 32 (weeks 45-46, November) are positively correlated and correlation coefficient is more than 0.6. Mosquito observed throughout the year but the main season was during the rainy season between July and October with single peak. So we will consider period 20 (weeks 28-29, July), 25-26 (weeks 36-38, September).

Correlation for Dhaka and Rajshahi division is positively and negatively correlated and correlation coefficient is more than 0.5 and it is not stable correlation. So we can not predict malaria cases based on this correlation.

Figure 7.9 shows that temperature of Chittagong division for period 20 (weeks 28-29, July) and period 25-26 (weeks 36-38, September) 1995 higher than temperature in same period of 1992. We can conclude that temperature of period 20 (weeks 28-29, July) and 25-26 (weeks 36-38, September) has influence to malaria cases.

Temperature of Dhaka division for 1995 higher than temperature in same period of 1997.

Temperature of Rajshahi division for the 1999 higher than temperature in same period of 1997. We can conclude that temperature has influence to malaria cases. The number of malaria cases is larger for higher temperature.

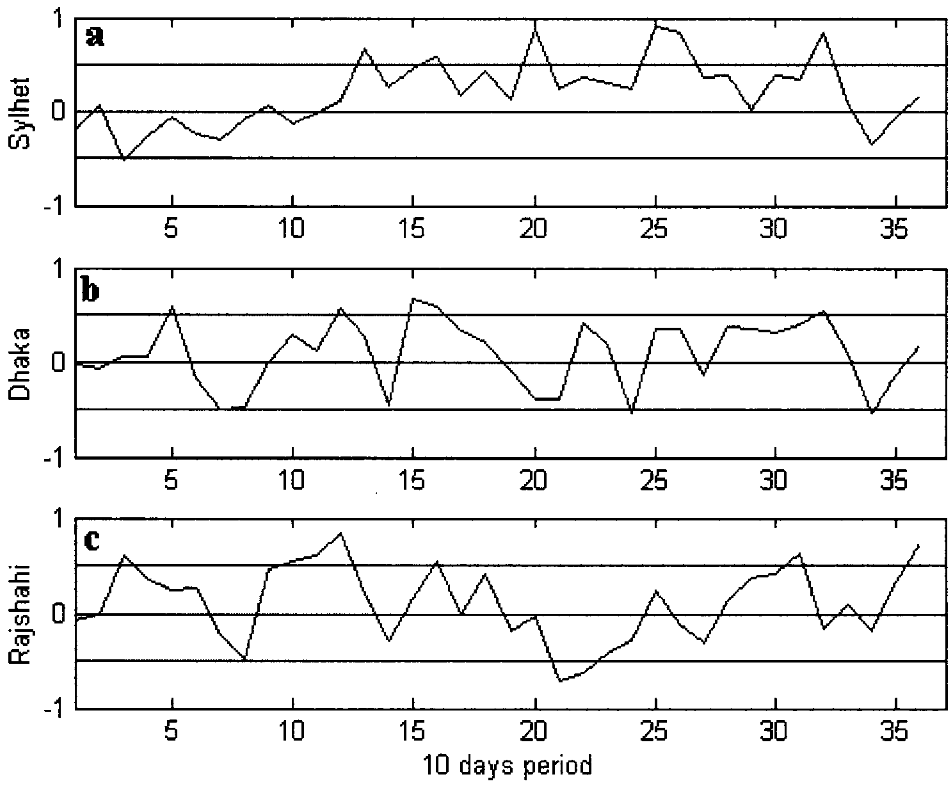


Figure 7.8 Correlations between DY (deviation of malaria cases) and DT (deviation from mean temperature), (a) Sylhet; (b) Dhaka; (c) Rajshahi

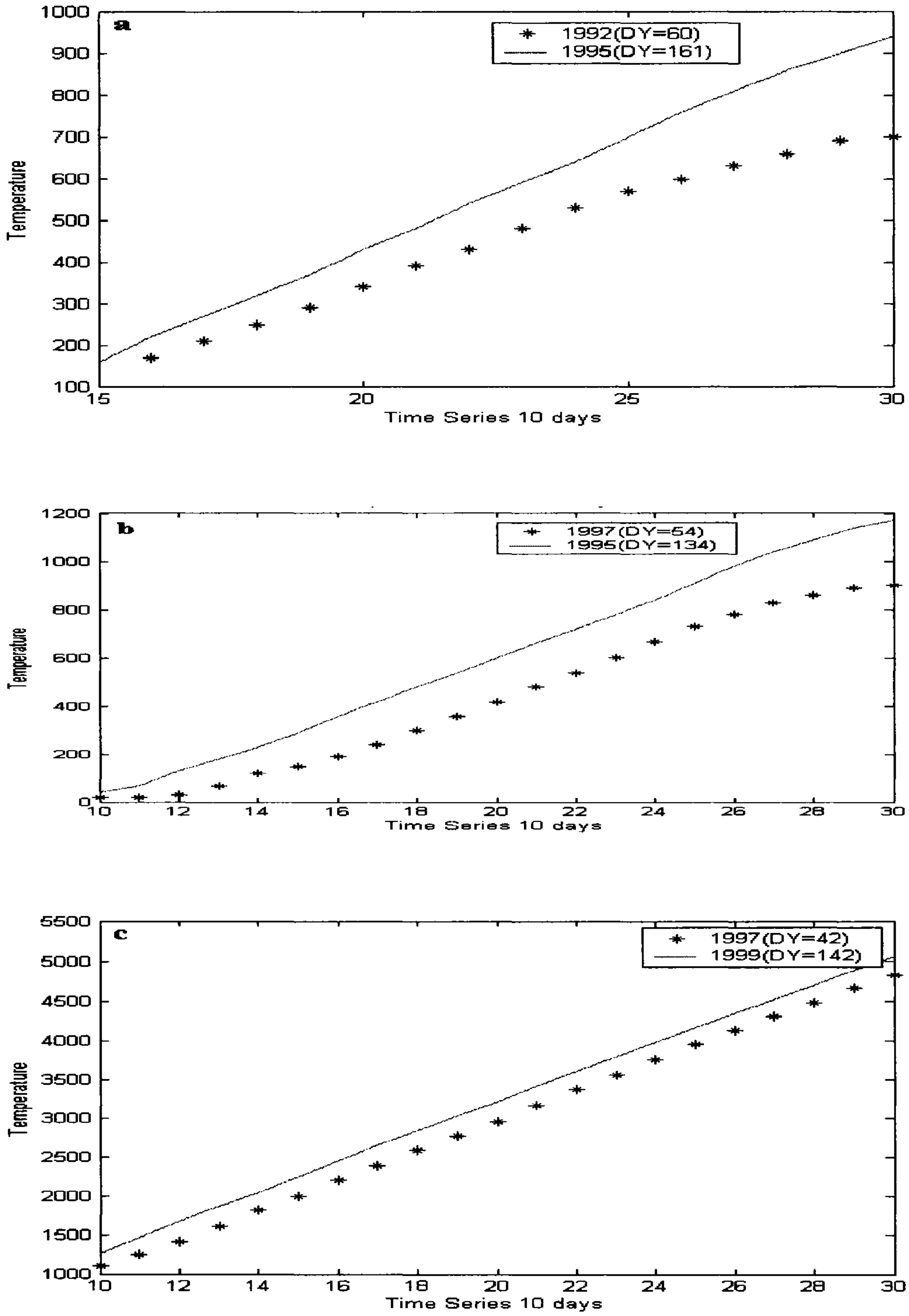


Figure 7.9 Temperature graphs for years with highest and lowest number of malaria cases, (a) Sylhet; (b) Dhaka; (c) Rajshahi

7.7.2 Correlation between malaria cases and rainfall

Correlation between DY (percent of malaria cases) and deviation from cumulative rainfall DR are shown in **Figure 7.10**.

For Sylhet division period 2, 10, 23, 29 and 32 are correlated and correlation coefficient is more than 0.6. Mosquito observed throughout the year but the main season was during the wet hot –April to October with single peak. So we will consider period 10 (week #15-16, April), period 23 (week #33-34, August) and period 29 (week #42-43, October).

Correlation for Dhaka division is several times positively correlated and correlation coefficient is more than 0.5 and it is not stable correlation. So we can not predict malaria cases based on this correlation.

Correlation for Rajshahi division is positively and negatively correlated and correlation coefficient is more than 0.6 and it is not stable correlation. So we can not predict malaria cases based on this correlation.

Rainfall graphs for two extreme years for coastal division are shown in **Figure 7.11**.

Rainfall of Sylhet division for period 10 (weeks 15-16, April), period 23 (weeks 33-34, August) and period 29 (weeks 42-43, October) of year 1995 are higher than in 1992. Larger number of malaria cases associated with larger rainfall.

Rainfall of Dhaka for two extreme years 1995 and 1997 are not stable. It is not possible to predict malaria cases from rainfall.

Cumulative rainfall of Rajshahi division for period 21-30 for two extreme years 1999 and 1997 are shown in **Figure 7.11**. It should be noted that rainfall in 1997 is higher than rainfall in the same period of 1999 and indicates that higher rainfall associates with fewer malaria cases.

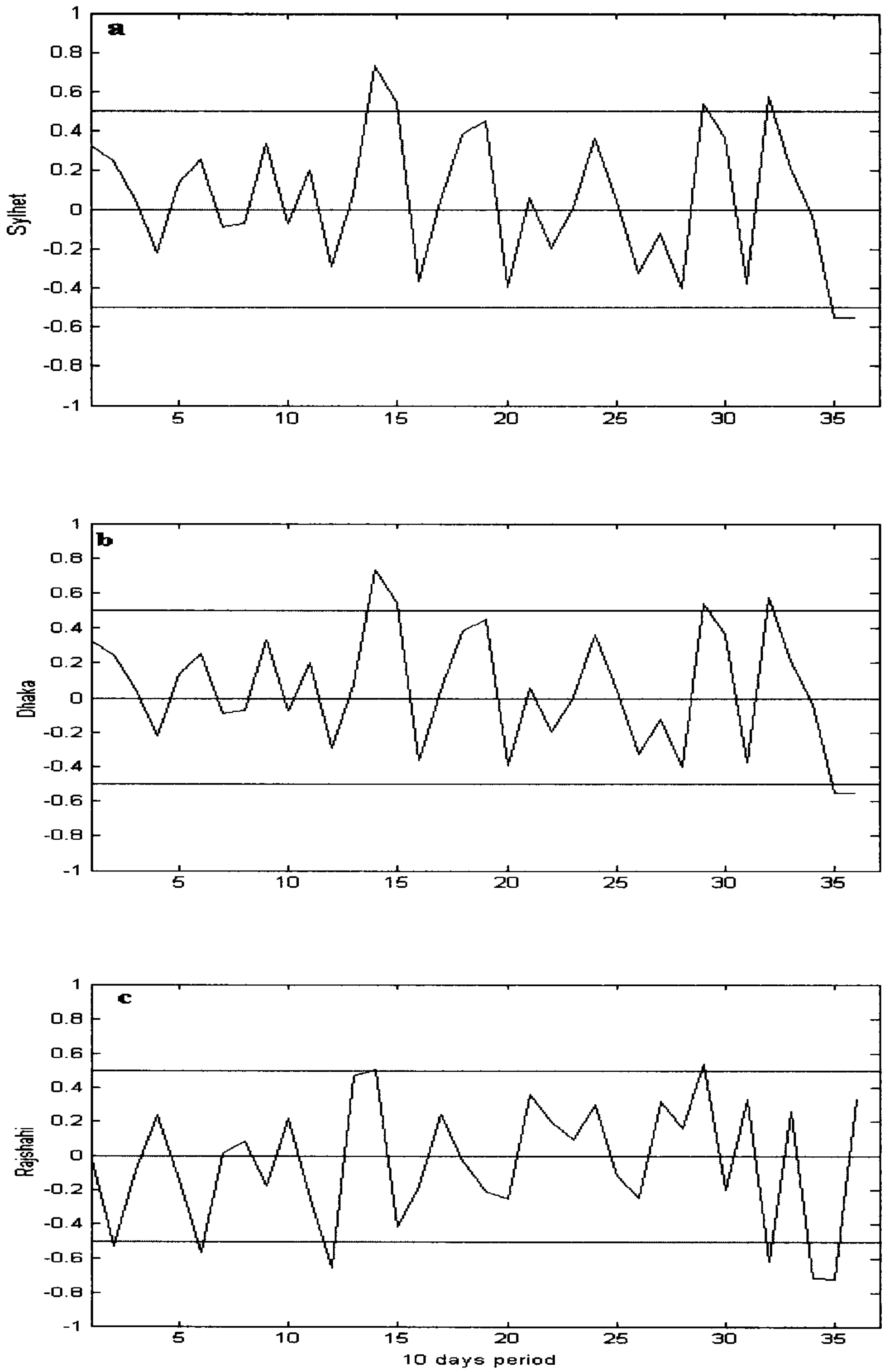


Figure 7.10 Correlations between DY (deviation of malaria cases) and DR (deviation from cumulative rainfall), (a) Sylhet; (b) Dhaka; (c) Rajshahi

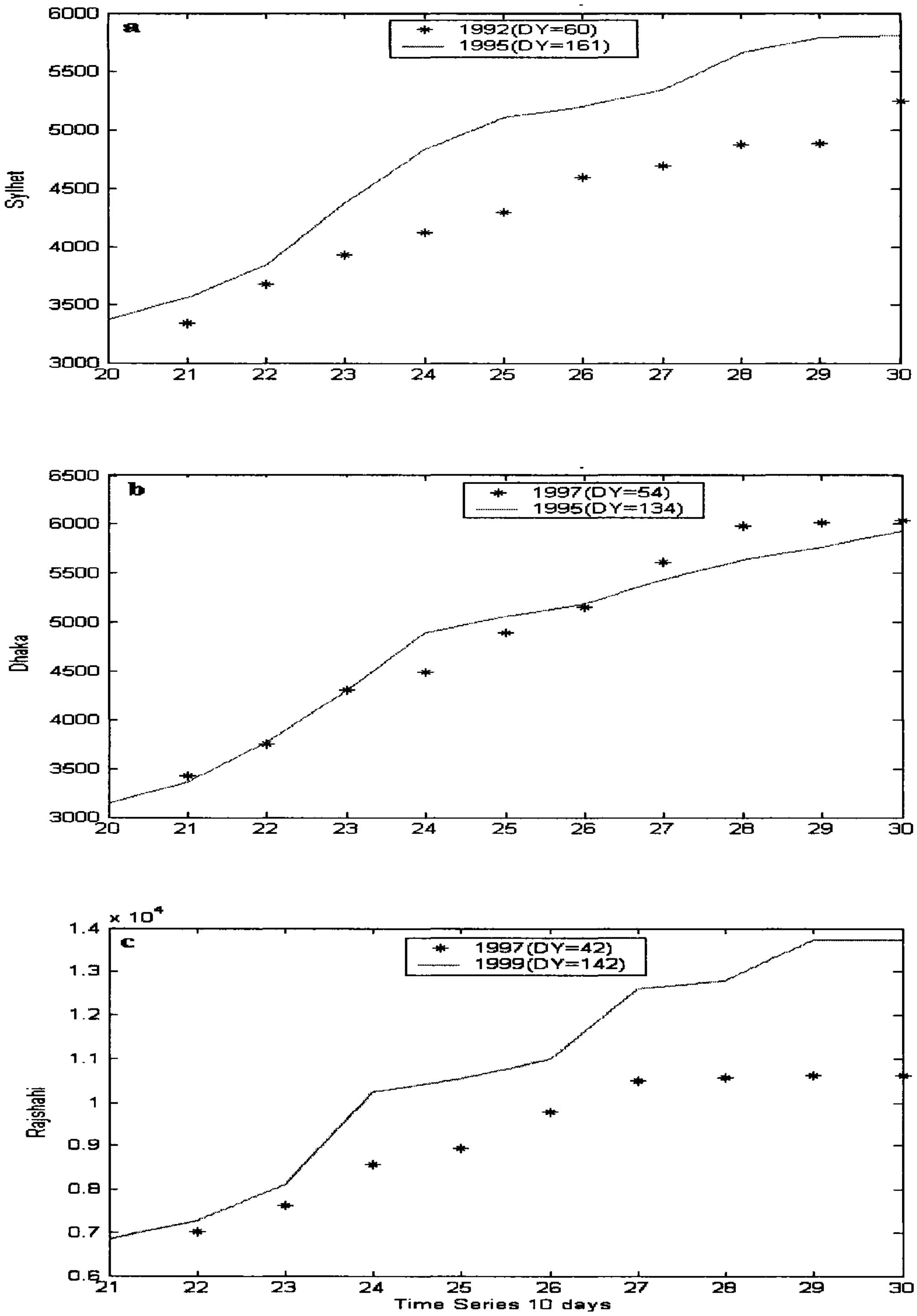


Figure 7.11 Rainfall graphs for years with highest and lowest number of malaria cases (a) Sylhet; (b) Dhaka; (c) Rajshahi

7.7.3 Correlation between malaria cases and relative humidity

Correlation between DY (percent of malaria cases) and deviation from mean relatively humidity DH is shown in **Figure 7.12.**

Correlation for Sylhet division is positively and negatively correlated and correlation coefficient is more than 0.6. It has very poor correlation. So humidity does not have impact on mosquito and vector development.

Correlation for Dhaka and Rajshahi divisions are not stable correlation. So we can not predict malaria cases based on this correlation.

Humidity graph for two extreme years 1992 and 1995 for Sylhet division, 1995 and 1997 for Dhaka division and 1999 and 1997 for Rajshahi division are shown in **Figure 7.13**.

