

APPLICATION OF AVHRR-BASED ON THE VEGETATION HEALTH INDICES FOR MALARIA VECTOR DETECTION

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Abstract

In this study, we discuss a technique to determine the correlation between various environmental factors affecting malaria transmission and the possibility for application of remote sensing data as a proxy for monitoring the number of malaria cases. The specific area of study in Bangladesh represented 60 to 80 percent of the entire country's malaria cases. Malaria statistics, satellite data and meteorological data were used in this study. Remote sensing data consisted of Vegetation Health Index (VHI), Vegetation Condition Index (VCI) and Temperature Condition Index (TCI) derived from radiances, measured by the Advanced Very High Resolution Radiometer (AVHRR) flown on NOAA afternoon polar orbiting satellites. The investigation of factors contributing to malaria transmission was performed using correlation and regression analysis. The goal was to investigate whether vegetation health indices can be used for detection, surveillance and numerical estimate of malaria development. Regarding the seasonal dynamics, it should be emphasized that during cooler months (January–April) when mosquitoes are less active, the correlation is low. After April (week 16) when mosquito activity season starts, the correlation increases, quickly reaching maximum (0.6 for TCI and -0.5 for VCI) around week 25 (end of June). We can use satellite data to predict malaria outbreak regions globally in advance and that data allows for life-saving early intervention.

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 heart-worm and yellow fever. Among the aforementioned, malaria is the most widely spread, creating a global problem. These diseases are pandemic across many countries, infect millions of people every year, and are a leading cause of morbidity and mortality. Presently, vaccines and effective drug treatment for malaria are limited by the development of drug-resistant pathogen strains. Due to these issues, public health interventions must target the mosquito vector. The *Anopheles* mosquitoes that transmit malaria un-

der specific large-scale environmental conditions of temperature, humidity and standing water that vary somewhat by mosquito species and strain. Vector-borne diseases are spread by mosquitoes that create different types of epidemics, and some of the following are regarded as contributing factors to those epidemics: living conditions of people, climates and landscapes. The type of standing water in which the mosquito chooses to lay eggs depends on 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, saucers, plastic covers or tarpaulins. Some of the potentially dangerous mosquito species, such as the Asian tiger mosquito, come from these sites. Wet and warm weather normally stimulate mosquito multiplication and trigger an increase in the number of people bitten by mosquitoes, which is potentially favorable for the development of epidemics.

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) provides 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. 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 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.

We aim to develop the capability to monitor and predict the occurrence of favorable environmental conditions that promote malaria or dengue fever transmission using observations from earth-monitoring satellites. We wish to rely on remote sensing as much as possible because it provides regular coverage in space and time, which is particularly important in areas where ground-based weather and hydrological monitoring stations are sparse. As well, remote sensing of attributes that exercise a persistent influence on regional weather patterns, such as sea surface temperatures, snowpack, and soil moisture, offer the possibility of predicting the development or persistence of environmental conditions that promote malaria or dengue fever transmission weeks to months in advance. In this paper, we focus on malaria and dengue fever in Bangladesh, a country where we conducted studies on the relationship between remotely sensed indices and malaria and urban dengue epidemics. The risk mapping system developed will guide interventions, including vector control, prevention of transmission (e.g. through mosquito netting), and treatment efforts. We expect that the techniques we develop for integrating different remote sensing products (in a GIS framework) to create an outbreak warning system based on epidemiological data will be readily extendable to create analogous monitoring and early warning systems for waterborne diseases, food shortages, and other hazards that are strongly affected by environmental conditions; proxy to study climate change, epidemic analysis, drought prediction and similar applications.

Study Area

Bangladesh is located in a tropical region in Southeast Asia and lies between 20°34' and 26°38' north latitude, and 88°01' and 92°41' east longitude. Bangladesh has its borders, on all sides but south, 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 [1]. Bangladesh has 64 districts and 6 administrative divisions: Barisal, Chittagong, Dhaka, Khulna, Rajshahi and Sylhet (Figure 1). It has a population of 88 million with a population density of 868 persons per square kilometers. Eighty percent of the total population lives in a rural area. Bangladesh is mainly comprised of low, mostly flat alluvial plain; it's hilly in the southeast, intersected by numerous rivers and rivulets, canals, swamps and marshy lands. Nearly two-thirds of the people in Bang-

ladesh are employed in the agricultural sector, with rice as the single most important product. Natural resources found there are natural gas, arable land, timber and coal.

In Bangladesh, the malaria parasite (plasmodium) is transmitted by female Anopheles mosquitoes. Among the 15 species, *Anopheles Dirus* (AD) is widely spread in the southeast of Asia [8]. Breeding habitats of AD can be puddles on footpaths and turbulence pits at the heads of drainage gullies, which are able to hold water for some time without supplemental rainfall.

