STUDY OF POTENTIAL RISK OF DENGUE DISEASE OUTBREAK IN SRI LANKA USING GIS AND STATISTICAL MODELLING

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ABSTRACT

Objectives: The increasing incidence of dengue fever has become a priority health issue for Sri Lanka. Recent dengue outbreaks in Sri Lanka show two trends: yearly increase of total number of dengue incidence and increasing dengue outbreaks outside the endemic urbanised areas in the south and the west. Identification of factors responsible for dengue outbreaks and the mapping of potential risk areas in Sri Lanka are long overdue. This study examines the association between weekly rainfall patterns and dengue outbreaks in the western province between 2000 and 2004. **Methods:** The study develops a model to quantitatively assess the relationship between rainfall and dengue outbreaks and then evaluate the suitability of the model for predicting dengue outbreaks. A power regression model was constructed using rainfall and dengue incidence data. The Inverse Distance Weighted (IDW) interpolator and Geographic Information System (GIS) techniques were used in mapping the spatial distribution of dengue risk surfaces. **Results:** The results show that there is a strong correlation between dengue outbreaks and rainfall for majority of the towns studied. An error analysis was conducted to assess the validity of the model comparing model outputs and actual outbreaks. The analysis shows that the error component for selected cases is within a single outbreak. **Conclusions:** The ability to predict dengue outbreaks and mapping the spatial patterns facilitates dengue surveillance and monitoring.

KEY WORDS: Dengue; Sri Lanka; Vector-borne Disease; GIS; *Aedes aegypti;* Risk Mapping

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INTRODUCTION

The control of vector-borne diseases presents a major challenge to global health officials. According to the World Health Organization, every year hundreds of millions people suffer from malaria, dengue fever, yellow fever and Japanese encephalitis (WHO, 2005). Geographically, the majority of these diseases have been closely associated with tropical and subtropical climatic regions (Khasnis and Nettleman, 2005). Global warming may expand the areas suitable for mosquito habitats thus, increasing the number of dengue transmissions. This predicted increase is the most pronounced at the borders of the endemic areas and at higher altitudes (CDC, 2005). During the recent years, a significant rise in the number of dengue cases were reported in some geographic regions (outbreak), particularly in tropical Africa, Central America and Asia. Expansion within the countries as well as new dengue outbreaks in other parts of the world have been receiving considerable attention by international bodies (Tabachnick and Powell,1979; CDC, 2005) as well as in epidemiological research fields (Canyon, 2001; Martens, 1998). In addition to climatic factors, it is apparent now with the changes of other global drivers such as pollution, land use patterns, urbanization and human mobility, the vector-borne diseases, (e.g., dengue) are spreading outside humid tropical and sub-tropical urban centres where dengue was commonly found (Hay *et al.,* 2002; Jacobs *et al*., 2005; Sutherst, 2004). According to the WHO, some 2500 million people are now at risk of dengue which is about 2/5 of world population (WHO, 2002). Unfortunately, there is no vaccine currently available to prevent dengue infection. However, pain relievers such as paracetamol and anti-nausea medications are commonly being used with patients.

In recent years, investigation of vector-borne disease has received increased interest together with new concern about climate change and the availability of a variety of research tools. Spatial information techniques such as Geographic Information Systems (GIS), remote sensing and spatial statistics not only allow researchers to identify and model these disease patterns but also to help examine the association between climate, climate variability and vector-borne diseases. (Alto and Juliano, 2001; Kolivras, 2006; Napier, 2003). However, applications of these techniques to study dengue are still limited to few studies and geographically limited to Africa or Central and South America.