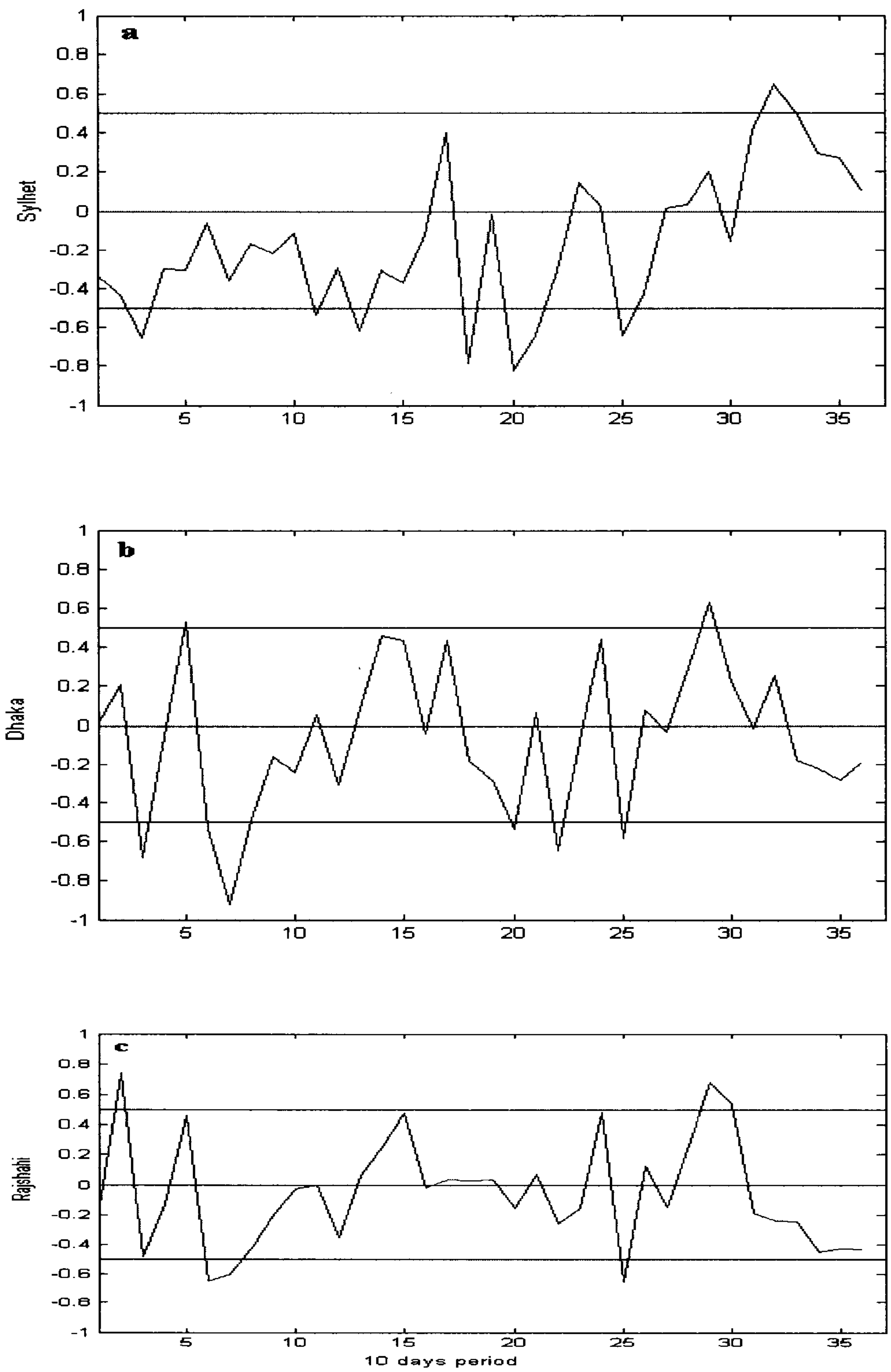


Figure 7.12 Correlations between DY (deviation of malaria cases) and DH (deviation from mean relatively humidity), (a) Sylhet; (b) Dhaka; (c) Rajshahi

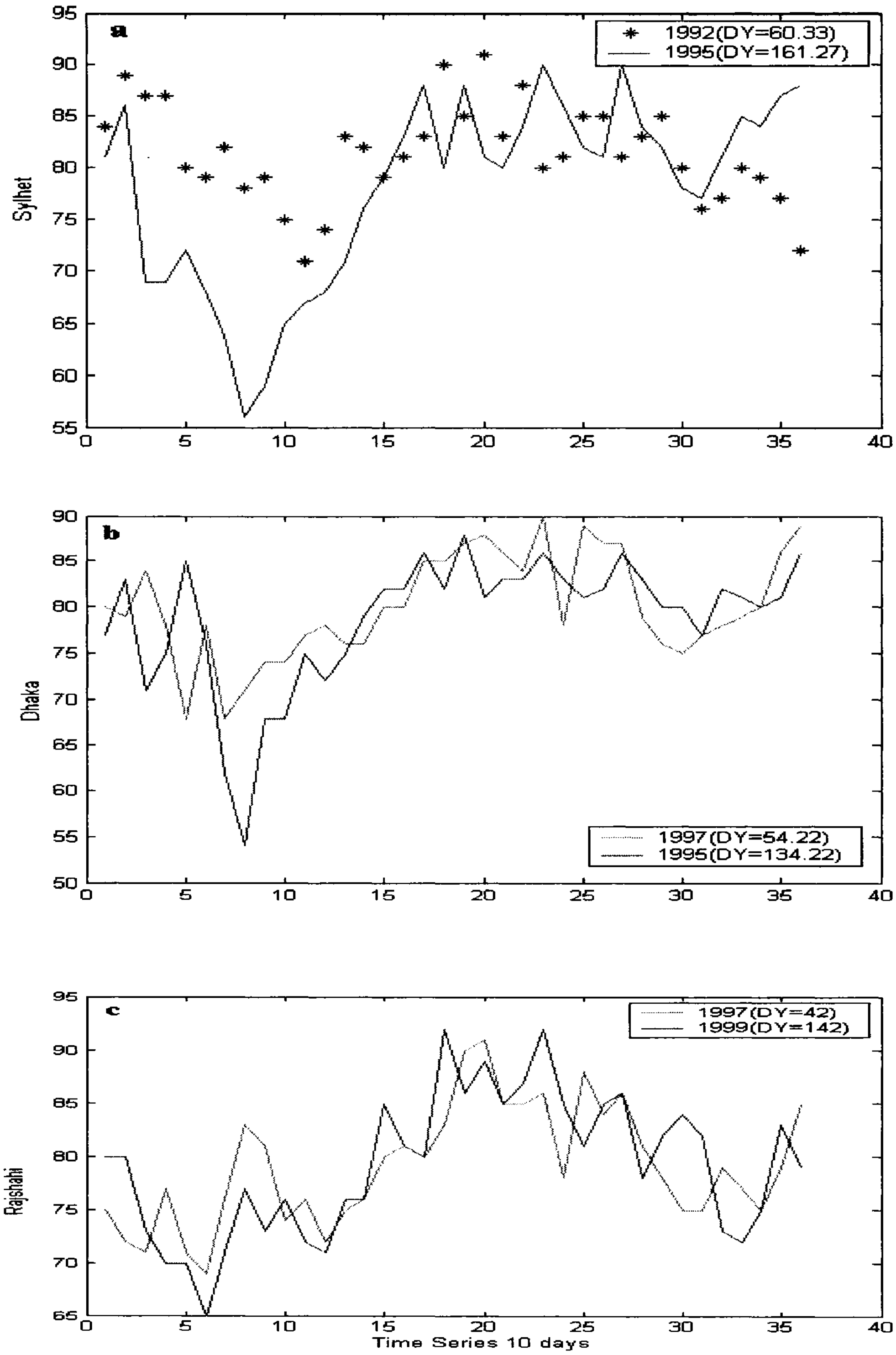


Figure 7.13 Humidity graphs for years with highest and lowest number of malaria cases (a) Sylhet; (b) Dhaka; (c) Rajshahi

7.7 Summary

The number of malaria cases in highland and forest covered divisions is decreasing and number of malaria cases is correlated with TCI and VCI. Correlation analysis was used to develop regression equations.

The result of this study showed that AVHRR-based vegetation health indices (VCI and TCI) can be used as a proxy for numerical estimation of number of malaria cases for highland and forest covered divisions of Bangladesh.

Higher temperature makes mosquitoes more active and malaria cases increase. The number of malaria cases is larger for higher temperature.

For Sylhet division larger number of malaria cases associated with larger rainfall while for Rajshahi higher rainfall associates with fewer malaria cases. It is not possible to estimate malaria cases from rainfall for Dhaka division.

Humidity for highland and forest covered divisions can not be used as estimator.

Chapter 8

Analysis for whole Bangladesh

8.1 Introduction

Bangladesh is located in the tropical region in Southeast Asia and lies between 20°34' and 26°38' north latitude, and 88°01' and 92°41' east longitude. From the east to the north and the west, Bangladesh has its borders with the Indian states of Mizuram, Tripura, Assam and West Bengal. The southern deltaic region faces the Bay of Bengal. It has a small inter-country border with Myanmar (**Figure 4.1**).

Bangladesh has 64 districts and 6 administrative Divisions: Barisal, Chittagong, Dhaka, Khulna, Rajshahi and Sylhet.

8.2 Malaria

Annual total clinical malaria cases for 1992-2001 were collected from Directorate General of Health (DG Health), Ministry of health Bangladesh and shown in **Table 8.1**. Distribution of malaria cases for year 1993 are shown in **Figure 8.1**. Data was collected at all local administrative unit (Thana) health center and aggregated to districts level and region wise. Only Dhaka, Chittagong and Sylhet division are the mostly malaria affected areas and others are significantly low. So we aggregated data of Dhaka, Chittagong and Sylhet division and considered for number of malaria cases for whole Bangladesh.

We calculated the coefficient of malaria cases for Dhaka, Chittagong and Sylhet division for period 1992-2001 by equation 31;

$$K = RM/WM \qquad (31)$$

Where,

K – Coefficient.

RM - Number of Malaria Cases for Region.

WM- Number of Malaria Cases for whole Bangladesh.

Coefficients are shown in **Table 8.2**.

Table 8.1 Malaria statistics of Bangladesh 1992-2001

Year	Malaria cases in Percent
1992	6.02
1993	7.6
1994	10.24
1995	10.45
1996	8.7
1997	7.17
1998	13.7
1999	16.5
2000	15.53
2001	15.39

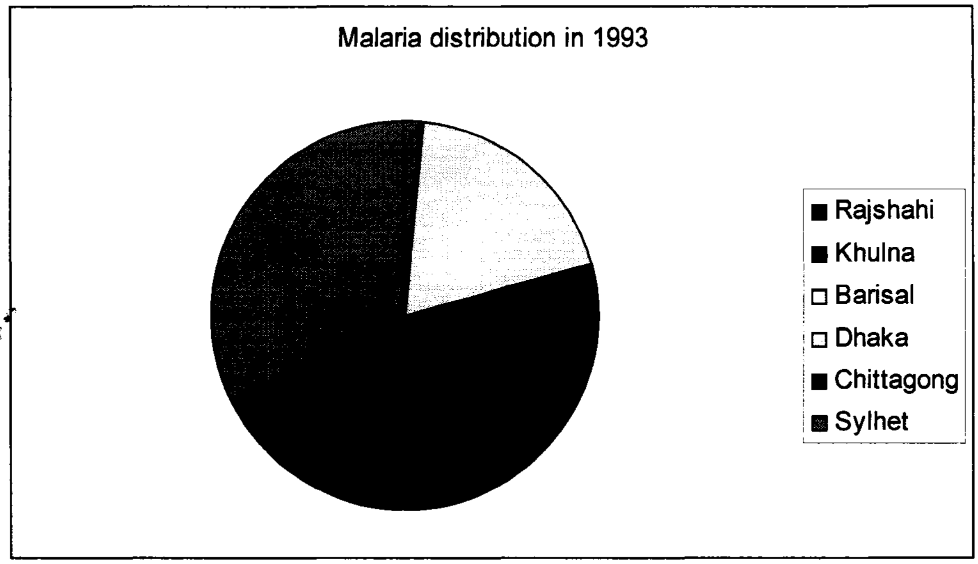


Figure 8.1 Distribution of malaria cases of Bangladesh for year 1993

Table 8.2 Coefficients for malaria cases for Dhaka, Chittagong and Sylhet division

Y\N	Dhaka division	Chittagong division	Sylhet division
1992	0.29	0.63	0.07
1993	0.33	0.58	0.09
1994	0.26	0.57	0.17
1995	0.22	0.60	0.18
1996	0.11	0.79	0.10
1997	0.08	0.86	0.06
1998	0.05	0.92	0.04
1999	0.03	0.90	0.06
2000	0.03	0.93	0.04

8.3 Environment

Three weather parameters are important for mosquito activity and malaria epidemiology: temperature, humidity, and rainfall. Temperature and humidity in Bangladesh are fairly stable from year-to-year. But annual rainfall fluctuates between 2000 and 3000 mm. In general, two seasons are defined in the annual cycle: wet and warm during April-October, and cool and dry during November-March. During the cooler season mosquitoes are less active and the number of malaria cases is small. This number increases considerably during the warm and wet season· Variation in monthly rainfall between dry and wet years as seen in **Table 8.3**

8.4 Trend and statistical analysis

Figure 8.2 shows annual percent of malaria cases of Bangladesh during 1992-2001. As seen, malaria is on a rise during the 1990s. Although the Government of Bangladesh makes an effort to eradicate malaria, the number of cases of Bangladesh is growing which is associated with poverty in this region. Variations in the number of cases around the trend are associated with weather changes from year to year.

For example, the smallest percent of malaria cases was 7% in 1997 compared to 10% in 1994. The long-term tendency in malaria cases dynamics shown in Figure 8.2 was approximated by linear equation (32) and weather-related variations around the trend were expressed as a ration (equation 33) of actual cases to the estimated from the trend.

$$Y_{trend} = 5.15 + 1.09 * \text{Year} \qquad (32)$$

$$DY = (Y / Y_{trend}) * 100 \qquad (33)$$

Where, Y_{trend} is percent of malaria cases for weather conditions near normal; Y is % of malaria cases; Year is year number; DY is deviation from trend expressed in percentage.

Table 8.3 Annual precipitation and mean temperature of Bangladesh

	Precipitation (mm)					Temperature (°C)			
	Jan	Apr	Jul	Oct	Annual	Jan	Apr	Jul	Oct
Rajshahi	7	37	222	76	1102	17	29	30	29
Khulna	7	33	157	77	822	19	30	29	28
Barisal	3	45	205	68	972	20	29	28	28
Dhaka	2	35	119	63	600	8	23	26	23
Chittagong	4	77	425	84	1895	14	24	26	24
Sylhet	10	37	111	37	530	8	22	25	23
Bangladesh	33	264	839	445	5921	16	26	27	26

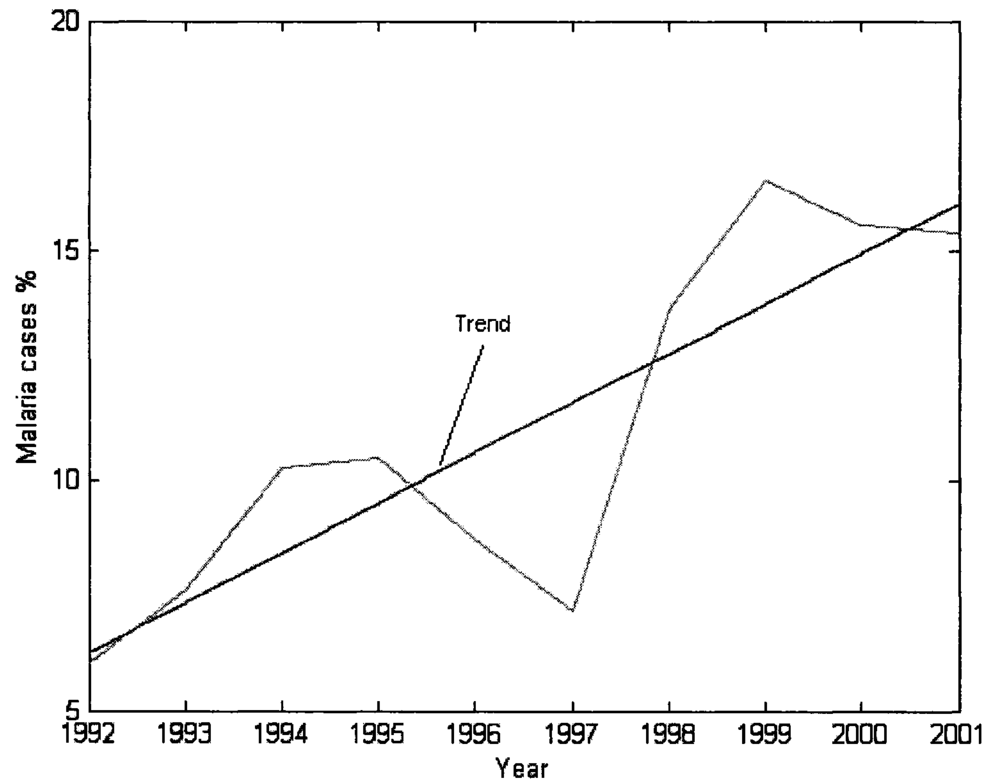


Figure 8.2 Annual malaria cases of Bangladesh and trend line, 1992-2001

The DY can be explained by comparing two years 1997 and 1994. In 1994, DY was 73% or 27% below the trend, while in 1997 DY was 116% or 16% above the trend. These estimates indicate that the 1997 was an unfavorable year for mosquito's development, while 1994 was favorable. Malaria distribution of Bangladesh for the years 1994 and 1997 are shown in **Figure 8.3**.