Mosquitoes transmit malaria year around. However during the cooler season (November-March) mosquitoes are less active and the malaria cases are few. This number increases considerably during warm and wet seasons. Malaria is transmitted by an adult infected female, which bites in order to get human blood for laying eggs. A mosquito-hatching period from egg to the adult stage is 7-15 days, and the incubation period for development of malaria after being bitten by an infected mosquito 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 to five cycles of malaria transmission may occur. After laying eggs, larvae appear 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. The distribution of malaria cases in Bangladesh in 1994 is shown in Figure 1.

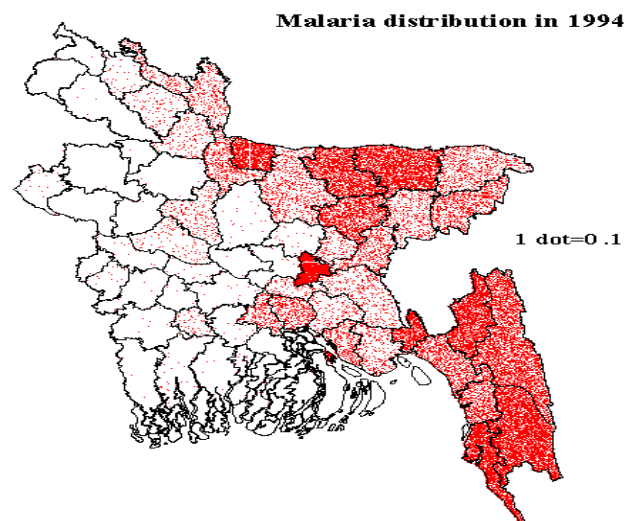


Figure 1. Geographical Map Of Bangladesh With The Area Study (Malaria Distribution Area)

Methodology

The percentage of malaria cases for Bangladesh per division for 1992-2001 from DG Health of Bangladesh is shown in Table 1.

Table 1 shows that Countrywide, between 1998 and 2001 a general increase in the number of reported cases by four to five percent. This increase can be explained in two ways: one, the government adopted a new program “Essential Services Package” for fighting malaria and vector-borne diseases, and two, most importantly, is the reoccurrence of malaria outbreaks along the border area [8]. The positive cases increased in the Chittagong, Khulna and Rajshahi division, which are the border areas and mostly forest covered.

Three data types were used in this study: malaria statistics, satellite data, and meteorological data. 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 in Bangladesh. The data were aggregated by local administrative unit health centers and district level. These data included the number of people tested and the number of positive malaria cases. In this study, the latter was expressed in percentages of the former.

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 a 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 (emanating from fluctuating transmission of atmosphere, sun/sensor geometry, bi-directional reflectance, random noise, 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 cycles in NDVI and BT become evident. Climatology of NDVI and BT was approximated by multi-year maximum (MAX) and minimum (MIN) values taken from smoothed data [2, 3]. The MAX and MIN for each pixel and week were calculated from twelve years of historical data described in Kogan (2001) [7]. The 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 eco-

system’s “carrying capacity” [4, 5]. 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) [6, 10, 11].

$$VCI = 100 * (NDVI - NDVI_{min}) / (NDVI_{max} - NDVI_{min}) \quad (1)$$

$$TCI = 100 * (BT_{max} - BT) / (BT_{max} - BT_{min}) \quad (2)$$

$$VHI = a * VCI + (1 - a) * TCI \quad (3)$$

Where NDVI, NDVI_{max}, and NDVI_{min} (BT, BT_{max}, and BT_{min}) 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 [7]. 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 0 then conditions are deteriorating, indicating vegetation stress. On the opposite side of the scale, the conditions are estimated as favorable.

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 1992-2001. Meteorological parameters (T, R and H) were expressed as a deviation from mean value during 1992-2001 (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.

Results and Discussion

The malaria parasite (plasmodium) in coastal divisions is transmitted by female Anopheles mosquitoes. The Chittagong division has 60-80 percent of all malaria cases in Bangladesh. Breeding habitats of AD are puddles on footpaths 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) mosquitoes are less active and malaria cases are few. This number increases considerably during warm and wet seasons. Malaria cases of coastal divisions are shown in Table 1.

Figure 2 shows annual percent of malaria cases in coastal division during 1992-2001. As shown, malaria was on the rise during the 1990s. Although the Government of Bangla-

desh made efforts to eradicate malaria, the number of cases in Chittagong division was growing which is associated with

Table 1 Malaria Statistics Of Coastal Divisions 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

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 ratio (equation 2) of actual cases to the cases estimated from the trend.

$$Y_{\text{trend}} = a + b * \text{Year} \quad (4)$$

$$DY = (Y / Y_{\text{trend}}) * 100 \quad (5)$$

Where, Y_{trend} is the percent of malaria cases for weather conditions near normal; Y is % of malaria cases; Year is the year number; a is the intercept; b is the slope; DY is the de-

viation from the trend expressed in percentages. Intercepts and slopes for these divisions are shown in Table 2.