Since the end of last decade, dengue has been a serious threat to public health authorities in Sri Lanka. There were two important trends related to dengue outbreaks in Sri Lanka: the total number of reported dengue cases was significantly increased, and dengue started to appear in the districts outside the western province. In response to public and political concern, a dengue task force has been established and a several control strategies were identified (Kulatilaka and Jayakuru, 1998). One of the tasks has been the use of modern spatial information technologies such as Geographical Information Systems and remote sensing to improve the monitoring and surveillance, understanding the control factors and explore potentials of predicting disease outbreaks (Weekly Reports, Epidemiological Unit, 2005). This study examines the weekly rainfall patterns and dengue outbreaks in the western

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province of Sri Lanka between 2000 and 2004. Specifically, this research attempts to answer three questions:

- What is the association between rainfall variability and dengue outbreaks in the western province of Sri Lanka?
- How do we model the association between spatial and temporal patterns of rainfall and dengue to predict the outbreaks?
- What are the potential risk areas for dengue outbreaks?

The model developed in this study quantitatively assesses the relationship between rainfall and dengue outbreaks and then evaluate the suitability of the model for predicting dengue outbreaks incorporating GIS and spatial statistical techniques. Understanding the patterns of current and potential dengue transmissions will assist monitoring the disease and surveillance efforts by the relevant authorities.

BACKGROUND

The dengue mosquito's habitats vary according to man's habitats (Harrison *et al.,* 1972; Kay *et al.,* 1995; Kemp and Jupp, 1991; Strickman and Kittayapong, 2002). Urban areas appeared to be favourable for mosquitoes with a abundance supply of plastic water containers, discarded bottles, tins, tyres, water coolers, house plants, air conditioners, used tyres and places where rain-water collects or stored (Biswas *et al.,* 1993) providing ideal breeding grounds for mosquitoes. Recent tsunami has also created a plenty of mosquito breeding grounds in the rainfall-filled containers and blocked drainages in the rubbles in the affected areas.

First known reported case of dengue virus in Sri Lanka goes back to the middle of the last century. The presence of virus was serologically confirmed in 1962 (Kulatilake and Jayakuru, 1998). Both *Aedes aegypti* and *Aedes Albopictus* which are common dengue transmitting vectors are also found in Sri Lanka (Jatanasen, 1993). Before 1989, dengue hemorrhagic fever (DHF) was common in Southeast Asia but rare in the Indian subcontinent, particularly in Sri Lanka. The situation had changed by the end of 1980s with the reporting of 200 cases of DHF around greater Colombo area (Messer *et al*., 2002). There was a sharp increase of dengue cases since 1990s, with 656 cases in 1992 and 15933 in 2005 (Quarterly Reports, Ministry of Health, Sri Lanka, 2006).

Dengue incidence pattern in Sri Lanka is appeared to be closely related to population increase. Earlier, the disease was mainly restricted to urban and semi-urban areas of the country. However, over the years dengue is spreading to rural areas, may be due to population movement through transport development, economic activities and the changes in climatic factors. Recent outbreaks of dengue have concerned the authorities to act by collecting comprehensive epidemiological data and developing control strategies (Epidemiological Unit, 2005).

Currently both dengue fever (DF) and dengue hemorrhagic fever (DHF) are endemic in Sri Lanka. As no immunization against dengue virus has been developed, vector control has been identified as the best approach to address the problem (Weekly Reports, Epidemiological Unit, 2005). A national Dengue Control Program was setup at provincial and district levels in 1998. Training in clinical management, surveillance and diagnoses were emphasized to reduce morbidity and mortality due to DF and DHF. The control strategies introduced to include: 1) Surveillance: (a) Disease surveillance; (b) Vector surveillance; and (c) Laboratory active surveillance; 2) Vector control; 3) Social mobilization; 4) Clinical management of DF/DHF cases, and 5) Emergency response. To coordinate all these activities, a dengue task force has been established at the national level (Weekly Health Bulletin, Ministry of Health, 2002).