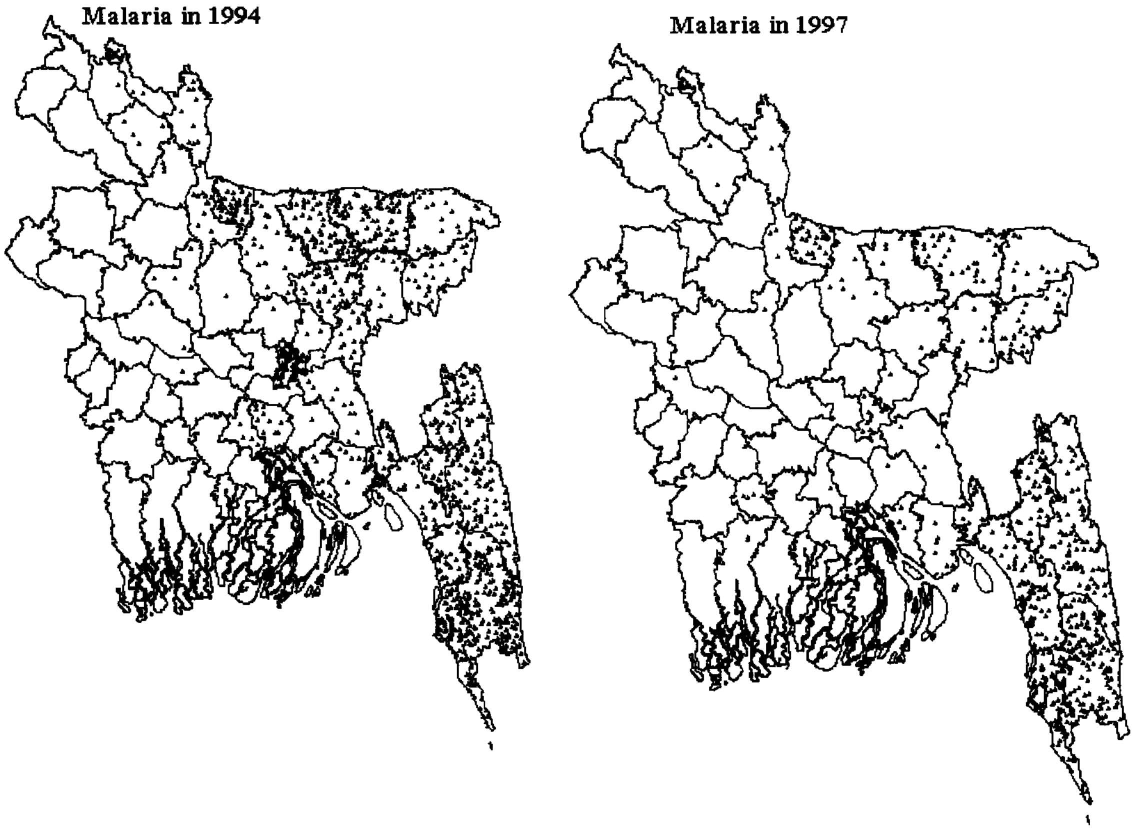


Figure 8.3 Malaria distribution of Bangladesh for the years 1994 and 1997

8.5 Correlations Analysis for satellite data

8.5.1 TCI, VCI, Smoothed Normalized Difference Vegetation Index (SMN) and Smoothed Brightness Temperature (SMT) for two extreme years (highest and lowest number of malaria cases)

First, the differences, in SMN and SMT dynamics were investigated during the years with the extreme differences in the percent of DY (below and above trend). Two years were selected 1997 (DY=73% de-trended malaria cases or 27% less cases than in the average weather year) and 1994 (DY=116% or 16% more cases than in the average weather year).The assumption was that the environmental conditions of these years were quite different and they would be reflected in SMN and SMT values. The 1994 and 1997 SMN and SMT map are shown in **Figure 8.4**. This preliminary analysis has already indicated that in the environment of Bangladesh, thermal conditions are more important factor for controlling malaria epidemics.

The assumption was that the environmental conditions of these years were quite different and they would be reflected in VCI and TCI values. The 1997 and 1994 VCI and TCI time series shown in **Figure 8.5** indicate that if TCI is above 60 (indicating cooler temperature) during weeks 30-45, than larger number of malaria cases (DY above trend) occurs as it was in 1994. Vegetation map of these two years are shown in **Figure 8.6**.

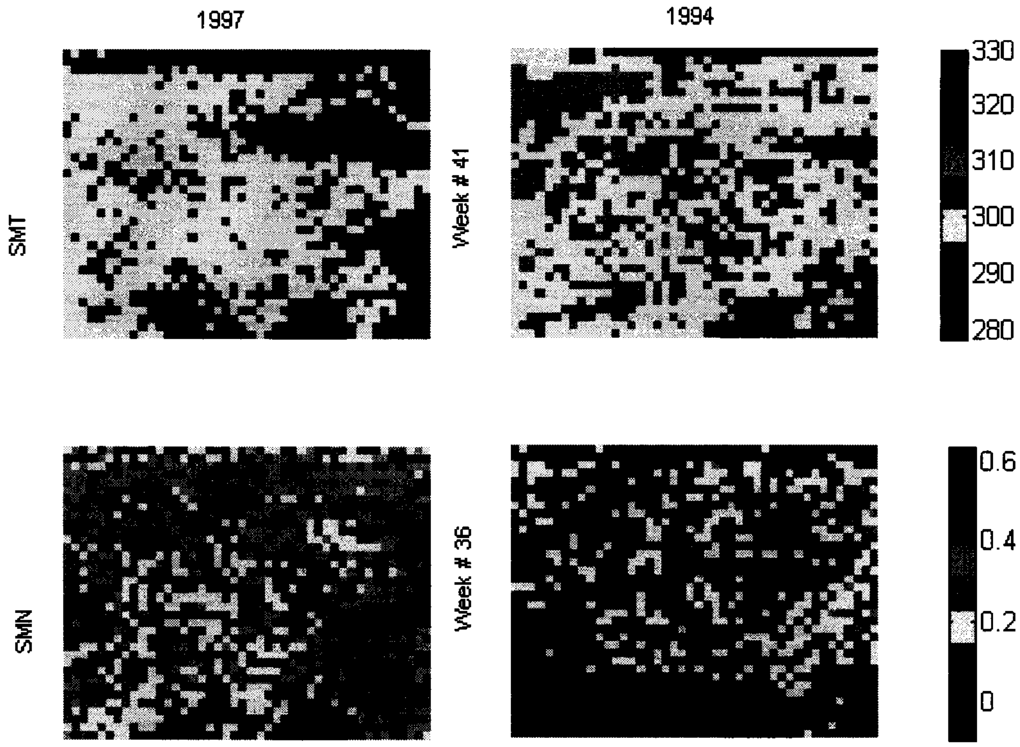


Figure 8.4 Smoothed Normalized Difference Vegetation Index (SMN) and Smoothed Brightness Temperature (SMT) vegetation map for years with highest and lowest number of malaria cases

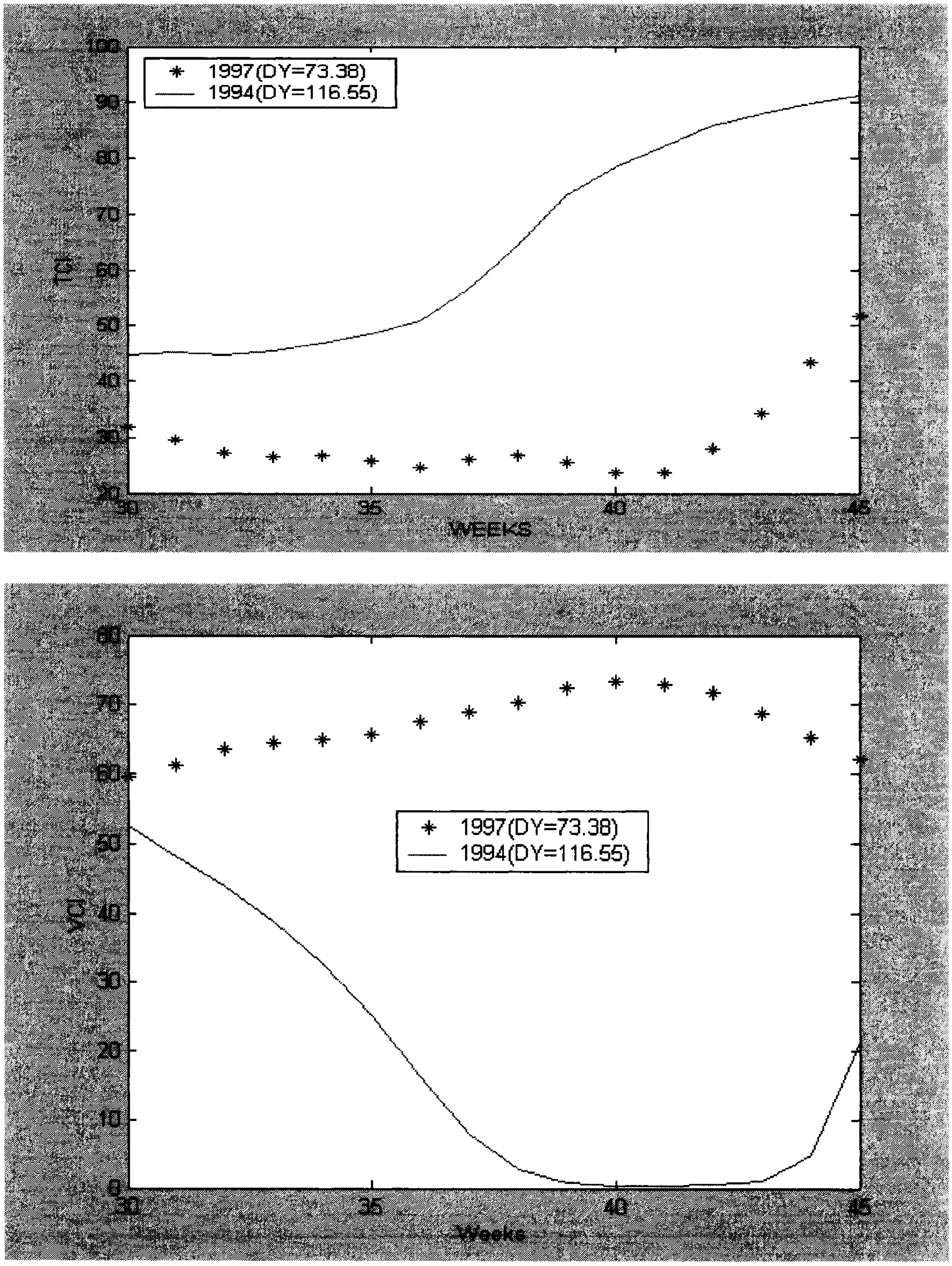


Figure 8.5 Temperature Condition Index (TCI) and Vegetation Condition Index (VCI) dynamics for years with highest and lowest number of malaria cases for Bangladesh

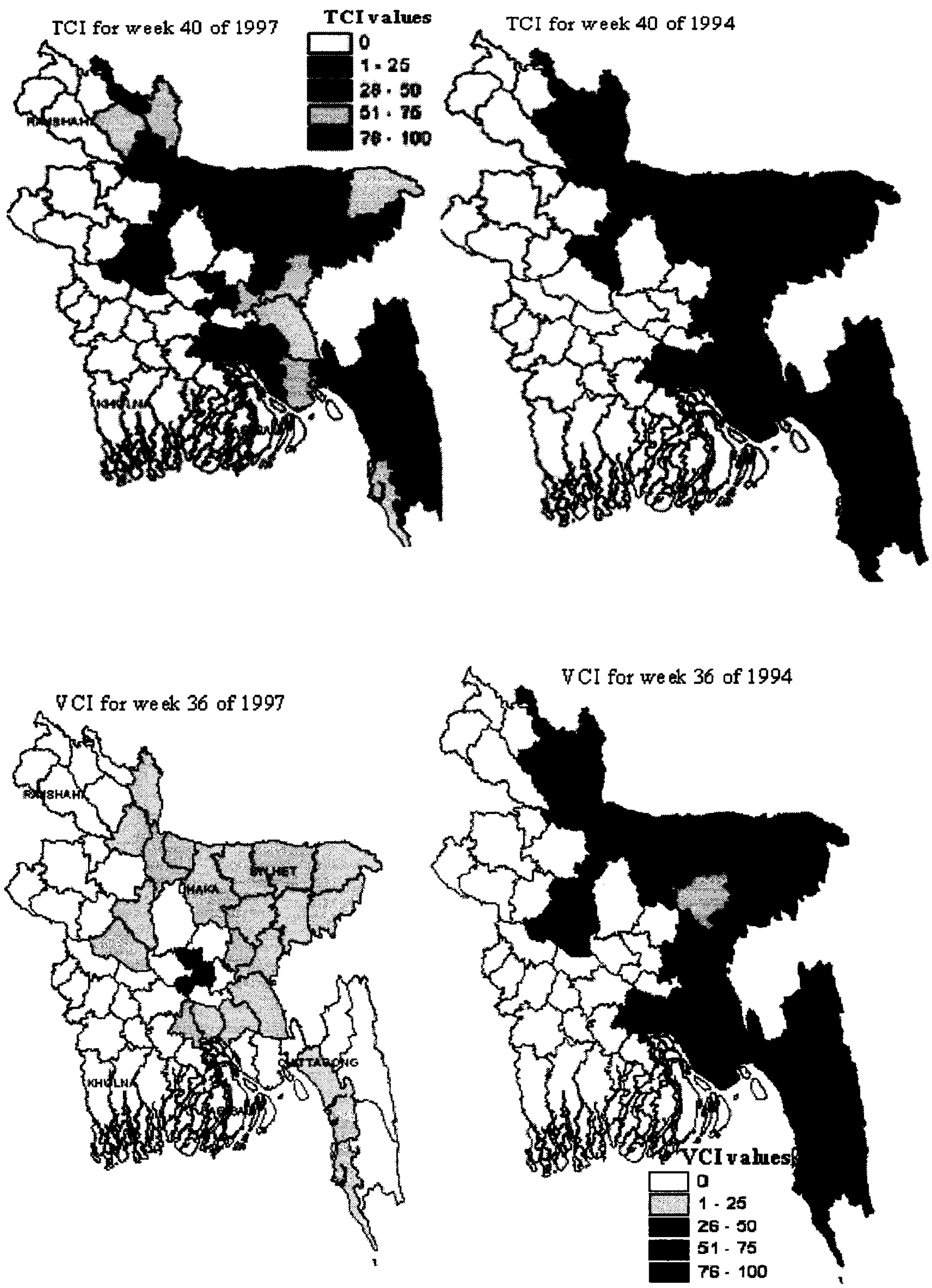


Figure 8.6 Vegetation map of Temperature Condition Index (TCI) for week 40 and Vegetation Condition Index (VCI) for week 36 for 1997 and 1994 for Bangladesh

8.5.2 Correlation between malaria cases and TCI and VCI

TCI and VCI for Bangladesh were collected from most populated and malaria affected areas of Dhaka, Chittagong and Sylhet division are shown in **Figure 8.7**.

Average TCI and VCI for Bangladesh were calculated for Dhaka, Chittagong and Sylhet division are shown in equation 44 and 45 respectively.

$$TCI_{BD} = K_D * TCI_D + K_C * TCI_C + K_S * TCI_S \quad (34)$$

$$VCI_{BD} = K_D * VCI_D + K_C * VCI_C + K_S * VCI_S \quad (35)$$

Where, TCI_{BD} is average TCI value for Bangladesh; VCI_{BD} is average VCI value for Bangladesh; $K_{D,}$ K_C and K_S are the coefficients of malaria cases (**Table 8.2**) for Dhaka, Chittagong and Sylhet respectively; $TCI_{D,}$ TCI_C and TCI_S are TCI for Dhaka, Chittagong and Sylhet respectively; $VCI_{D,}$ VCI_C and VCI_S are VCI for Dhaka, Chittagong and Sylhet respectively;

Investigation included correlation analysis of detrended malaria cases (DY) versus VCI and TCI (**Figure 8.8**). It should be emphasized that during cooler month (spring and fall) when mosquitoes are less active correlation is low for both indices.

In spring (week 16) when mosquito activity season starts, correlation for Chittagong division increases reaching maximum (0.6 for TCI and 0.5 for VCI) at the end of June (week 25-26). In week 35 correlation for Sylhet division starts increase reaching maximum (0.5 for TCI) at the middle of October (week 40) but for Dhaka divisions correlation starts decreasing week 20 reaching maximum (-0.53 for TCI) at the end of June (week 28) and correlation stats increase and reaching maximum (0.64 for TCI) at the middle of October (week 40). In spring (week 16) when mosquito activity season starts, correlation for entire Bangladesh increases reaching maximum (For TCI 0.7 and for VCI -0.60 and -0.66) around week 40 (middle of October) and week 17 (end of April) and 36 (middle of September) respectively; by fall, the correlation is gradually decreasing. These results are compatible with mosquito's activity. After laying eggs in April-May, new mosquitoes female reach adult stage in 7-15 days. After that their biting activity increases, leading to enhanced malaria transmission. It is important to emphasize that correlation of DY with VCI is negative indicating that DY decreases from above trend values (larger malaria cases) for smaller VCI (hotter conditions) to below trend (fewer number of malaria cases) for larger VCI (cooler conditions). These results are in line with climate impact analysis literature indicating that hot weather depresses mosquito activity and malaria transmission.