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

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

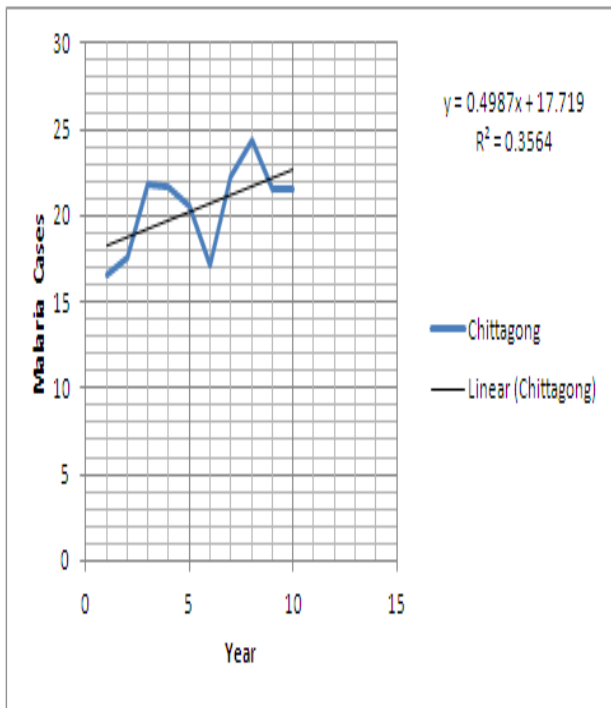


Figure 2 (a). Annual Malaria Cases In Coastal Division Chittagong And Trendline , 1992-2001

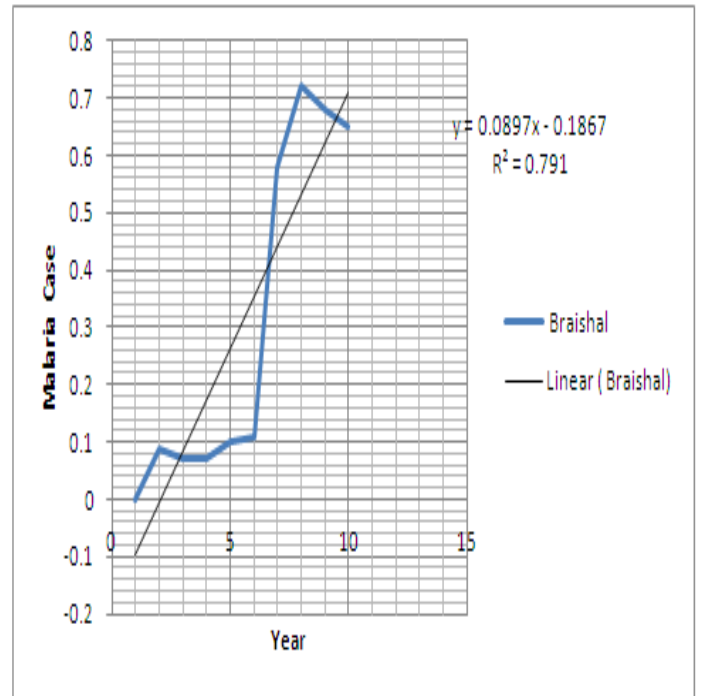


Figure 2 (b). Annual Malaria Cases In Coastal Division Barishal And Trendline , 1992-2001

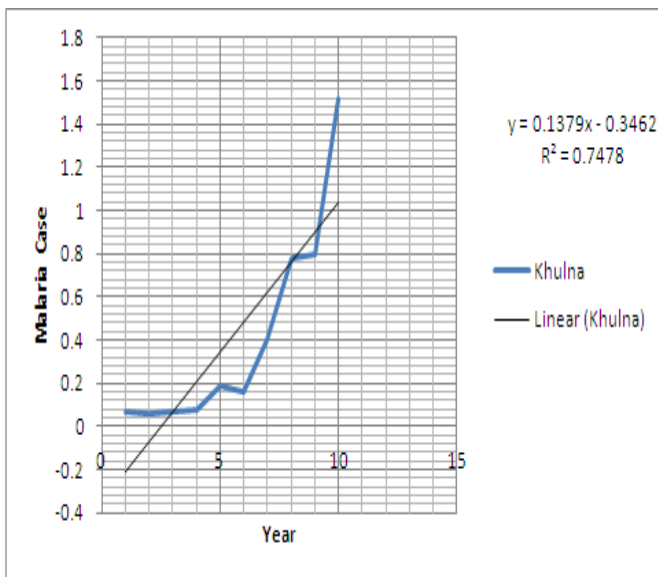


Figure 2 (c). Annual Malaria Cases In Coastal Division Khulna And Trendline , 1992-2001