Even though there have been a wealth of information on malaria in Sri Lanka, there is only a handful of studies conducted on dengue. The published studies were mainly limited to examining clinical and epidemiological characteristics of dengue and dengue transmission (Jatanasen, 1993; Kularatne *et al*., 2005; Kulatilaka and Jayakuru, 1998; Messser *et al*., 2002). There were no known studies that have used spatial statistics, GIS and remote sensing which can be applied to understanding the spatial patterns of dengue transmission incidents and to evaluate statistical models for prediction of dengue outbreaks.

GEOGRAPHICAL INFORMATION SYSTEMS AND RISK MAPPING

Spread of many diseases within a population characterises a spatial component. Spatial analysis tools such as GIS and spatial statistics enable epidemiologists to address the spatial distribution and to predict the outbreaks of diseases more accurately (Chaput *et al.,* 2002). Recently, there has been a keen interest in mapping vector-borne diseases such as malaria and dengue using GIS and remote sensing techniques (Arlinghaus, 1996; Brooker *et al*., 2004; Carbajo *et al*., 2001; Connor *et al*., 1998; Jones *et al*., 2003; Kolivras, 2006; Liu *et al*., 2003; Martin *et al*., 2002; Ross, 2003). Such maps would make it possible to plan control measures in high-risk areas and greatly increase the cost efficiency of these control programs. These spatial information techniques can be effective tools in dengue monitoring and surveillance contributing to fill the gaps in the current understanding of disease distribution. In this research, GIS and remote sensing techniques are used to map the spatial distribution of dengue incidence and potential risk areas. Dengue risk mapping in this work involves analysis of dengue incidences, population at risk (under 18 years) and their relationships to particular geographical environments.

METHODS

STUDY AREA

Sri Lanka is primarily a tropical country with high humidity and warm temperature through out the year. Sri Lanka gets rainfall mainly from two rainy seasons: southwest Monsoon (May to August) and northeast Monsoon (November to February). Spatial variation of rainfall is high from southwest (wet zone) to southeast and to northeast (dry zone). In the wet zone, annual rainfall varies between 2540 mm to over 5080 mm while in the northeast and southeast, it comes below 1250 mm. Nearly one quarter of the island is in the "Wet Zone" which includes the densely populated western province. The mean temperature ranges from a low of 15.8˚ C in Nuwara Eliya in the Central Highlands to a high of 29˚ C in Trincomalee on the northeast coast (where temperature may reach 37˚ C). The average yearly temperature for the country ranges between 26° C to 28° C and the day and night temperatures may vary by 4° C to 7°

C. Most of the island's surface consists of plains between 30 and 200 meters above sea level. In the southwest, ridges and valleys rise gradually to merge with the Central Highlands, giving a dissected appearance to the plain. A coastal belt is about thirty meters above sea level surrounding the island. Much of the coast consists of scenic sandy beaches indented by coastal lagoons.

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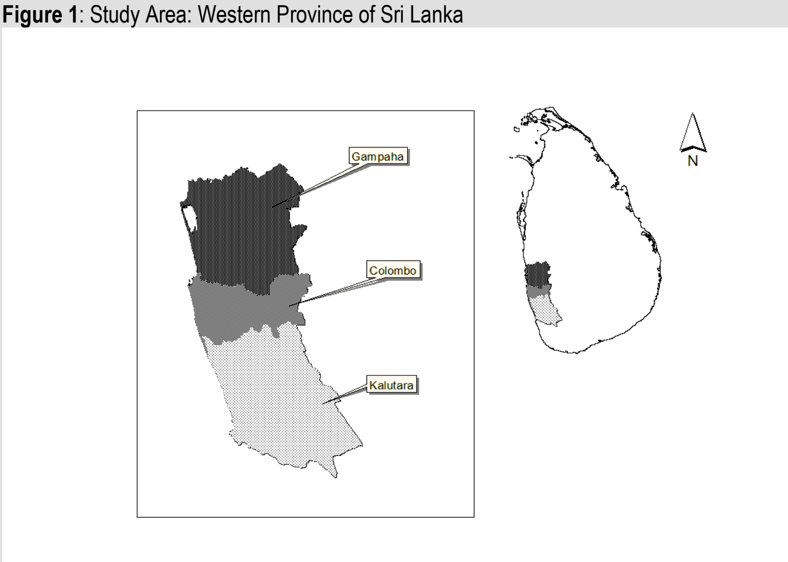
The study was conducted in the western province of Sri Lanka where there is a marked increase of dengue cases evidenced during the last few years (Table 1). Western province is the most urbanized and densely populated region of Sri Lanka and has a number of urban centres including Colombo, the capital (Figure 1). The numbers of dengue cases were determined as the infected patients sought treatment at government and private medical facilities in these districts.