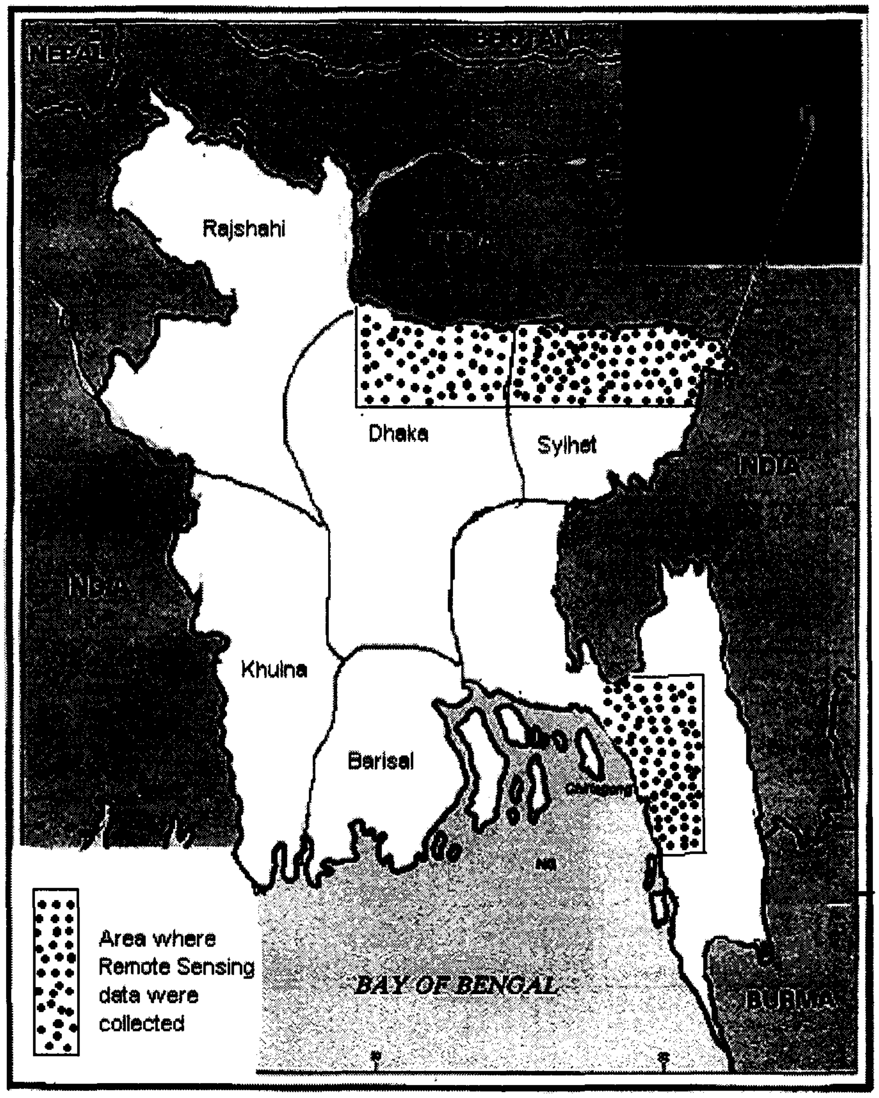


Figure 8.7 Bangladesh and area of satellite data collection

Although the correlation of DY with VCI during the same wet period is weaker than with TCI, the dynamics of correlation coefficient (CC) in **Figure 8.8** rightly emphasize seasonal cycle (increase of CC at the beginning of the warm season, maximum CC, during the critical period and decrease of CC during the end of the warm season). The correlation of DY with VCI has opposite sign to TCI.

We should note that interpretation of favorable conditions based SMN or VCI indices are different than the ones based on SMT and TCI indices. The VCI approaches to 0 (vegetation stress), when vegetation becomes less green (SMN decreases). In opposite situation, VCI approaches to 100 (favorable conditions) when vegetation becomes greener (SMN increases). The TCI decreases approaching to 0, when weather becomes hotter (SMT increases); In contrast, TCI increases approaching to 100, when weather becomes cooler (SMT decreases). Since both malaria cases and vegetation health indices were expressed as anomalies (from trend for malaria and from MAX-MIN for indices) they were compared directly with each other.

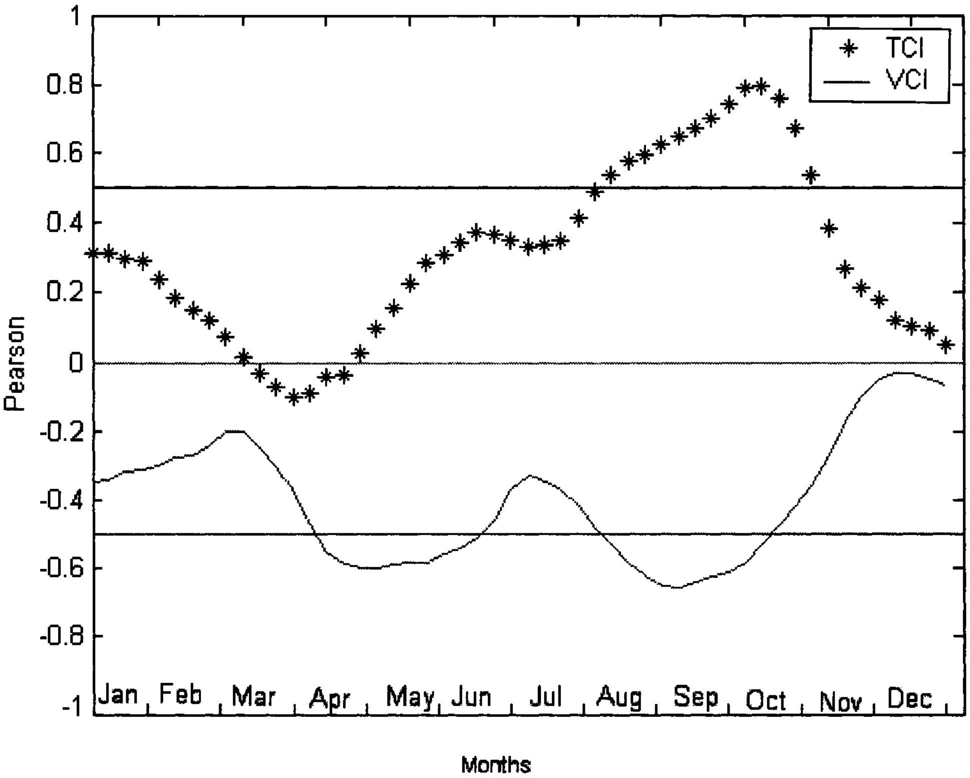


Figure 8.8 Correlation coefficient dynamics of versus Temperature Condition Index (TCI) and Vegetation Condition Index (VCI)

8.5.2 Scatter Plot for TCI and VCI

TCI of week 40 and VCI of week number 36 are shown in **Table 8.4.** It is important to emphasize that correlation of DY with TCI is positive (**Figure 8.9**) indicating that DY increases from below trend values (fewer malaria cases) for smaller TCI (hotter conditions) to above trend (larger number of malaria cases) for larger TCI (cooler conditions). These results are in line with climate impact analysis literature indicating that hot weather depresses mosquito activity and malaria transmission.

Table 8.4 DY (deviation of malaria cases) and Temperature Condition Index (TCI) for week 40 and Vegetation Condition Index (VCI) values for week 36

Year	DY	TCI_{40}	VCI_{36}
1992	96	29	63
1993	104	48	39
1994	82	78	16
1995	110	49	46
1996	82	13	71
1997	61	24	67
1998	107	34	51
1999	119	72	40
2000	104	67	13
2001	96	52	78

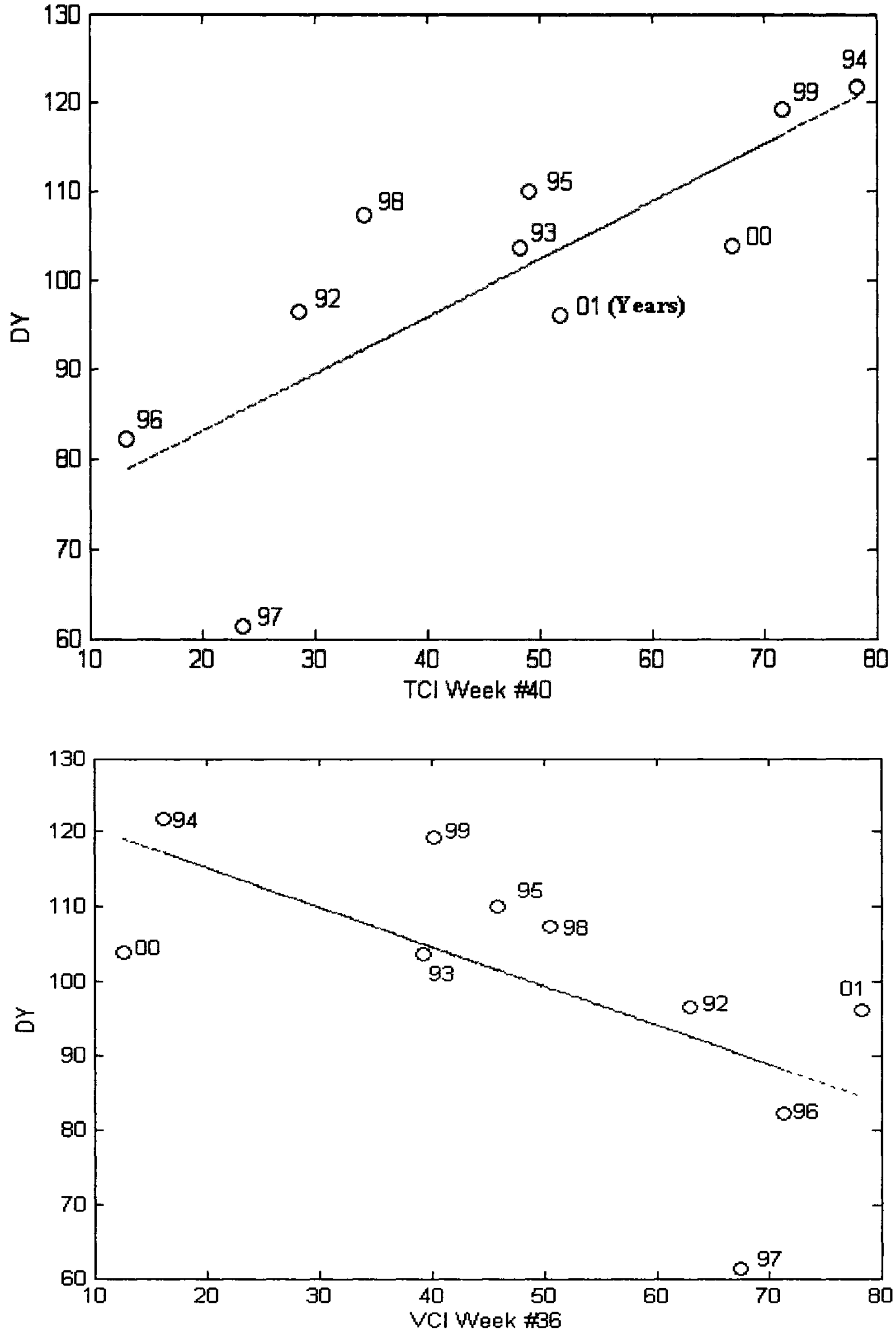


Figure 8.9 Scatter plot of DY (deviation of malaria cases) versus Temperature Condition Index (TCI) for week 40 and Vegetation Condition Index (VCI) for week 36 for Bangladesh

8.6 Regression Analysis for satellite data

The result of correlation analysis in **Figure 8.8** was used to develop a regression equation. Two options were investigated: using TCI only and both TCI and VCI for the week of the highest correlation. The equations are shown below

$DY=79.53+ 0.42\ TCI_{40}$ (36)

$MCC=0.72;\ E=9.5\%$ (37)

$DY=115.55 - 0.29\ VCI_{36}$ (38)

$MCC=0.44;\ E=8.31\%$ (39)

$DY= 90.51+ 0.32\ TCI_{40}- 0.13\ VCI_{36}$ (40)

$MCC=0.74;\ E=9.92\%$ (41)

TCI_n is TCI value for week number n and VCI_n is VCI value for week number n.

The results of regression show that MCC increases slightly when both TCI and VCI are used, however regression coefficients indicate larger contribution of TCI (0.30) versus VCI (0.13).

VCI for week 36 and TCI for week 40 parameters were accepted as the best estimation of DY.

8.7 Correlation Analysis for Meteorological data

8.7.1 Correlation between malaria cases and temperature

Correlation between DY (percent of Malaria Data) and deviation from mean temperature DT is shown in **Figure 8.10**. Correlation in time series (10 days) is positively and negatively correlated and correlation coefficient is more than 0.6 and it is not stable correlation. So we can not predict malaria cases based on this correlation.

Figure 8.11 shows that accumulative temperature in time Series (10 days) of 1997 higher than temperature in same period of 1994. We can conclude that temperature of time series (10 days) has influence to malaria cases. The number of malaria cases is larger for higher temperature.

8.7.2 Correlation between malaria cases and rainfall

Correlation between DY (percent of Malaria Data) and deviation from cumulative rainfall DR are shown **Figure 8.12**. Correlation in time series (10 days) is several times positively and negatively correlated and correlation coefficient is more than 0.5 and -0.5 and it is not stable correlation. So we can not predict malaria cases based on this correlation.

In **Figure 8.13** shows that accumulative rainfall for period 15-30 for two extreme years 1994 and 1997. It should be noted that rainfall in 1997 is higher than rainfall in the same period of 1994 and indicates that higher rainfall associates with fewer malaria cases.

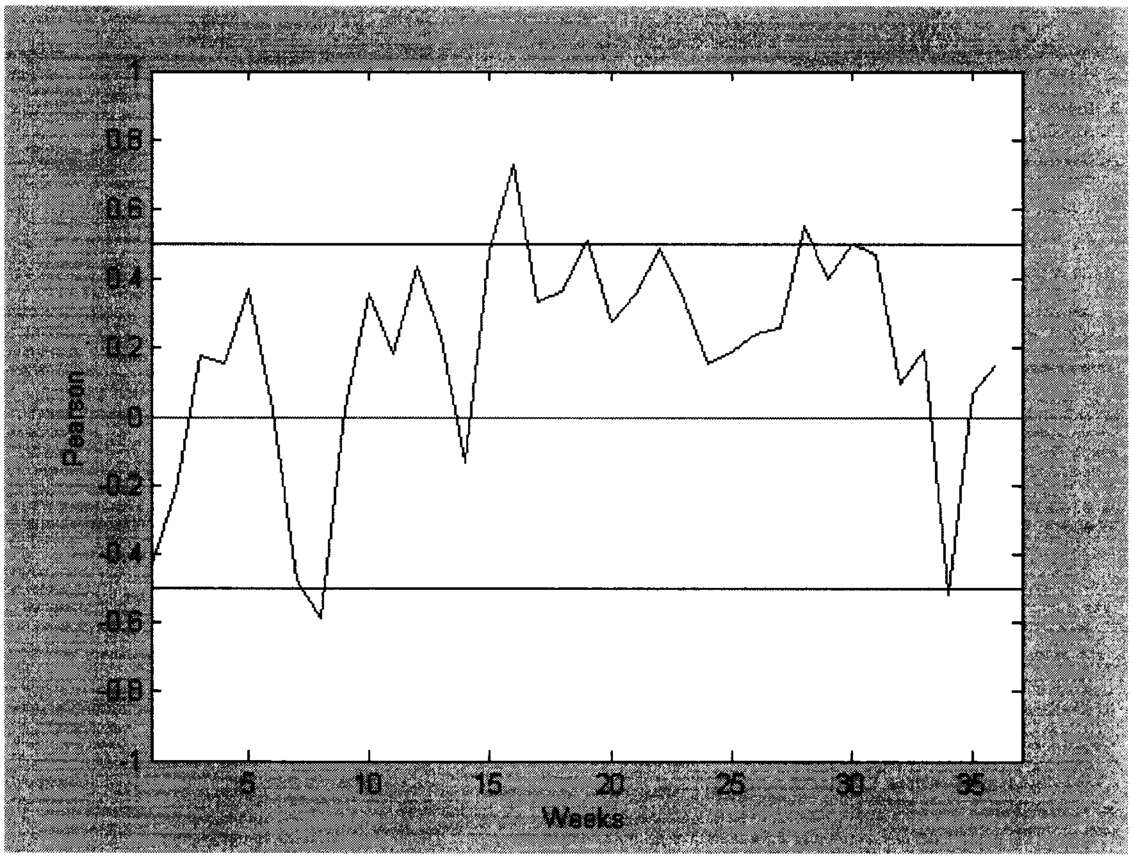


Figure 8.10 Correlations between DY (deviation of malaria cases) and DT (deviation from mean temperature) of Bangladesh