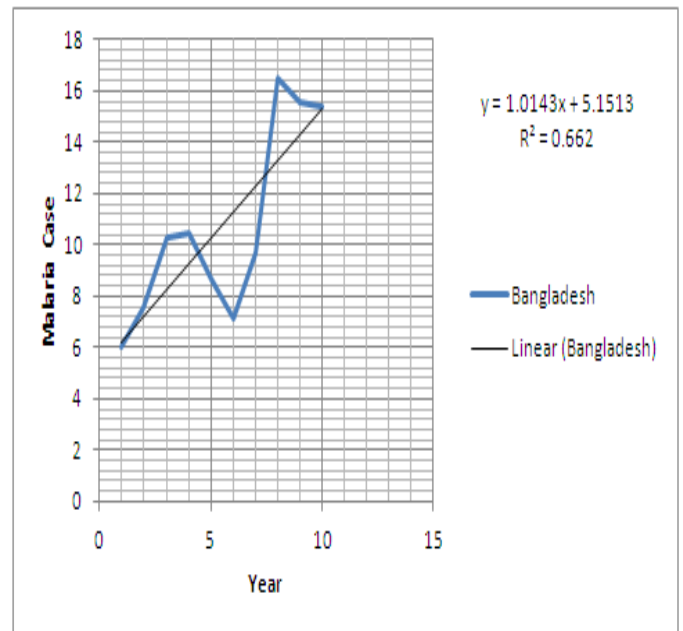


Figure 3. Annual Malaria Cases In All Of Bangladesh And Trend Line, 1992-2001

Table 2. Intercepts And Slopes For Coastal Divisions

Division	Intercept(a)	Slope(b)
Chittagong	18.65	0.50
Khulna	-0.35	0.14
Barisal	-0.18	0.089
Bangladesh	5.153	1.014

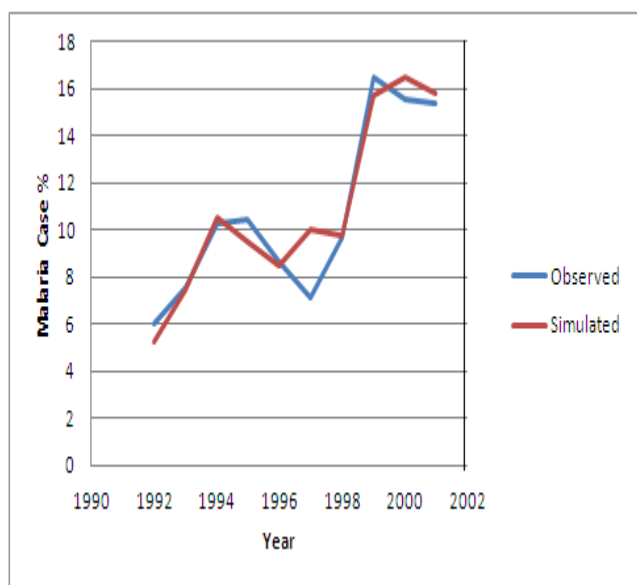


Figure 4. Simulated And Observed Malaria Cases For All Of Bangladesh

Statistical analysis for all of Bangladesh

Figure 4 shows the modeled and observed percent of malaria cases for 10 years. In general, for each year, the simulated percent of malaria cases differs 1-2% with those of observed percents, except for the year of 1997. This provides additional qualitative evidence that the model will be able to effectively predict the percent of malaria cases.

Conclusions

Malaria and dengue fever affect the health and wealth of nations and individuals alike. Malaria and dengue fever are understood to be both diseases of poverty and causes of poverty, have significant measurable direct and indirect costs, and have been shown to be major constraints to economic development. Annual economic growth tends to rise when the risk of vector-borne diseases is low. Public expenditures include spending by government on maintaining health facil-

ities and health care infrastructure, publicly managed vector control, education and research. Mosquitoes in Bangladesh, 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. Throughout the cooler season mosquitoes are less active and the number of malaria cases are few. These numbers increase considerably during the warm and wet season. From Table 2 administrative divisions malaria is developed in the coastal zone (Chittagong, Khulna, Barisal). In mountain plain areas malaria is much less prevalent due to climate. Our research in the coastal division's mosquito activity season starts at the end of April (week 16) when the correlation between number of malaria cases and VHI increases. In the case of dengue fever we could not develop an equation for monitoring the disease since the data sample was limited. The decline in risk of contracting vector-borne diseases in endemic areas should get investment, both internally and externally, and will 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 could be used as a proxy for analysis and numerical estimation of the number of malaria cases in all of Bangladesh and for all divisions. However, these estimations and analyses are limited to certain time periods of the year and should not be used for all seasons.

Acknowledgments

The authors are appreciative to IJRSG Journal for the support to develop this paper.

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