Table 1: Dengue Transmission Incidents in the Western Province of Sri Lanka

Districts	2000	2001	2002	2003	2004
Gampaha	1005	1310	1466	828	3030
Colombo	1255	1470	1915	989	3434
Kalutara	143	203	592	287	1178

Source: Epidemiological Unit, Ministry of Health, Colombo, Sri Lanka

Figure 1: Study Area: Western Province of Sri Lanka



DATA

Collection of *Ae. aegypti* data, population and environmental data were carried out in December 2004 and 2005 during first author's visits to the study area. Weekly dengue fever and DHF data for divisional sections of the 3 districts in the western province were collected from the Epidemiology Unit, Colombo. In addition, the Island wide dengue transmission data were obtained from the Weekly and Quarterly Epidemiological Reports of the Epidemiology Unit, Ministry of Health, Sri Lanka.

Daily rainfall and temperature data were acquired from the Department of Meteorology, Colombo. Population data and demographic characteristics were obtained from the Census Department, Colombo, Sri Lanka.

MAPPING SPATIAL DISTRIBUTIONS

Mapping spatial distribution of dengue cases and potential risk areas requires converting points into surfaces. The inverse distance weighted (IDW) interpolation techniques is commonly used in GIS programs for producing surfaces using interpolation of scatter points such as rainfall point data and dengue transmission incidents. The technique is based on the assumption that the interpolating surface should be influenced mostly by the nearby points and less by the more distant points (Fisher *et al.,* 1987). The interpolated surface is a weighted average of the scatter points and has commonly been applied to climate data (Legates and Willmott, 1990; Woodruff *et al.*, 2006). In this research, the simplest form of inverse distance weighted interpolation (Shepard's method) is used to produce surfaces from rainfall and dengue cases. The interpolated values at point (*x, y*), are

$F(x, y) = \sum_{i=1}^{n} w_i f_i$, where n is the number of scatter points in the set, f_i are the prescribed function values at the scatter points, and w_i are the weight functions assigned to each scatter point. The weight function at ith index is:

$w_i = h_i^{-p} \Big/ \sum_{j=1}^{n} h_j^{-p}$, where p is an arbitrary positive real number (power parameter) and h_i is the distance from the scatter point to the interpolation point.

To produce spatial distribution of dengue cases in the western province, Geographical Information Systems (GIS) techniques were used to register the maps of dengue incidence with topographical information at divisional administrative unit level. Rainfall and dengue data interpolations were carried out using IDW technique in ArcView/ArcGIS.

ASSOCIATION BETWEEN RAINFALL AND DENGUE INCIDENCE

A relation between the rainfall and disease outbreaks is long being suspected (Curriero *et al.,* 2001; Rose *et al.,* 2000; Thammapalo *et al.,* 2005). In this research, a mathematical model has been established to ascertain either rainfall or disease outbreak in terms of other available data to predict the possible future scenarios from the model. Other parameters that could possibly hinder this model have also been investigated.

First, the weekly (52 weeks) rainfall and disease data for all district sites including Colombo, Sri Lanka for years from 2000 to 2004 has been averaged out. The data for all districts have been statistically analysed to obtain regression models for the data. The data obtained for Colombo, Sri Lanka has been used in the model development as it has the highest number and a rate of increase of dengue cases over the study period.