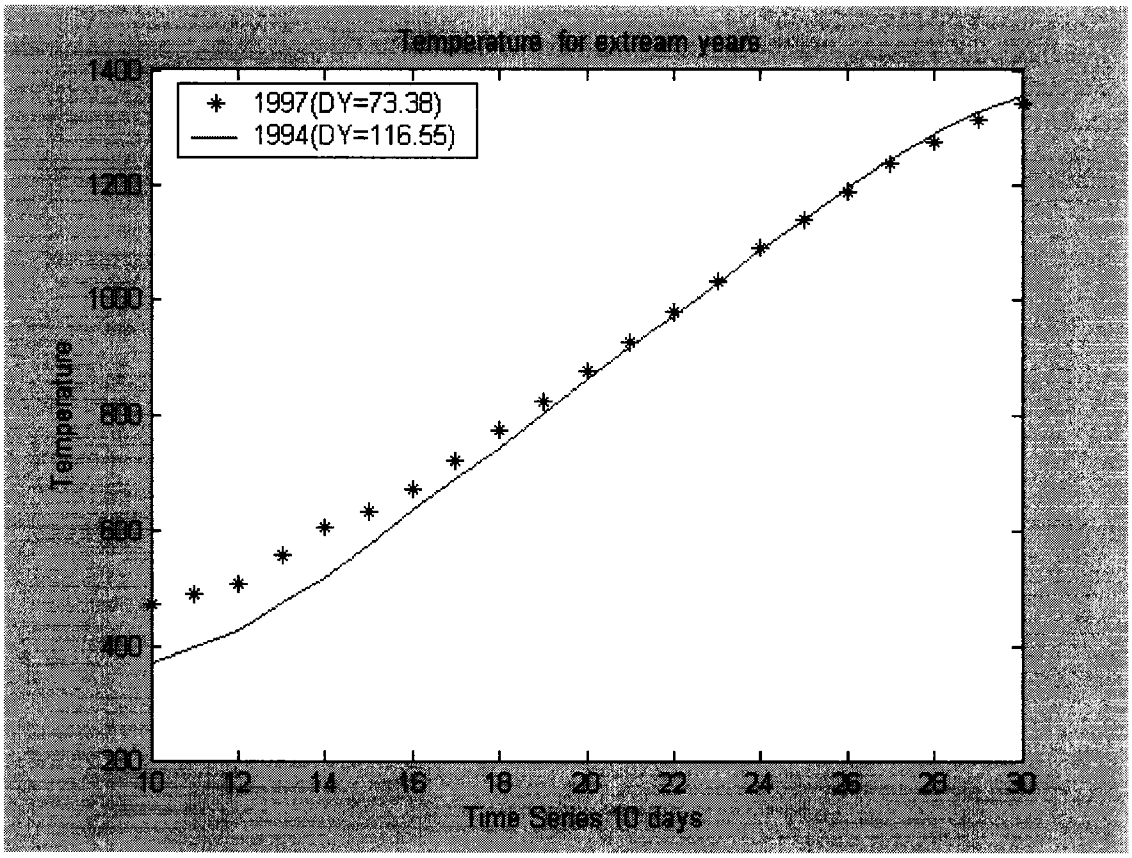


Figure 8.11 Cumulative temperature of Bangladesh for years with highest and lowest number of malaria cases

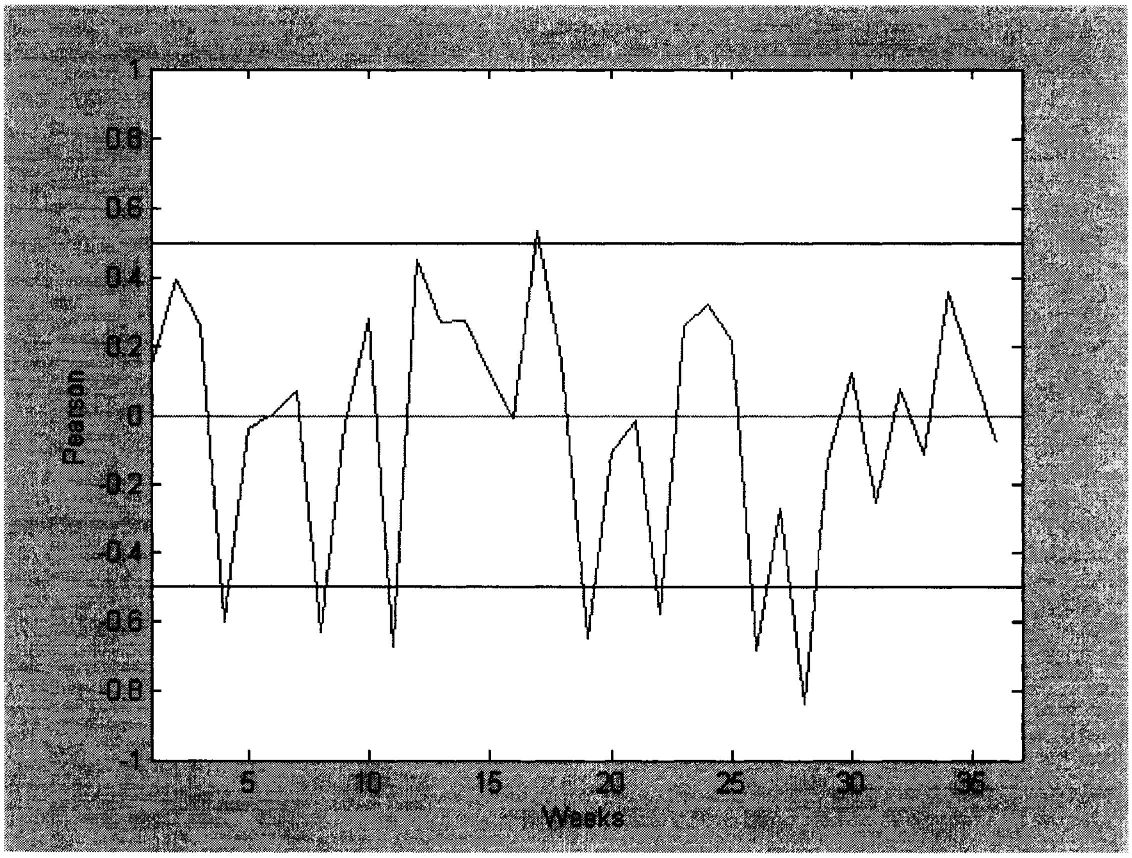


Figure 8.12 Correlations between DY (deviation of malaria cases) and DR (deviation from cumulative rainfall) for Bangladesh

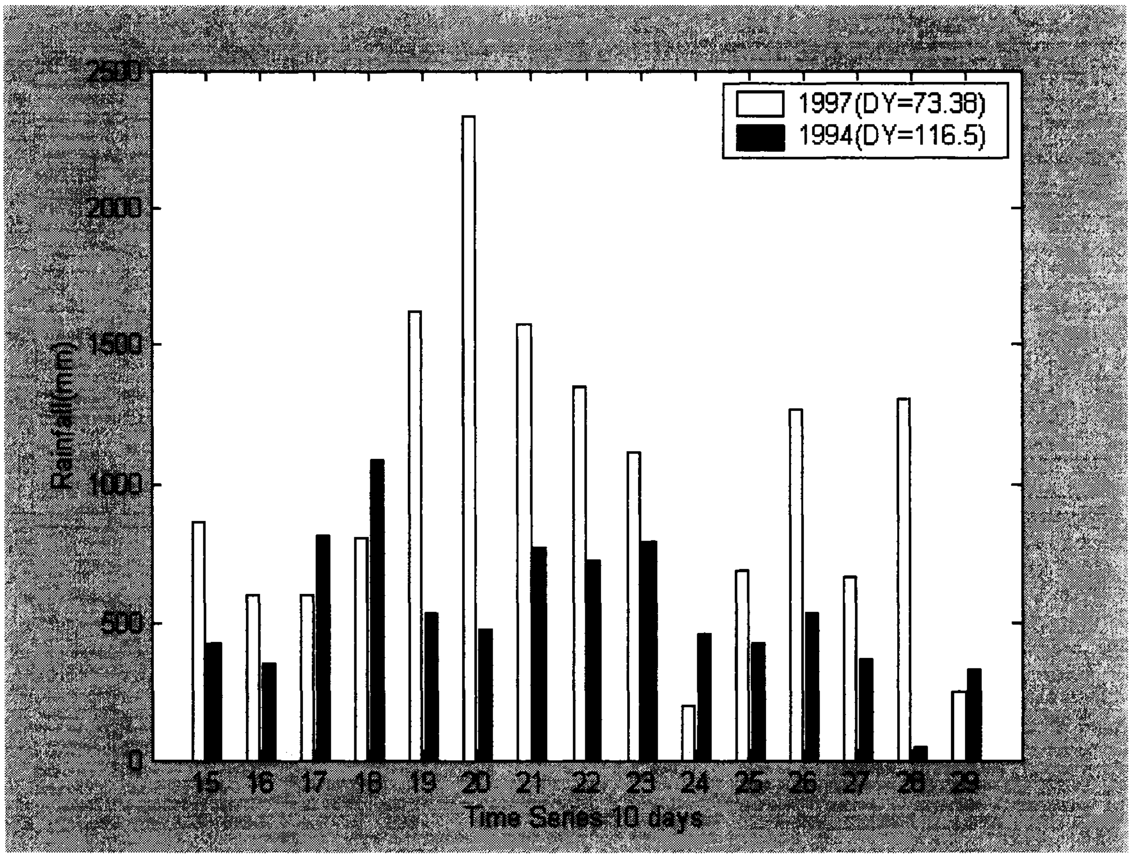


Figure 8.13 Cumulative rainfall of Bangladesh for years with highest and lowest number of malaria cases

8.7.3 Correlation between malaria cases and relative humidity

Correlation between DY (percent of malaria Data) and deviation from relatively mean humidity DH is shown in **Figure 8.14**. Correlation in Time Series (10 days) is not stable correlation. So we can not predict malaria cases based on this correlation.

Humidity graph for two extreme years 1994 and 1997 are shown in **Figure 8.15**. Humidity is always higher than 60% and it is favorable for mosquitoes' development.

8.8 Summary

Number of malaria cases of Chittagong, Sylhet and Dhaka division was aggregated for number of malaria cases for whole Bangladesh. Trend and statistical analysis shows that number of malaria cases are on rise. TCI, VCI, SMN and SMT for two extreme years (Highest and lowest number of malaria cases) were used to estimate malaria cases. TCI and VCI were correlated with number of malaria cases and regression equation was developed using correlation analysis.

The results of regression show that VCI for week 36 and TCI for week 40 parameters were accepted as the best estimation of DY.

Humidity can not be used as estimator. Higher temperature makes mosquitoes more active and malaria cases increase. Higher rainfall makes less hatching of mosquitoes and malaria cases as it washed out mosquito's eggs.

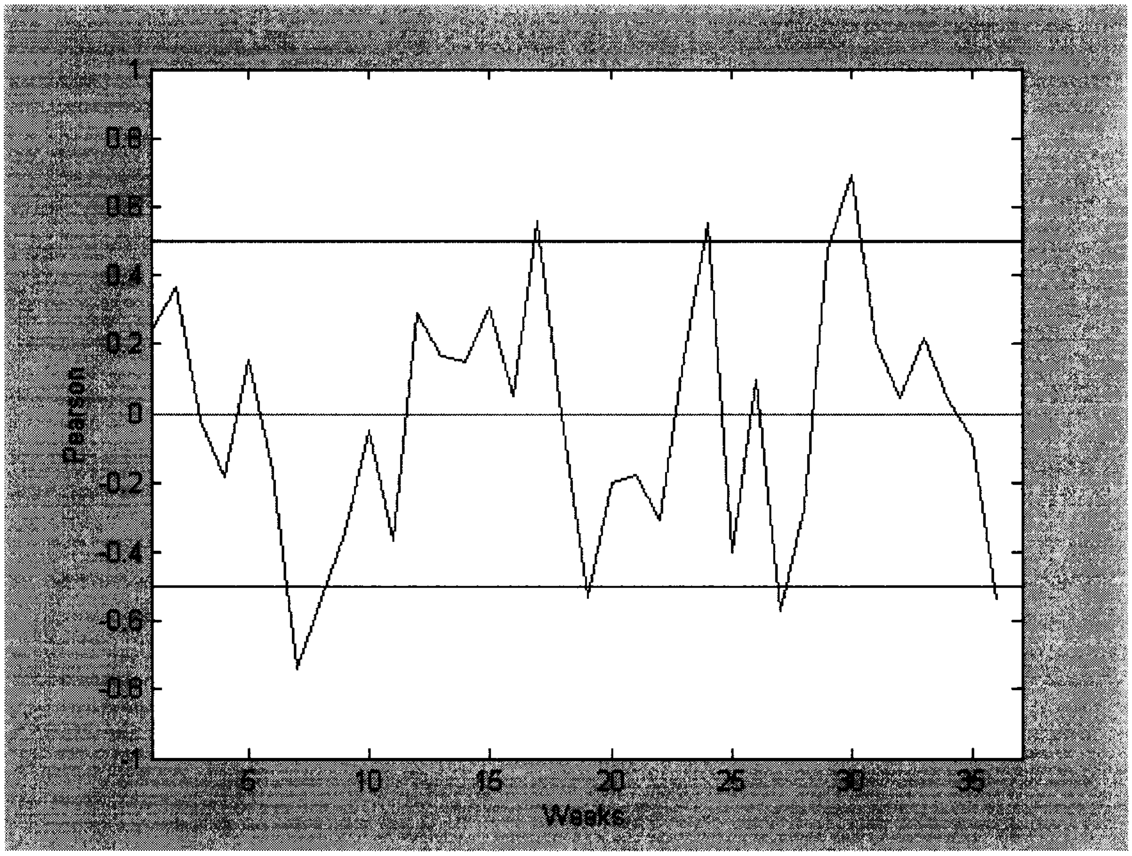


Figure 8.14 Correlations between DY (deviation of malaria cases) and DH (deviation from mean relatively humidity) for Bangladesh

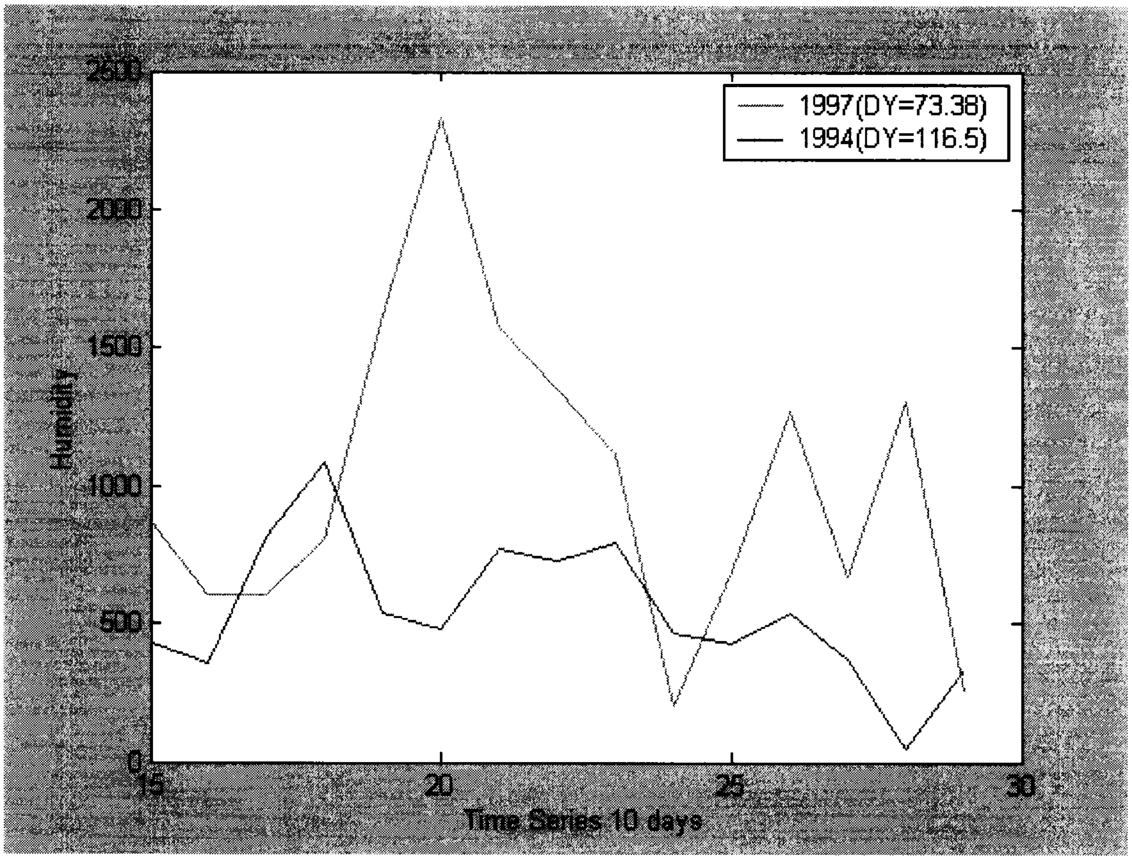


Figure 8.15 Cumulative relative humidity of Bangladesh for years with highest and lowest number of malaria cases

Chapter 9

Analysis for the period 1982-1991 for whole Bangladesh

9.1 Introduction

Annual countrywide results of malaria blood slide examinations for the 35-year period, 1963–97 from WHO (World Health Organization) bulletin, are listed in **Table 9.1**. The percentage of blood slides positive for malarial parasites was calculated using slides from all sources. Since the inception of the global Malaria Eradication Programme in 1961, malaria blood slide results and related indicators have been at the centre of the malaria eradication strategy worldwide, and have been used to analyse the malaria situation in Bangladesh. In 1969, the global malaria strategy changed from eradication to control, yet the surveillance practices of the malaria eradication era continue to be used in Bangladesh. Bangladesh is not unique in this respect. Following the Amsterdam Ministerial Conference in 1992 a change from specialized information systems to integrated ones was seen as essential, together with ''a radical redefinition of the information that should be collected''. So we will analyze malaria cases from 1982-1991 and data of malaria cases for 1982- 19991 except 1985 are shown in **Table 9.2**.

