MATHEMATICAL MODELLING OF DENGUE DYNAMICS AND CLIMATE VARIABILITY IN SRI LANKA

Thiyanga Shamini Talagala

(128912F)

Degree of Master of Science

Department of Mathematics

University of Moratuwa
Sri Lanka

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Declaration of the candidate

I declare that this is my own work and this thesis does not incorporate without acknowledgement any material previously submitted for a Degree or Diploma in any other University or institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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The above candidate has carried out research for the Master's thesis under my supervision.

Signature of the supervisor: Date: 27 - 8 - 2015

Dr. R. S. Lokupitiya

B.Sc. Special (Stat), M.Sc. (Stat.) (USA), Ph.D. (Stat.) (USA)

Head/ Department of Statistics

University of Sri Jayewardenepura

Dedication

This thesis is dedicated to my mother and father who have supported me throughout my studies.

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This thesis would not have come to the conclusion as it is today without the help and support of several people at various stages. All the help I have received has been warmly appreciated.

First and foremost, I would like to express my sincere gratitude to my supervisor Dr. R. S. Lokupitiya, Head/ Department of Statistics, University of Sri Jayewardenepura for his advices regarding my research. His advices and prompt comments on written work were highly valuable. I would like to convey my utmost gratitude to Mr. T. M. J. A Coorey, Coordinator/ MSc in Financial Mathematics, Department of Mathematics, University of Moratuwa and Mr. A. R. Dissanayeka, Senior Lecturer, Department of Mathematics, University of Moratuwa for their valuable guidance.

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It is my parents who are always behind with me, caring about me in every second of my life, whose heartiest love, encouragement, guidance and motivation enables me to build better foundation for my life. Hence certainly my deep appreciation is expressed to my parents for their endless love and caring.

Abstract

Dengue fever (DF) is a life threatening infectious mosquito borne disease that places a heavy burden on public health system in Sri Lanka as well as on most of the tropical countries around the world. Currently, there is no antiviral drug for treatment of DF. The objective of this study is twofold, first is to analyze the epidemic outbreak patterns of dengue cases in 25 districts in Sri Lanka, second is to identify the association between climatic variables and dengue counts in Colombo district where dengue is predominant. Weekly data on dengue cases were obtained between January, 2009 – September, 2014. Temperature (maximum, minimum, mean), precipitation, visibility, humidity, and wind speed were also recorded as weekly averages. Wavelet analyses were used to explore the periodicity of dengue cases. Wavelet coherence was performed to identify the association between dengue and climatic factors. Further, a Poisson regression combined with distributed lag nonlinear model (dlnm) was used to quantify the impact of climatic factors on dengue counts while taking the lag time into account. Change point analysis was performed as a complementary analytic method to identify changes in variance of dengue and climate time series. Dengue dynamics showed multiple periodic patterns (1-8 weeks, 26 weeks and 52 weeks) across twenty five districts which can be divided into two groups based on wavelet cluster analysis. Wavelet coherency revealed a significant non-stationary association between climatic variables and dengue incidence in annual and semi-annual scale. Results of dlnm revealed mean temperature around 25^0C – 26^0C prior to 5 weeks, high precipitation (>30mm), humidity 65% - 75% prior to lag of 10-15 weeks, and high visibility have an harmful impact on increasing relative risk of dengue incidence. These findings can aid the targeting of vector control interventions and planning for dengue vaccine implementation.

Keywords: Dengue, Wavelet Analysis, Climate, Distributed lag nonlinear model, Change point analysis

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LIST of ABBREVIATIONS

CWT – Continuous Wavelet Transformation

DF – Dengue Fever

DHF – Dengue Hemorrhagic Fever

DLNM – Distributed Lag Nonlinear Models

DSS – Dengue Shock Syndrome

GAM – Generalized Additive Models

GAMAR – GAM with Autoregressive terms

GLM – Generalized Linear Models

PELT – Pruned Exact Linear Time

RR – Relative Risk

SARIMA – Seasonal Autoregressive Integrated Moving Average

WER – Weekly Epidemiological Report

WHO – World Health Organization

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CHAPTER 1

INTRODUCTION

1.1 Overview

In this chapter, we provided a brief background of the crucial aspects of climate change and its adverse impact on the dengue dynamic and transmission. This chapter describes the background, objectives and the significance of the study in sections 1.2, 1.3 and 1.4, respectively. Organization of the thesis is summarized in section 1.5.

1.2 Background of the Study

"Small bite – big threat". The theme of World Health Day, 2014 is a timely reminder of the huge harm caused by small creature, called "vectors", such as mosquitoes, ticks, fleas, mites, sand files and freshwater snails. These animals help spread a range of parasitic, viral and bacterial diseases that affect people of all ages across all socio-economic backgrounds. Out of these diseases dengue is the world's most dangerous viral vector-borne disease transmitted via infective female mosquitoes, namely *Aedes aegypti* and *Aedes albopictus* (Alshehri, 2013). The geographic distribution of dengue, both the classical dengue fever (DF) and its more severe form dengue hemorrhagic fever (DHF), has been expanded dramatically in recent decades (Cazelles, Chavez, McMichael, & Hales, 2005). According to current estimates, this disease is now endemic in more than 100 countries in Africa, the Americas, the Eastern Mediterranean, South-east Asia and Western Pacific (Hii, 2013). South-east Asia and the Western Pacific are the most seriously affected (Hii, 2013). Estimates of the World Health Organization (WHO) indicated that up to 100 million people get infected with dengue every year and another 2.5 billion are at risk of getting infected.