Urban population, demographic characteristics, dengue incidences and land cover/land use data were used to produce potential dengue risk maps. Land cover/land use data have been derived from Landsat 7 ETM satellite data using the maximum likelihood supervised classification technique. All satellite data sets were geometrically corrected and registered to other GIS data layers.

The weekly averages of dengue and rainfall data have been plotted. Figure 2 shows the line graph obtained for these two averages.

The patterns of annual average rainfall reported for 52 weeks were nearly periodic and compared closely with the periodicity of disease outbreaks. As far as rainfall is concerned, there seems to be a tremendous fluctuation of weekly rainfall data. The data needs to be graduated (smoothened) for further analysis. There are various forms of graduations available for seasonal data (London, 1985). First, let D and R be disease outbreak and rainfall data, respectively. The two consecutive weekly rainfall data obtained for each district has been averaged out three times repeatedly, that is,

$$R_i^{(j+1)} = \frac{R_i^{(j)} + R_{i+1}^{(j)}}{2},\ j = 1, 2, 3.$$

As a result, we lost some weekly data from the beginning of the data set, thus resulting in a shifted feature of data as reflected from its line graph. Finally, they were inversely rescaled using the averages of these data sets, that is,

$$y = \left(\frac{\sum_i R_i^{(j)}}{\sum_i D_i} \right) \frac{1}{R_i^{(j+1)}}.$$

This produces the line graph in Figure 3. The purpose of Figures 2 and 3 is to see whether there is any periodic pattern as to the rainfall and disease outbreak for ongoing analysis. They were helpful in the determination of the regression model.

Figure 2: Five Year Averages of Weekly Disease Outbreaks and Dengue Data.

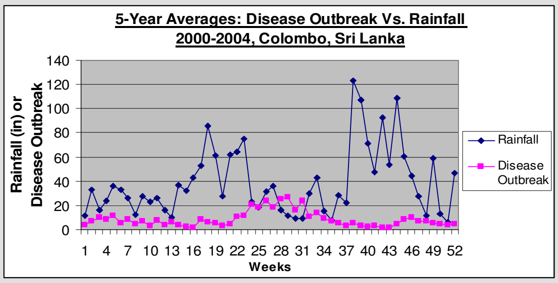


Figure 3: Graduated Inversely Related Scaled Rainfall and Disease Outbreaks.

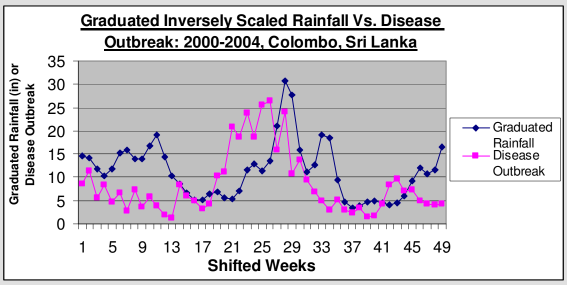


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Figure 3 shows that the graduated rainfall data with the appropriate shift maintains nearly equal periodicity as that of the outbreak. Therefore, with the appropriate shift, the graduated rainfall data can be used to predict the disease outbreak suggesting that there is an inverse relationship among weekly rainfall and disease outbreak obtained in Colombo, Sri Lanka according to the 2000-2004 data available. This paves the way to realize that there might be some inverse proportionality among the appropriate variables; one includes either difference or quotient of variables. Borrowing the proceeding remark, we compute the quotient of disease outbreak/rainfall to plot it against the corresponding rainfall. The scatter plot in Figure 4 provides evidence for a power model with a strong power correlation coefficient.