Table 9.1 Malaria statistics for 1961-1997 for Bangladesh

Year	Country population	Number of blood slides examined	No. of malaria positive slides	SPR[a] (%)
1963	1 895 000	86 345	402	0.47
1964	8 962 000	474 569	756	0.16
1965	12 035 000	975 918	649	0.07
1966	21 203 000	1 715 771	3 137	0.20
1967	26 874 000	2 485 901	4 080	0.16
1968	47 002 000	2 988 322	6 244	0.21
1969	59 444 000	4 880 511	7 871	0.16
1970	62 810 000	6 107 144	6 660	0.11
1971	63 570 000	2 212 660	2 944	0.13
1972	65 220 000	5 311 988	18 384	0.35
1973	69 288 000	3 259 190	14 007	0.43
1974	71 565 000	1 884 109	15 855	0.84
1975	72 730 000	2 929 935	31 247	1.07
1976	73 930 000	3 537 269	48 844	1.38
1977	76 395 000	1 414 731	29 673	2.10
1978	78 916 000	1 391 055	33 326	2.40
1979	81 520 000	1 374 104	49 776	3.62
1980	84 210 000	2 634 773	67 717	2.57
1981	88 100 000	2 338 853	45 902	1.96
1982	90 300 000	2 808 765	46 781	1.67
1983	92 200 000	2 516 110	42 529	1.69
1984	94 300 000	2 552 513	32 977	1.29
1985	96 400 000	2 823 028	31 050	1.10
1986	98 000 000	2 685 529	93 128	1.46
1987	99 800 000	2 771 577	35 848	1.29
1988	101 500 000	2 704 563	33 824	1.25
1989	103 800 000	3 152 310	50 738	1.61
1990	106 100 000	2 444 415	53 875	2.20
1991	109 900 000	2 081 137	63 578	3.05
1992	112 100 000	1 919 349	115 660	6.03
1993	114 500 000	1 635 589	125 402	7.67
1994	117 000 000	1 661 701	166 564	10.0
1995	119 000 000	1 461 556	152 729	10.4
1996	120 000 000	1 146 736	100 864	8.80
1997	124 300 000	955 542	68 594	7.18

SPR = Slide Positivity Rate.

Number of malaria-positive slides per 100 slides examined, expressed as a percentage of total blood sample.

Table 9.2 Malaria statistics of Bangladesh 1982-1991

Year	Malaria cases in Percent
1982	1.67
1983	1.69
1984	1.29
1986	1.46
1987	1.29
1988	1.25
1989	1.61
1990	2.2
1991	3.05

9.2 Trend and statistical analysis

Figure 9.1 shows annual percent of malaria cases of Bangladesh during 1982-1991. As seen, malaria is on a rise during the 1990s.Variations in the number of cases around the trend are associated with weather changes from year to year.

For example, the smallest percent of malaria cases was 1.25% in 1988 compared to 3% in 1991. The long-term tendency in malaria cases dynamics shown in **Figure 9.1** was approximated by linear equation (42) and weather-related variations around the trend were expressed as a ration (equation 43) of actual cases to the estimated from the trend.

$$Y_{trend} = 1.2 + .06 * \text{Year} \qquad (42)$$

$$DY = (Y / Y_{trend})*100 \qquad (43)$$

Where, Y_{trend} is percent of malaria cases for weather conditions near normal; Y is % of malaria cases; Year is year number; DY is deviation from trend expressed in percentage. The DY can be explained by comparing two years 1988 and 1991. In 1988, DY was 67% or 33% below the trend, while in 1991 DY was 141% or 41% above the trend. These estimates indicate that the 1988 was an unfavorable year for mosquito's development, while 1991 was favorable.

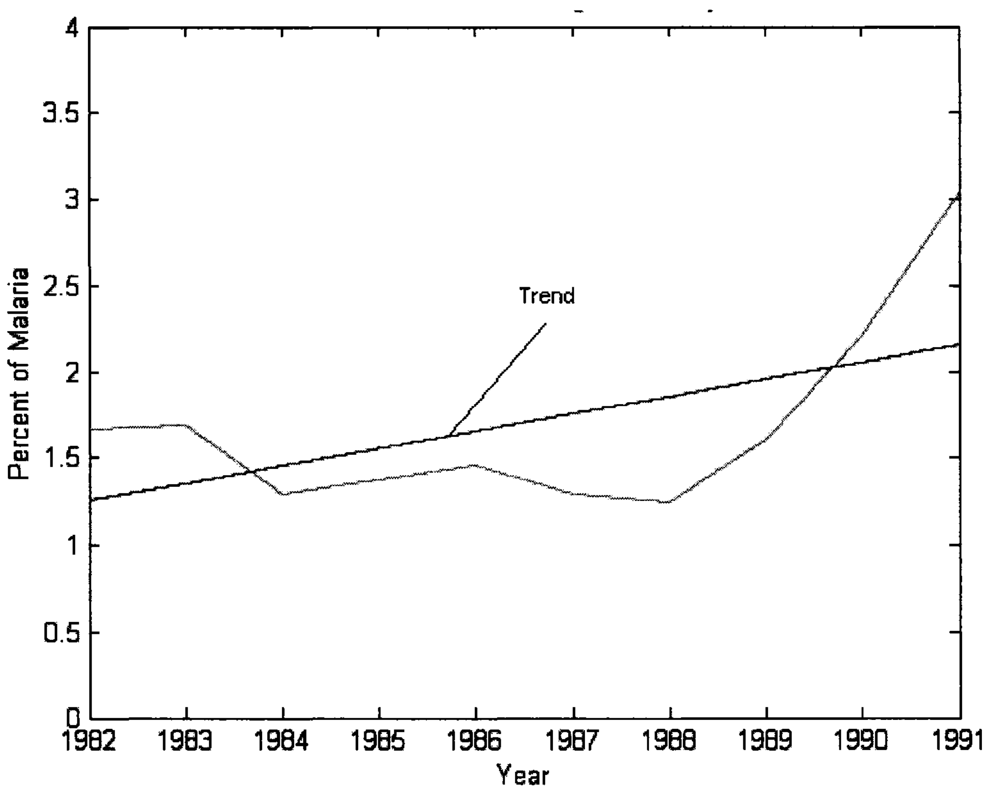


Figure 9.1 Annual malaria cases of Bangladesh and trend line, 1982-1991

9.3 Correlation Analysis

9.3.1 VCI and TCI of Bangladesh for two extreme years (highest and lowest number of malaria cases) for period 1982-1991

VCI and TCI dynamics were investigated during the years with the extreme differences in the percent of DY (below and above trend). Two years were selected 1988 (DY=67% de-trended malaria cases or 33% less cases than in the average weather year) and 1991 (DY=141% or 59% more cases than in the average weather year).

The assumption was that the environmental conditions of these years were quite different and they would be reflected in VCI and TCI values. The 1988 and 1991 VCI and TCI time series shown in **Figure 9.2** indicate that if TCI is above 40 (indicating cooler temperature) during weeks 22-40 of 1988, than larger number of malaria cases (DY above trend) occurs as it was in 1991.

9.3.2 Correlation between malaria cases and TCI and VCI

Investigation included correlation analysis of malaria cases (DY) versus VCI and TCI, shown in **Figure 9.3**. In week 20 when mosquito activity season starts, correlation decreases reaching maximum (-0.6 for TCI) at the middle of June (week 20-26); by fall, the correlation is gradually increasing. After that their biting activity increases, leading to enhanced malaria transmission.

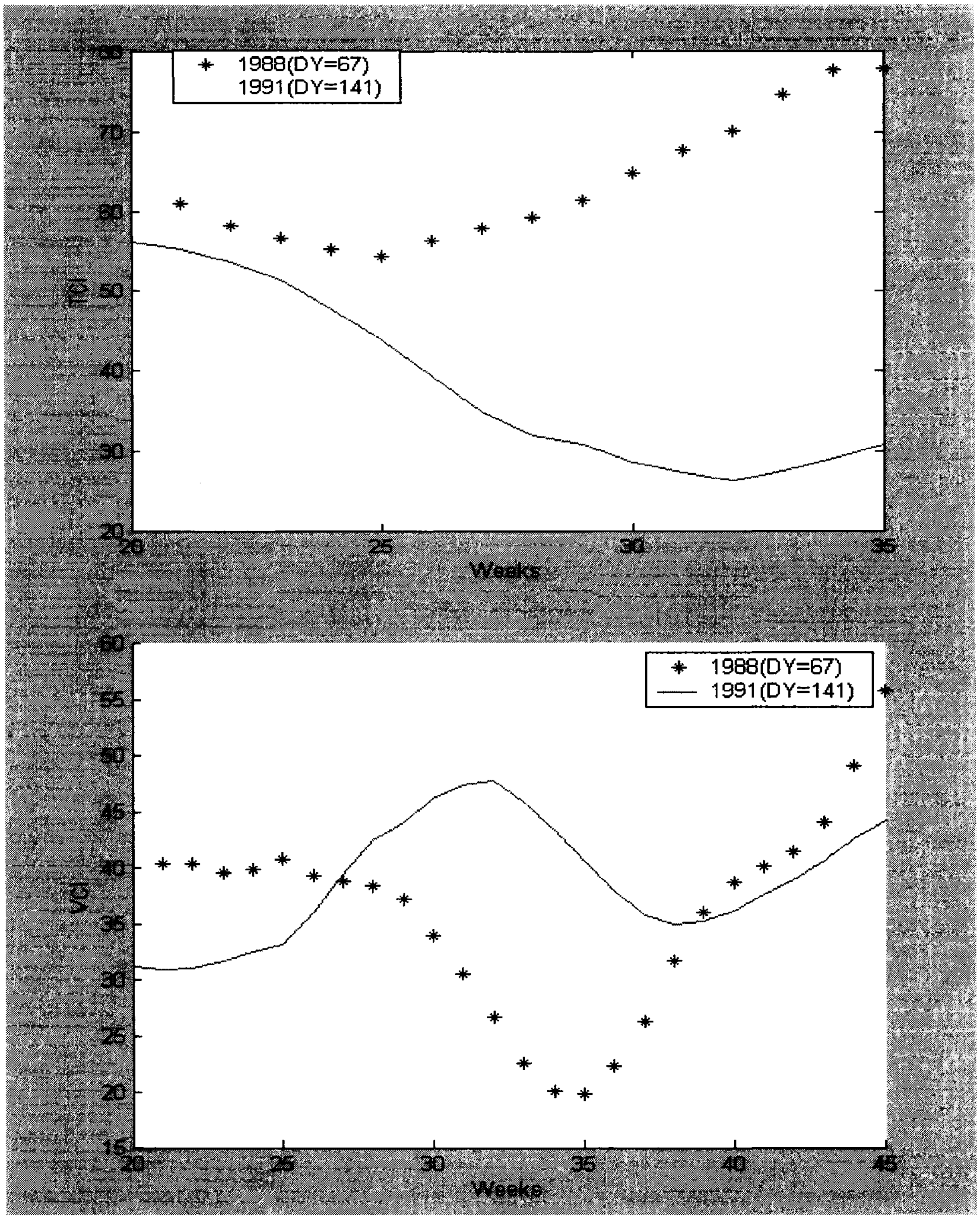


Figure 9.2 Temperature Condition Index (TCI) and Vegetation Condition Index (VCI) dynamics for years with highest and lowest number of malaria cases for period 1982-1991 for Bangladesh

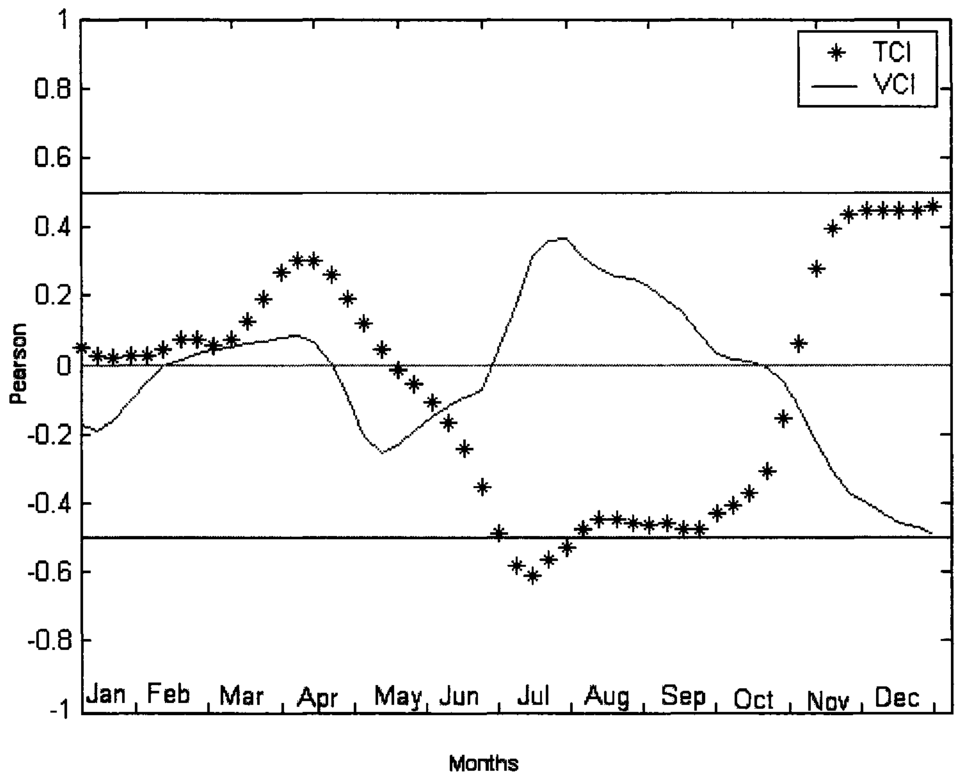


Figure 9.3 Correlation dynamics of DY (deviation of malaria cases) versus Temperature Condition Index (TCI) and Vegetation Condition Index (VCI) dynamics for period 1982-1991 for Bangladesh

9.3.3 Scatter Plot for TCI

TCI of week number 26 are shown in **Table 9.3**. It is important to emphasize that correlation of DY with TCI for week 26 is negative (**Figure 9.4**) indicating that DY increases from above trend values (larger malaria cases) for larger TCI (cooler conditions) to below trend (fewer number of malaria cases) for smaller TCI (hotter conditions). These results are in line with climate impact analysis literature indicating that hot weather depresses mosquito activity and malaria transmission.

9.4 Summary

Number of malaria cases for the period 1982-1991 was decreasing in early 1980's and it was on rise from 1989. AVHRR-based vegetation health indices (TCI and VCI) were correlated with number of malaria cases. TCI and VCI for two extreme years were showed for analysis. Results of correlation analysis showed that only TCI is negatively correlated in the middle of July and VCI is not correlated at all.

Table 9.3 DY (deviation of malaria cases) and Temperature Condition Index (TCI) values of Bangladesh for week 26 for period 1982-1991

Year	DY	TCI_{26}
1982	93	21
1983	125	23
1984	89	54
1986	88	21
1987	73	42
1988	67	56
1989	82	31
1990	107	41
1991	141	39

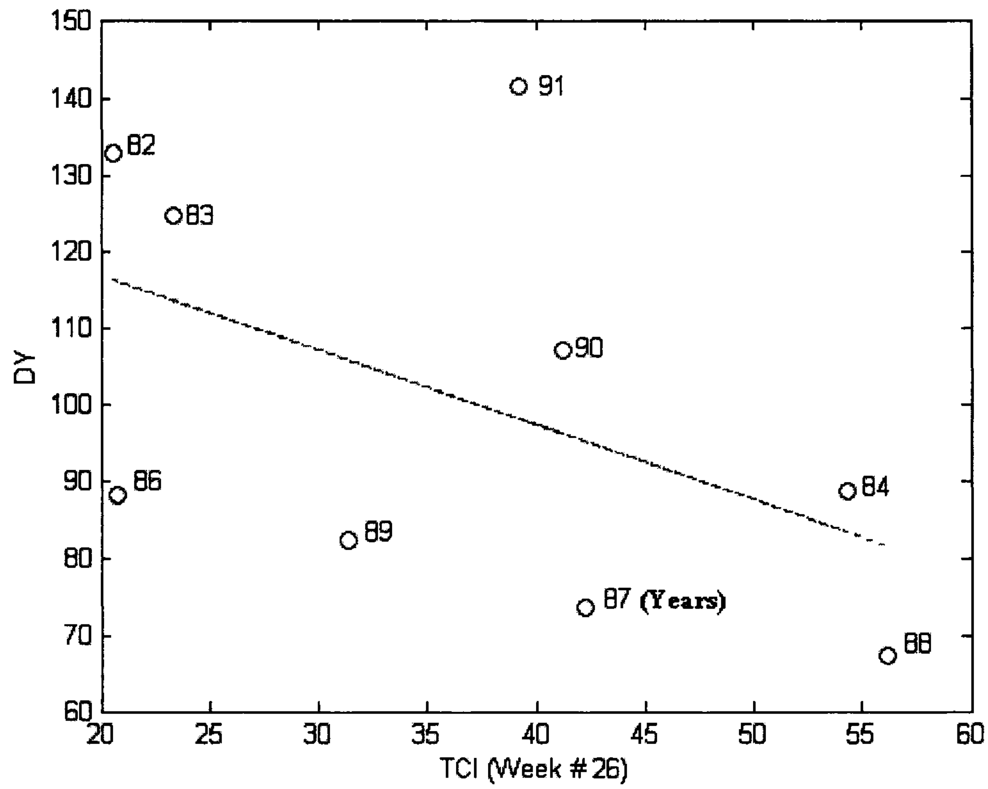


Figure 9.4 Scatter plot of DY (deviation of malaria cases) versus Temperature Condition Index (TCI week 26 for period 1982-1991 for Bangladesh

Chapter 10

Dengue analyses for Dhaka City of Bangladesh

10.1 Introduction

Dengue is becoming a major health problem in Bangladesh. It has long been among the top four of the most common communicable diseases in the country, which are diarrhoeal diseases, asthma, dengue, and malaria. The factors that facilitate the spread of dengue include rapid demographic and societal changes, population movement, uncontrolled urbanization, poor water management systems and indiscreet disposal of used automobile tires and plastic materials in the environment. Although the mortality and case fatality rates of dengue have been gradually decreasing, thanks to the technical advancements and the higher quality of medical care. Dengue out break history of Bangladesh started in 1964 but it became epidemic from 2000. In the first few outbreaks, the disease was mainly found in Dhaka and its surrounding areas. Since 2000, the disease has been reported from all regions of the country. There are many deaths caused by dengue in 2000, 2001 and 2002.

10.2 Data Analysis

Clinical Data for 2001-2002 were collected from Directorate of Health under Ministry of health, Bangladesh. Dengue affected zones of Dhaka city are shown in the Figure 10.1 with "X" marked and data are shown in Table 10.1. Number of cases per day for dengue is shown in Table 10.2 and Figure 10.2. Number of dengue cases is higher in August, 2001 and July, 2002 as these periods are rainy season. Period from January, 2002 to April, 2002 has only few cases, because this period is dry season. Therefore we will investigate only period August 8-29, 2001 and July 02-27, 2002.

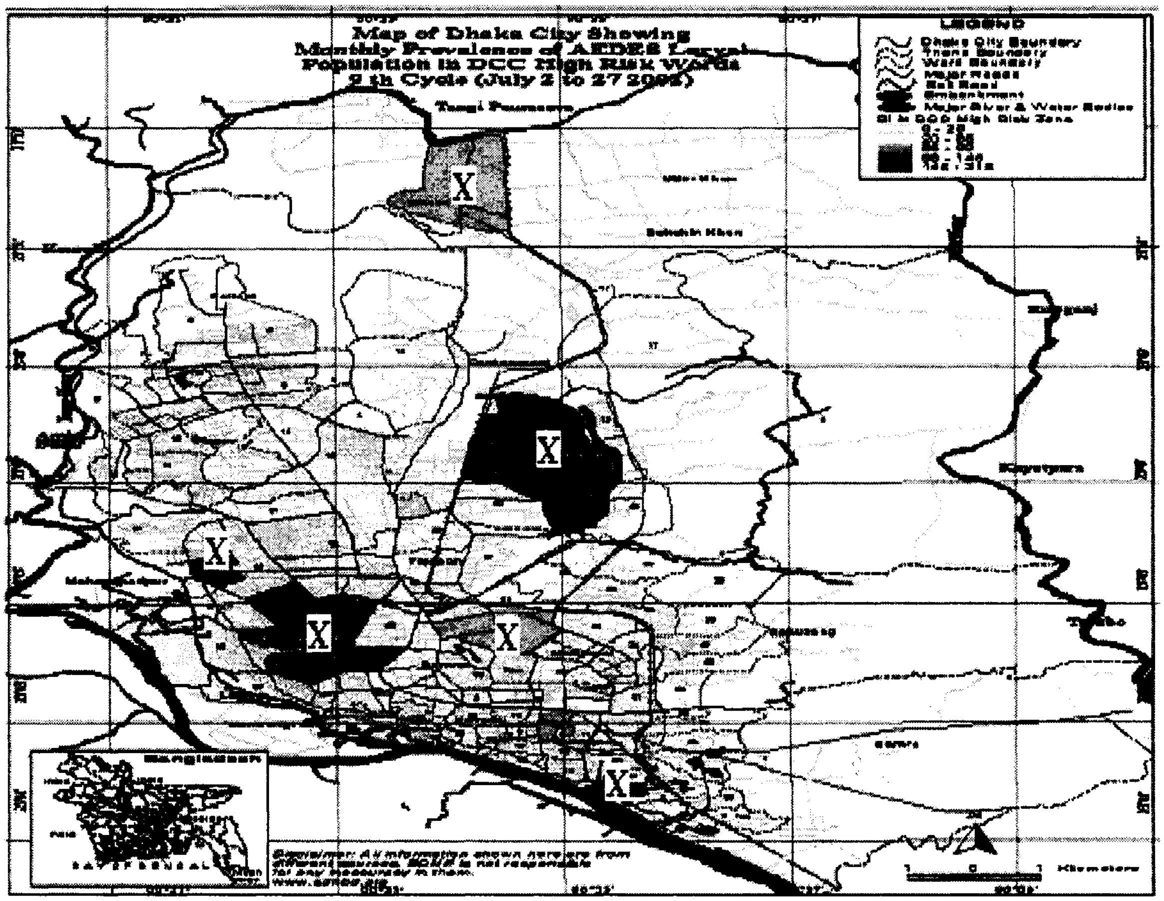


Figure 10.1 Dengue affected zones of Dhaka City

Table 10.1 Dengue data for some zones of Dhaka city

Zone	1st Cycle Aug 8-29, 2001	2nd Cycle Dec12, 01-Jan6, 2002	3rd Cycle Jan.6-30, 2002	4th Cycle Mar4-21, 2002	5th Cycle Mar21-Apr10, 2002	6th Cycle Apr13-May4, 2002	7th Cycle May 4-28, 2002	8th Cycle June 6-29, 2002	9th Cycle July 02-27, 2002
1	81.25	10	0	0	20	10	40	60	115
2	44	46.67	5	0	5	20	5	110	75
3	33.33	5	0	0	0	0	5	5	60
4	15	0	0	0	0	0	0	5	50
5	179.21	80	0	40	10	10	20	265	330
6	51.29	6.67	0	0	30	0	0	45	180
7	46.05	5	6.67	0	0	0	0	10	105
9	92.86	0	0	0	0	25	75	130	215
10	15	10	0	0	0	0	0	15	90
Total	558	163	12	40	65	65	145	645	1220

Table 10.2 Per day dengue cases for the different periods

Period	1st	2nd	3rd	4th	5th	6th	7th	8th	9th
Dengue Data	557	163	12	40	65	65	145	645	1220
Days in period	21	24	24	17	20	21	24	23	25
Number of cases per day.	27	7	1	2	3	3	6	28	49

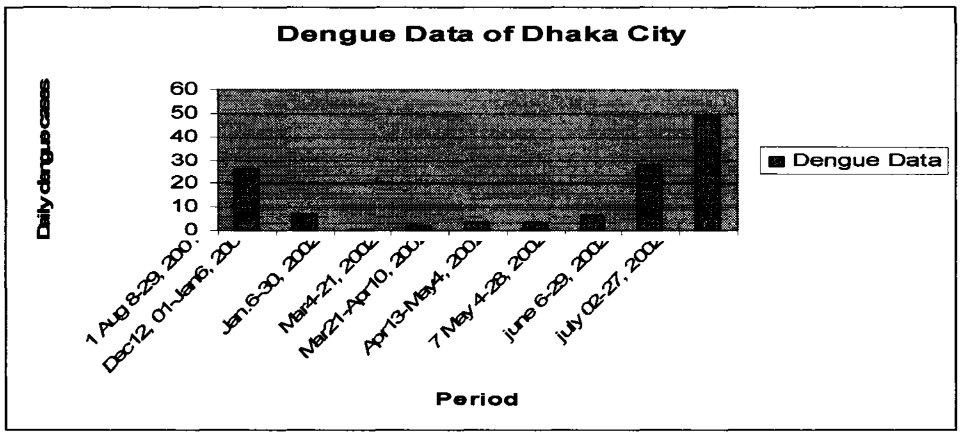


Figure 10.2 Per day dengue cases graph for Dhaka city

10.3 TCI Analysis for dengue

First, the differences, in TCI dynamics were investigated during the years with the extreme differences in the dengue cases. The assumption was that the environmental conditions of these years were quite different and they would be reflected in TCI values. TCI time series for 2001 and 2002 is shown in **Figure 10.3** indicate that if TCI is above 60 (indicating cooler temperature) during rainy season (weeks 10-26); than larger number of dengue cases occurs as it was in 2002.

However, when TCI is below 40 (indicating thermal stress), the number of dengue cases is much smaller as it was in 2001. In late summer and during fall (weeks 27-40), TCI differences between two extreme years were smaller. Similarly, smaller differences were observed during the entire rainy season (May-September). This preliminary analysis has already indicated that thermal conditions are more important factor for controlling dengue epidemics.

Since there was no appropriate statistics, we did qualitative analysis of two year dengue cases. In 2002 in Dhaka city had more dengue cases than in 2001. As seen in the **Figure 10.3** this corresponds to cooler weather condition in 2002.

10.4 Summary

Dengue data were collected from affected zones of Dhaka city and showed as number dengue cases per day. TCI analysis was done for estimating number of dengue cases in Dhaka city. Higher TCI during wet-warm season associates with higher numbers of dengue cases

The result of this study showed that AVHRR-based TCI can be used as a proxy for numerical estimation of number of dengue cases in Dhaka city of Bangladesh.

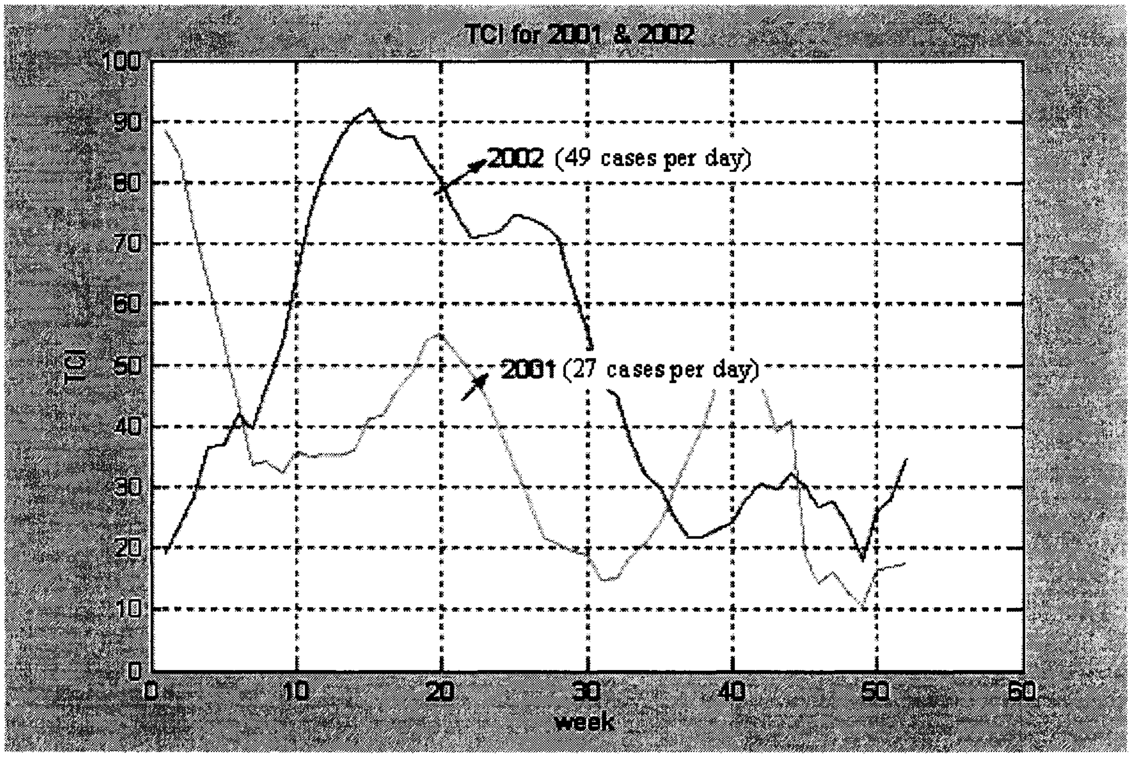


Figure 10.3 Temperature Condition Index (TCI) for years 2001 and 2002

Chapter 11
Model Validation

11.1 Introduction

Simulation models are increasingly being used in problem solving and in decision making. Before the model can be used for real-time forecast, validation of the model should be made on independent time-periods with independent data. Estimations were made using of Jackknife Cross-Validation procedure. Jack-knife forecasts were made for every year in the data set period. The forecast year is always excluded from the regression equation. Thus, this technique is also called leave one out. The process is repeated by removing the next year and so on until 10 forecasts have been made for the data set for Chittagong division and the whole Bangladesh from 1992 to 2001.

11.2 Datasets

Annual total clinical malaria cases for 1992-2001 were collected from Directorate General of Health (DG Health), Ministry of health Bangladesh. We collected satellite data TCI and VCI for 1992-2001 from NOAA.

11.3 Methodology

To use Jackknife technique one year malaria cases data were excluded from 1992-2001 dataset. Predicted deviation (DP) of malaria cases from trend was simulated based on satellite data (equation 1), Predicted malaria cases (*P*) was estimated from equation 45, Bias (*B*); Relative bias (*RB*); Mean bias error (*MBE*) were estimated from equations 46, 48 and 50; Y_{trend} is percent of malaria cases for weather conditions near normal; *Y* is % of observed malaria cases (% from total number of people to hospital with fever).

$$DP = a_o + a_1 * TCI + a_2 * VCI \qquad (44)$$

$$P = Y_{trend} * (DP/100) \qquad (45)$$

$$B = P - Y \qquad (46)$$

$$DB = B - \bar{B} \qquad (47)$$

$$RB = \frac{DB}{Y} \qquad (48)$$

$$\bar{Y} = \frac{\sum_{i=1}^{10} Yi}{10} \qquad (49)$$

$$MBE(\bar{B}) = \frac{\sum_{i=1}^{10} Bi}{10} \qquad (50)$$

Where i is year; a_o is intercept; a_1 and a_2 are slopes.

In order to ascertain the difference between the modeled and observed malaria cases, bias error were performed using equations 51-53.

The mean square error (MSE), root mean square error (RMSE) and % of root mean square error (RRMSE) given by

$$MSE = \frac{\sum_{i=1}^{10} (Bi)^2}{10} \qquad (51)$$

$$RMSE = \sqrt{MSE} \qquad (52)$$

$$RRMSE = \frac{RMSE * 100}{\bar{Y}} \qquad (53)$$

MBE measures the bias of the predicted value and should be close to zero for unbiased methods. *RMSE* is a measure of the precision of the predicted value and should be as small as possible for unbiased precise prediction. Relative RMSE should be as low as possible for good model.

We also calculated standard deviation (SD_B) of bias and Relative standard deviation (RSD_B) by equation 54 and 55.

$$SD_B = \frac{\sum_{i=1}^{10}(Bi - \bar{B})^2}{N-1} \qquad (54)$$

$$RSD_B = \frac{SD_B * 100}{\bar{Y} + \bar{B}} \qquad (55)$$

The final analysis will be a linear regression of the simulated data on the observed data, which fits a straight line to a set of independent and dependent data points based on a least-squares fit equation 56.

$$P = b_0 + b_1 * Y \qquad (56)$$

Where b_0 is intercept; b_1 is slope.

11.4 Results and Discussion

11.4.1 Statistical analysis for Chittagong division

A complete assessment of model performance should include at least one "Goodness-of-Fit" at least one absolute error measure (e.g., RMSE or MBE) with additional supporting information (e.g., a comparison between the observed and simulated mean and standard deviations). Statistical analysis by using equations 44-56 is shown in Table **11.1**. MBE value 0.01 is close to zero which indicates that the predicted value for unbiased. RMSE value 1.57 is small indicates unbiased precise prediction.

RMSE exceeds MBE is an indicator of the extent to which outlier exist in the dataset.

It is shown that % of malaria cases are modeled accurately by TCI and VCI. The MSE is only 2.46 indicating that estimated percent of malaria are quite close to observed percent of malaria cases.

Further accurate calculation of percent of malaria cases is evidenced by the linear regression analysis (**Figure 11.1**). The slope 0.71 is nearly one. Furthermore, R^2 (0.53) means that a large percentage of the data points fall near the regression line.

Figure 11.2 shows the modeled and observed % of malaria cases for 10 years. In general, for each year, the simulated percent of malaria cases is differ 1-2% with those of observed. This provides additional evidence that the model will be able to effectively estimate the percent of malaria cases.

Table 11.1 shows that from 10 years of tests, RB was below 10% in 7 years and below 15% in 3 years. Standard deviation (SD_B) value 1.68 is also small.