Let x be the quotient of disease outbreak and rainfall and let y be the rainfall. Then, according to this power model,

Rainfall = 13.588 $\times$ (Disease/Rainfall) $^{-0.5018}$

thus, leading to an expression for a number of disease outbreak in terms of rainfall. In other words, the number of outbreak can be computed from average rainfall and vice versa. The correlation coefficient for this proposed power model regression analysis is very high giving a strong correlation of the quantities involved (r^2 = 0.6362, or r = 0.7976).

A mathematical model for weekly rainfall vs. dengue disease outbreaks in Colombo, Sri Lanka needs to be determined. From this model, we have

$$R = 13.588\left(D/R\right)^{-0.5018}$$

$$\log R = \log(13.588) - 0.5018\{\log D - \log R\}$$

$$\log R = \log(13.588) - 0.5018\log D + 0.5018\log R$$

$$(1 - 0.5018)\log R = \log(13.588) - 0.5018\log D$$

$$R = e^{(1/0.4982)\{\log(13.588) - 0.5018\log D\}} \text{ or}$$

$$R = 188.1479\, D^{-1.0072}.$$

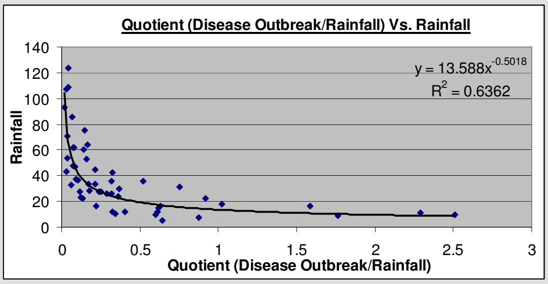
This provides an estimate for rainfall in terms of number of outbreaks. Similarly, a formula can be derived to find a number of outbreaks from rainfall in a given week or month. That is,

$$D = e^{(1/0.5018)\{\log(13.588) - 0.4982\log R\}} \text{, or}$$

$$D = 181.2098\, R^{-0.9928}.$$

This study also helps to estimate the dengue outbreaks over an extended period. However, continuous revision of the model can be sought periodically.

Figure 4: Quotient of Disease Outbreaks and Rainfall



RESULTS

A set of selected weekly rainfall data has been used to determine the number of outbreaks from the power model using the rainfall data reported from Colombo, Sri Lanka. They are compared with the actual number of outbreaks to determine the validity of the model. The error in all of these cases is less than a single outbreak as obtained in Table 2. Some rainfall data obviously do not agree with this model. The factors such as a large family environment, poverty, a lack of proper preventive care facilities, difficulty to diagnose the disease in time, unsafe drinking water, a lack of proper sanitation conditions and other situations similar to the above certainly affect this model causing disagreement between rainfall and the model.

Similar analyses have also been carried out for other towns, namely, Gampaha, Moratuwa, Horana, Kalutara, and Bandaragama. Their statistical findings are as appear in Table 3. From Table 3 we conclude that the power model regression analysis is the best suited for the models dealing with the weekly rainfall and disease outbreak data.

Table 2: Number of Observed Outbreaks versus Predicted Outbreaks

Week	Number of outbreaks	Number of outbreaks predicted from the model
4	8.6	7.8
6	5.6	5.6
9	6.6	6.7
11	7.4	7.1
40	2.4	2.6
41	3.4	3.9
42	1.6	2.0
47	7.0	6.7
52	4.4	4.0

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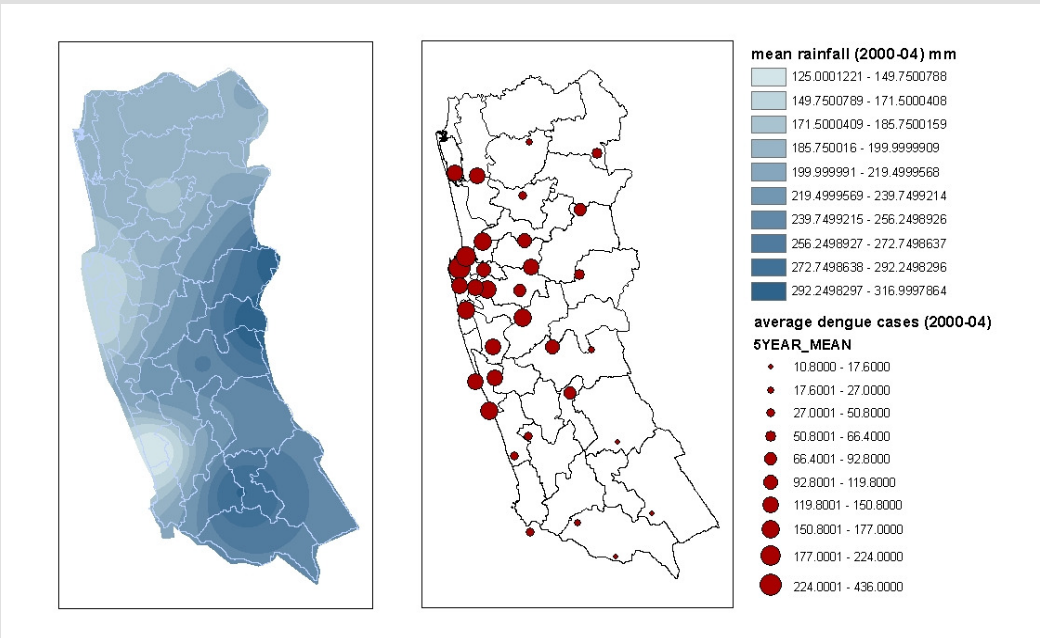
Table 3: Results of the Power Model for Selected Towns

Towns	Proposed regression model for the data	Proposed model equation	Coefficient of Determination (r^2) (Correlation Coefficient r)
Gampaha	Power Model	$R = 7.6265(D/R)^{-0.4788}$ or $D = 0.3780R^{1.4788}$	0.5499 (r = 0.7416)
Colombo	Power Model	$R = 13.5880(D/R)^{-0.5018}$ or $D = 0.2700R^{1.5018}$	0.6362 (r = 0.7976)
Moratuwa	Power Model	$R = 8.3121(D/R)^{-0.5067}$ or $D = 0.3420R^{1.5067}$	0.7718 (r= 0.8785)
Horana	Unable to obtain linear, logarithmic, polynomial of degree 2-6, power, or moving average model for the data	/	/
Kalutara	Exponential Model	$R = 64.633e^{-17.346(D/R)}$ or $D = R\{0.2403 - 0.0577\ln(R)\}$	0.5325 (r = 0.7297)
Bandaragama	Unable to obtain linear, logarithmic, polynomial of degree 2-6, power, or moving average model for the data	/	/

The correlation coefficients (r) for these proposed power model regression analyses for Gampaha, Colombo, Moratuwa, and Kalutara are very high giving a strong power correlation of the quantities involved. Note that in the case of Kalutara, an exponential model is suggested and for Horana and Bandaragama, we were unable to obtain linear, logarithmic, polynomial of degree 2-6, power, or moving average model for the data.

Similar line graph as appeared in Figure 2 has been obtained (Amarakoon *et al.,* 2004) for Caribbean countries. It found a well defined seasonality in the epidemics and concludes that warmer temperatures and less abundance of rainfall appeared to be influencing the epidemics. This study also showed that high dengue incidence is normally associated with the areas with less abundance of rainfall (Figure 5).