Table 11.1 Results of the statistical analysis for Chittagong division

Year	Regression coefficients			Variables		Observed malaria	Trend observed	Deviation Simulated	Simulated malaria	Bias	Relative Bias
	a_0	a_1	a_2	TCI	VCI	(Y)	(Yt)	(DP)	(P)	(B)	(RB)
1992	101.46	0.15	-0.14	25.1	45	18.18	19.20	98.74	18.96	0.78	3
1993	95.93	0.20	-0.08	29.5	66.3	18.6	19.76	96.55	19.08	0.48	1
1994	97.10	0.19	-0.10	70.9	37.1	21.91	20.31	106.61	21.65	-0.26	3
1995	84.66	0.32	0.02	28.2	44.5	21.95	20.86	94.46	19.71	-2.24	12
1996	98.23	0.23	-0.18	27.6	66.1	22.6	21.42	92.71	19.85	-2.75	14
1997	99.91	0.14	-0.09	26.6	59.9	18.94	21.97	98.35	21.61	2.67	12
1998	98.01	0.17	-0.11	60	43.7	24.23	22.52	103.33	23.27	-0.96	5
1999	96.48	0.20	-0.10	57.3	31.5	24.23	23.07	104.96	24.22	-0.01	1
2000	98.72	0.21	-0.13	52.5	38	23.14	23.63	104.58	24.71	1.57	5
2001	92.38	0.23	-0.03	40	74.7	23.14	24.18	99.09	23.96	0.82	2

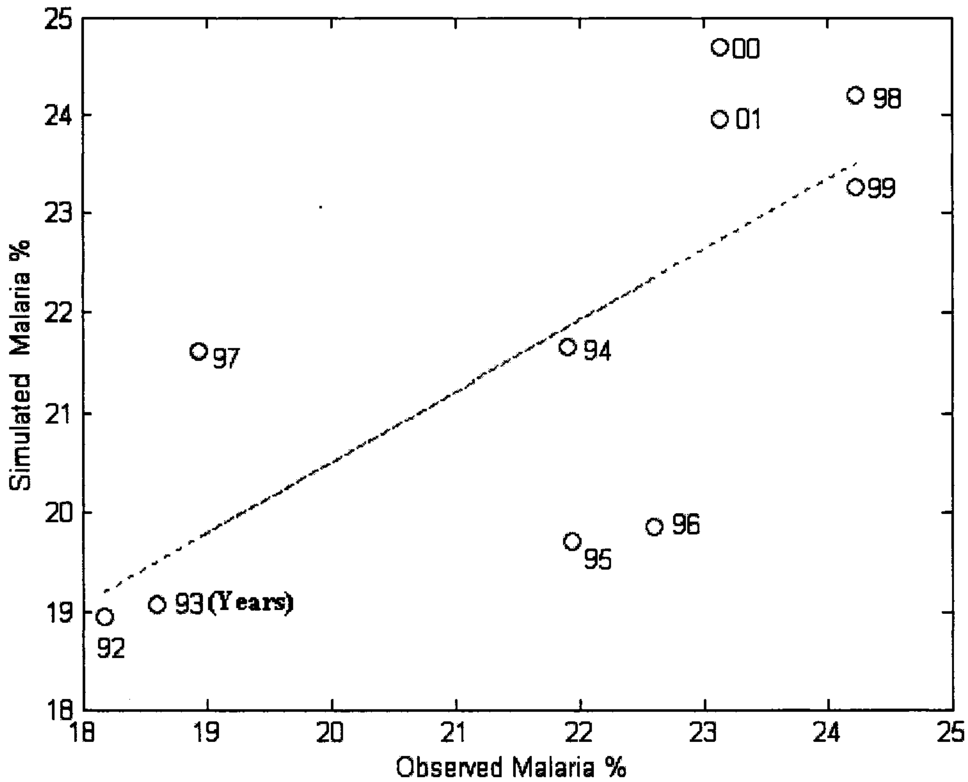


Figure 11.1 Linear regressions of independently simulated and observed malaria cases for Chittagong division

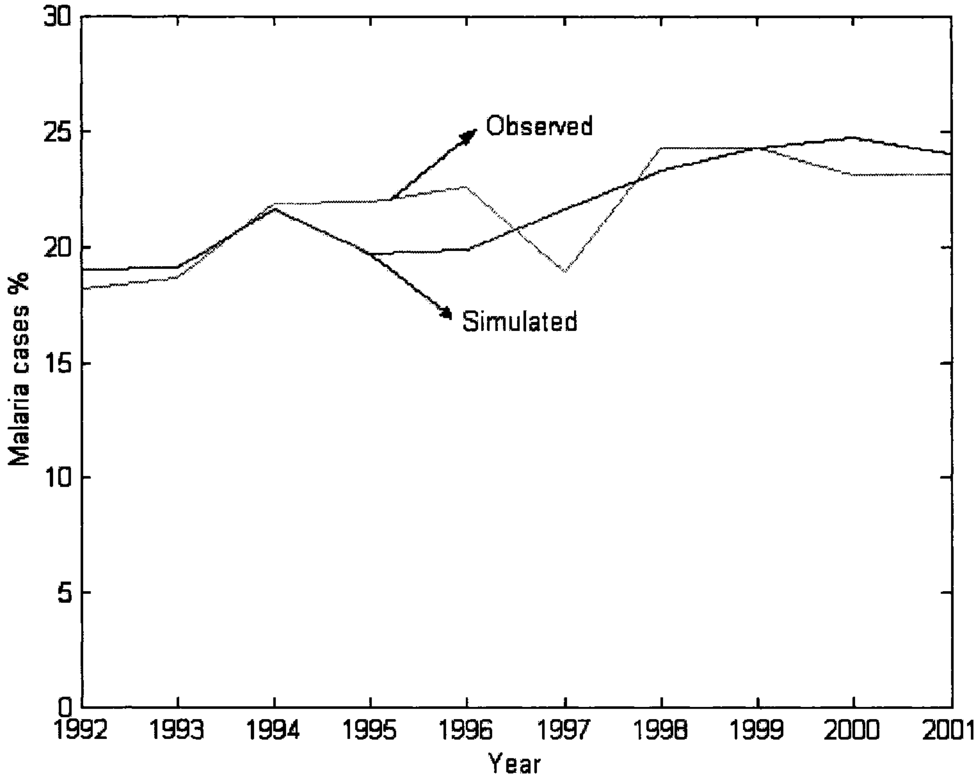


Figure 11.2 Simulated and observed malaria cases for Chittagong division

11.4.2 Statistical analysis for whole Bangladesh

Statistical analysis is shown in **Table 11.2**. MBE value 0.31 is close to zero it indicates that the simulated value for unbiased. RMSE value 1.71 is small and indicates unbiased precise estimation.

RMSE exceeds MBE and is an indicator of the extent to which outlier exist in the dataset. It is shown that percent of malaria cases are modeled accurately by TCI and VCI. The MSE is only 2.91 indicating that estimated % of malaria are quite close to observed % of malaria cases. Further accurate calculation of percent of malaria cases is evidenced by the linear regression analysis (**Figure 11.3**). The intercept is only 0.28, which is close to the optimum value of zero and the slope is nearly one. Furthermore, a high R^2 (0.82) means that a large percentage of the data points fall near the regression line.

Figure 11.4 shows the modeled and observed % of malaria cases for 10 years. In general, for each year, In general, for each year, the simulated percent of malaria cases is differ 1-2% with those of observed except for year 1997. This provides additional qualitative evidence that the model will be able to effectively predict the percent of malaria cases.

Table 11.2 shows that from 10 years of tests, RB was below 10% in 4 years, below 15% in 3 years and below 20% in 2 years. Only in 1997 RB was large (45%). Our investigation did not reveal the cause of such bias. Standard deviation (SD_B) value 1.77 is also small.

Table 11.2 Results of the statistical analysis for whole Bangladesh

Year excluded	Regression coefficients			Variables		Observed malaria	Trend observed	Deviation Simulated	Simulated malaria	Bias	Relative Bias
	a_0	a_1	a_2	TCI	VCI	(Y)	(Yt)	(DP)	(P)	(B)	(RB)
1992	75.68	0.62	-0.1	28.1	63	6.02	6.24	86.11	5.37	-0.65	16
1993	77.3	0.58	-0.09	47.4	39.3	7.6	7.33	101.28	7.42	-0.18	6
1994	77.88	0.6	-0.1	81.9	16.3	10.24	8.41	125.41	10.55	0.31	0
1995	77.31	0.58	-0.09	48.4	45.8	10.45	9.5	100.97	9.59	-0.86	11
1996	75.77	0.62	-0.09	13.5	71.4	8.7	10.59	77.73	8.23	-0.47	9
1997	87.78	0.42	-0.08	22.8	67.5	7.17	11.67	91.91	10.73	3.56	45
1998	68.78	0.68	-0.03	34	50.6	13.7	12.76	90.36	11.53	-2.17	18
1999	82	0.52	-0.13	70.8	40.2	16.5	13.85	113.62	15.73	-0.77	7
2000	94.2	0.48	-0.3	62.9	12.7	15.53	14.93	120.88	18.05	2.52	14
2001	61.97	0.75	0.11	49.9	78.3	15.39	16.02	107.38	17.2	1.81	10

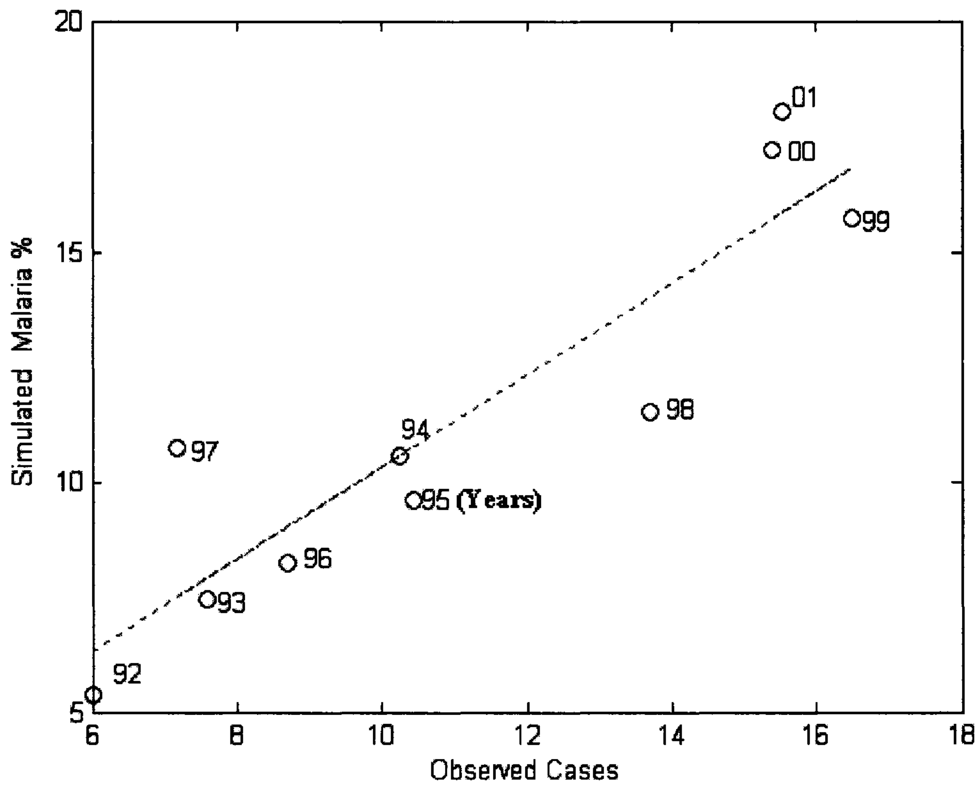


Figure 11.3 Linear regressions of independently simulated and observed malaria cases for whole Bangladesh

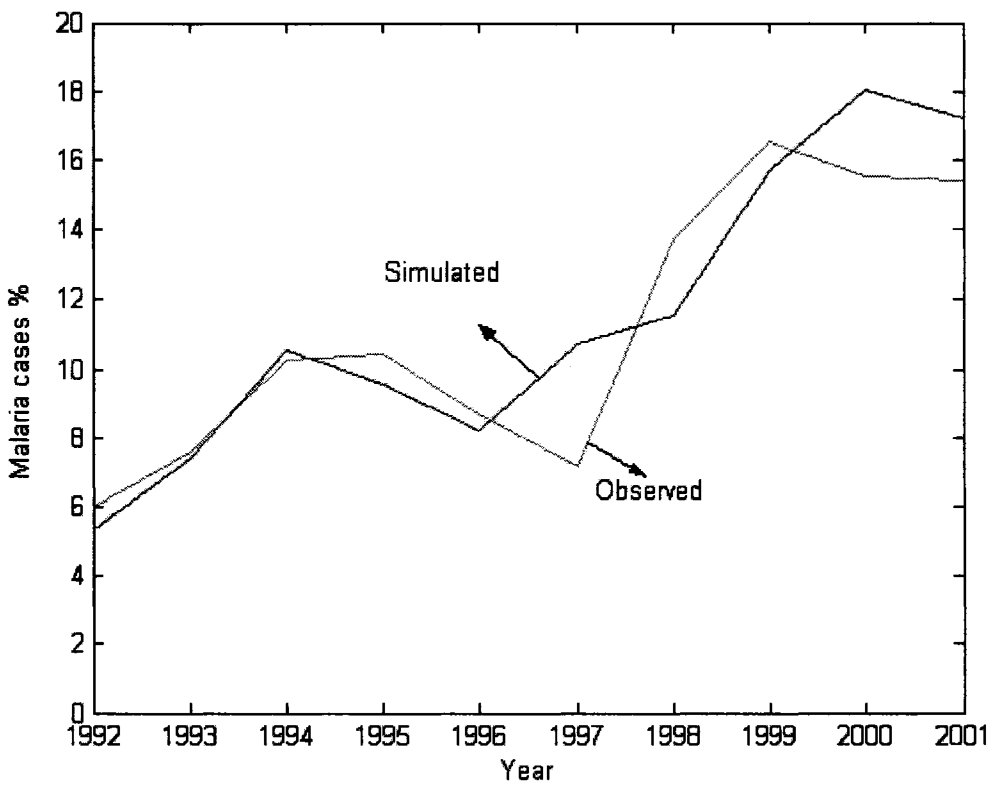


Figure 11.4 Simulated and observed malaria cases for whole Bangladesh

11.5 Summary

Regression models were validated for Chittagong and Bangladesh using Jackknife Cross-Validation method. Statistical analysis for Chittagong division shows that from 10 years of tests, RB was below 10% in 7 years and below 15% in 3 years. Standard deviation (SD_B) value 1.68 is also small. Statistical analysis for Bangladesh shows that RB was below 10% in 4 years, below 15% in 3 years and below 20% in 2 years. Only in 1997 RB was large (45%). Standard deviation (SD_B) value 1.77 is also small. The MSE is only 2.46 and 2.91 indicating that predicted percent of malaria are quite close to observed percent of malaria cases. Regression equations were developed for estimation malaria cases. Results of statistical analysis shows that the simulated percent of malaria cases differs 1-2% with those of observed.

Chapter 12

Conclusions

Malaria and dengue affect the health and wealth of nations and individuals alike. Malaria and dengue are understood to be both a disease of poverty and a cause of poverty, have significant measurable direct and indirect costs, and has been shown to be a major constraint to economic development. Annual economic growth will rise due to low risk of vector-borne diseases. Public expenditures include spending by government on maintaining health facilities and health care infrastructure, publicly managed vector control, education and research.

Although the government of Bangladesh takes measures to eradicate the mosquito-borne diseases, they still prevail in many regions. In order to reduce the consequences of vector-borne epidemics, especially in the years of their intensification, the Government Bangladesh needs to know in advance potential for the development of epidemics. Since the inception of the Global Malaria Eradication Program in 1961, malaria blood slide results and related indicators have been at the center of the malaria eradication strategy worldwide, and have been used to analyze the malaria situation in Bangladesh. In 1969, the global malaria strategy changed from eradication to control, yet the surveillance practices of the malaria eradication era continue to be used in Bangladesh. Bangladesh is not unique in this respect. Dengue outbreak history of Bangladesh stared from 1964 but very serious epidemics have affected the country from 2000.

Mosquitoes activities is controlled by weather (precipitation, temperature, humidity) [26, 28]. Unfortunately the number of weather stations in Bangladesh is limited for early detection of condition for development of mosquitoes and monitoring their activity.

Therefore, we investigated application of satellite data, especially vegetation indices (VCI, TCI, VHI) as a proxy for monitoring.

Mosquitoes in Bangladesh as well as in all divisions transmit malaria year round. In general, two seasons are defined in the annual cycle: wet and warm during April-October, and cool and dry during November-March. During the cooler season mosquitoes are less active and the number of malaria cases is small. This number increases considerably during the warm and wet season.

From 6 administrative divisions malaria is developed in the coastal zone (Chittagong, Khulna, Barisal). In mountain plain areas malaria is much less spread due to climate.

Our research in coastal division's mosquito activity season starts at the end of April (week16) when the correlation between number of malaria cases and VHI increases. For Chittagong division correlation reaches maximum (0.6 for TCI and 0.5 for VCI) with single peak in the end of June (week 25-26). For Khulna division correlation reaches maximum (0.6 for TCI) in the middle of June (week 20-26). By fall, the correlation is gradually decreasing. In the beginning of July (week 30) correlations starts increase and reaches maximum (0.5 for TCI) at middle of October; by late fall it gradually decreases. For Barisal division correlation increases reaching maximum (0.6 for TCI) in the middle of June (week 20-26 decreasing thereafter.

In Sylhet division when mosquito activity starts in early fall (week 35, end of August). Maximum correlation with VH indices reaches 0.5 for TCI and 0.4 for VCI at the end of September (week 38-39). In Dhaka division mosquito activity season starts in June (week 26). One month later July (week 26-30) correlation with temporal condition reaches maximum (-0.5 for TCI) decreasing thereafter. In the end of September (week 39) correlations starts increase and reaches maximum (0.6 for TCI); by late fall it gradually decreases. For Rajshahi division, where mosquito activity is controlled by temperature, correlation between number of malaria cases and TCI reaches 0.6 in the middle of October (week 40-41) decreasing thereafter.

For the entire Bangladesh, the correlation between number of malaria cases and VH indices start to increase in spring (week 16, end of April) reaching maximum (for TCI 0.7 and for VCI -0.60 and -0.66) around week 40 (middle of October) and week 36 (middle of September) respectively decreasing thereafter.

We developed equations can be used for estimate and analyses of the number of malaria cases in Bangladesh and all divisions.

For Chittagong: $DY=96.49 + 0.201\ TCI_{26} - 0.096\ VCI_{26}$

For Khulna: $DY= -19.4+ 2.11\ TCI_{22}$ and $DY= -34.7 + 2.34\ TCI_{39}$

For Barisal: $DY= -19.9+ 1.82\ TCI_{20}$

For Sylhet: $DY=62 + 0.94\ TCI_{39} - 0.002\ VCI_{39}$

For Dhaka: $DY=160 - 1.92\ TCI_{28}$ and $DY=45.86 + 1.46\ TCI_{41}$

For Rajshahi: $DY=47.59+ 1.34\ TCI_{41}$

Bangladesh: $DY= 90.51+ 0.32\ TCI_{40}- 0.13\ VCI_{36}$

Where, DY is deviation from trend expressed in percentage;

TCI_n is TCI value for week number n and VCI_n is VCI value for week number n.

Analysis of the correlation between the number of malaria cases with ground data (temperature, rainfall and humidity) showed that they are not correlated.

In chapter 11 we showed the validation of the model for Chittagong division and whole Bangladesh. It seems that models work with 90-95% accuracy.

For dengue we could not develop equation for monitoring the disease since the data sample was limited.

The risk free of contracting vector-borne diseases in endemic areas will get investment, both internal and external, and affect individual and household decision making in many ways that have a positive impact on economic productivity and growth.

The result of this study showed that AVHRR-based vegetation health indices (VCI and TCI) could be used as a proxy for analysis and numerical estimation of number of malaria cases in entire Bangladesh and for all divisions. However, these estimation and analysis are limited to certain period of the year and should not be used for all seasons.

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