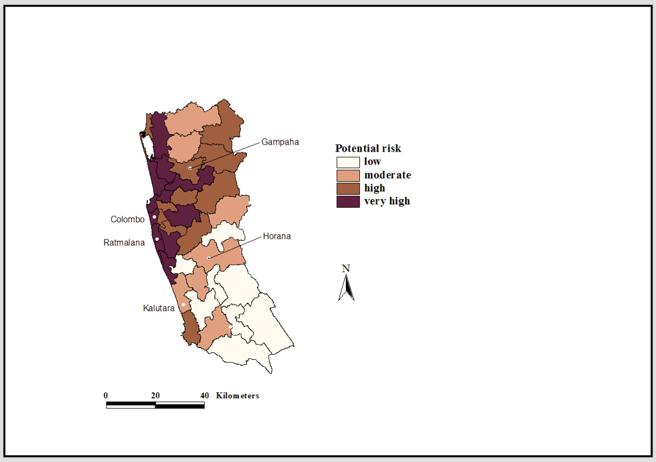
Figure 5: Spatial Distribution of Rainfall and Dengue Incidence: Western Province



Dengue incidence surface maps produced using the IDW interpolation technique shows a number of dengue clusters in the western province over the five-year period. Both dengue and dengue hemorrhagic fever incidence are commonly found among younger population, generally less than 19 years old. Statistical analysis can be done to show that there is a strong positive correlation between dengue incidence and younger population under 18 years.

The high risk age category was superimposed over the spatial distributions of dengue incidence to show that the distribution of population clusters are closely associated with dengue incidence clusters (Figure 6).

Figure 6: Spatial Distribution of Dengue Transmission Risk



DISCUSSION

This study found that temporal distribution of dengue cases was closely associated with the post rainfall period. The relationship was statistically supported by the power regression model established in this study indicating that there is a strong statistical association between dengue and rainfall. Dengue incidences were relatively low during the heavy rainfall and increase when the rainfall started to decrease, showing that about three to four weeks lag time between the rainfall and dengue outbreaks. The outbreaks predicted by the model were clearly related to the actual outbreaks indicating its ability to predict potential outbreaks. The applicability of the model can be further tested with other vector-borne diseases such as malaria and Ross River Fever at different geographical regions in other countries.

The production of the dengue risk map in this study used the spatial distribution of dengue incidence, rainfall and the high risk population category. The spatial distribution of dengue risk shows that dengue incidence is clustered in the north western part of the western province of Sri Lanka, mainly around the urbanized western coastal region of the province (Figure 6). Temperature and relative humidity have been reported as the other major and important climatic factors, which could alone or collectively be responsible for an outbreak (Chakravarti and Kumaria, 2005). However, they were not considered in this study as there have been no significant variations found in the study area.

The advantage of using GIS based methodology is its ability to incorporate diverse data and integrate expert knowledge using statistical techniques such as multi-criteria analysis. Using the GIS-based methodology, the future work can be undertaken to examine the impact of urbanization, climate variability on the changes of mosquito habitats incorporating remote sensing and climatic phenomena such as El Niňo/La Niňa data. More studies in this regard could perhaps reveal the strong correlation between the climatic changes and dengue outbreaks, which would help in making the strategic planning to forecast more accurately any outbreak and to deal with any outbreaks in future well in advance.

CONCLUSIONS

This study identified and mapped spatial distribution of dengue incidence, potential dengue risk based on dengue incidence, land use, high risk population age groups, and developed a model to predict dengue outbreaks analysing the association between rainfall and dengue outbreaks. The methodology developed using GIS, spatial statistics and power regression models have improved the understanding of disease outbreak patterns and its association with climatic changes. We found a temporal and spatial correlation between post rainfall seasons and dengue disease outbreaks for the western province of Sri Lanka based on analysis of climate, population and epidemiology data obtained for the 2000-2004 period. A power regression model was constructed to assess the quantitative statistical relationships between rainfall and dengue transmission. At major urban centres (e.g., Colombo, Gampaha, Moratuwa and Kalutara), the power regression model has closely predicted disease outbreaks using the data. Understanding the spatial and temporal patterns of climate and its impact on human health, particularly outbreaks of vector-borne diseases such as dengue is important in controlling the transmissions of the disease and treat infected population.

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