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 (Tissera et al., 2011). Currently both dengue fever and dengue hemorrhagic fever are endemic in Sri Lanka. There is a sharp increase in dengue cases since 2009. Transmission takes place all year round with two seasonal peaks extending from December to April and May to October. There are two important trends related to dengue outbreaks in Sri Lanka; the total number of reported dengue cases is significantly increasing, and dengue started to appear in the districts outside the western province. The infection remains a major threat to the community well being because it incurs significant health cost to the society. However, we have a limited understanding of the disease transmission dynamics in Sri Lanka.

Dengue epidemiology, incorporating both DF and DHF, is determined by a complex interaction of climate, physical environment and social factors (Morin, Comrie, & Ernst, 2013). While many factors play a role in the dynamics of dengue transmission and infection, climate variability has been shown to be important in explaining its occurrence, and is considered as a major determinant (Serfling, 1963). Temperature, humidity, and rainfall have been reported to affect the incidence of dengue either through changes in the duration of mosquitoes and parasite life cycles or through influences on human (Hii, 2013). The life cycle takes approximately 1-2 weeks or longer depending on temperature, and availability of water, and other climatic factors. The average life span of an adult mosquito ranges from 2 to 4 weeks (Banu, 2013). A study conducted by Hii et al. (2013) suggested that it is possible for Aedes to live up to approximately 100 days given the optimal environmental condition. Further Aedes can lay eggs on a dry surface and their eggs can withstand complete dryness for several months depending on humidity (Banu, 2013; Hii, 2013). Because of this ability, the eggs can be transported great distances by humans in a wide variety of containers or objects or by wind. These eggs can then be hatch within a short period after being exposed to rain and optimal temperature (Hii, 2013). Although heavy rainfall can potentially flush away immature stage of mosquito, the rainy seasons creates ample number of artificial and natural habitats for Aedes mosquitoes. Heavy rainfall can also increase the mortality rate of adult mosquitoes (An & Rocklov, 2014; Banu, 2013; Hii, 2013).

Even though climate change has a significant impact on the transmission and incidence of dengue fever there is no clear evidence to show that such impact has already occurred in the context of Sri Lanka. To date, there is still no effective vaccine available to control the occurrence and periodic recurrent outbreaks of DF and DHF. In the absence of a vaccine for the prevention and control of dengue fever, eliminating the breeding places of Aedes mosquitoes is still the only effective strategy to interrupt the transmission of the disease. To improve prevention and surveillance, public health officials need to know much more about the patterns of dengue virus transmission and about the climatic factors that underlie these patterns. Dengue prevention and control activities in diseases-endemic setting in Sri Lanka currently rely on targeted spraying of aduticides to reduce vector populations in and around the homes of reported patients. However, this does not provide a quantitative measure or much predictive lead. Therefore, a good understanding of the relationships between climate and dengue cases is needed to facilitate the analyses in the effort to prevent their occurrences.

In light of the biological relationship between climate and transmission potential, in this study, we aimed at estimating the effects of diverse climatic variables, such as temperatures (maximum, minimum, mean), absolute humidity, rainfall, visibility, and wind speed on the transmission of dengue and identifying the lag periods that have significant effect on the dengue incidence. An understanding of seasonal patterns of dengue, and their weather drivers can provide vital information for controlling and eliminating the activities.

In some studies, Generalized Linear Models (GLM) or Generalized Additive Models (GAM) with Poisson distribution was widely used to estimate association between meteorological factors and mortality or disease incidence (Kim, Park, & Cheong, 2012). But GAM/ GLM requires the data to be independent among each individual. Time series data are always autocorrelated, so that it is not proper to fit time series data with GAM or GLM. Moreover, climatic effect on the dengue incidence may be distributed in the days of different time lags and this feature has never been addressed in previous researches (Ma et al., 2013). Therefore, our study has been designed to estimate the effect of diverse climatic variables on the transmission of dengue fever while taking the lag time into account. Furthermore, dengue incidence data show complex nonlinear dynamics with strong seasonality, multiyear oscillations, and nonstationarity (changes in dominant periodic components over time). These features of the data mean that conventional statistical methods may be inadequate (Cazelles et al. 2005). To overcome the above mentioned problems in this thesis, we introduce wavelet analysis, change point analysis and distributed lag nonlinear models.

1.3 Objectives of the Study

The overall aim of this research is to identify epidemiological outbreak pattern of DF/ DHF in each district in Sri Lanka. Furthermore, this study aims to identify and quantify the nonlinear, nonstationary association between climatic factors and dengue counts in Colombo district, the most urbanized and density populated region in Sri Lanka, where dengue is predominant. The specific objectives are to:

1. To identify periodic pattern in dengue counts and how it progress through time and space.
2. To identify districts with similar dengue dynamic pattern.
3. To identify nonstationary association between dengue counts and climate variables
4. To identify the delayed effect of the climate variables on dengue counts.
5. To identify the non-linear association between climates variables and dengue counts.
6. To determine whether there are change-points, where dynamics shifted transmission pattern in dengue and climate variables.

1.4 Significance of the Study

Sri Lanka is primarily a tropical country with high humidity and warm temperature throughout the year forming ideal conditions for multiplication of the Aedes mosquito and the transmission of dengue fever. Even though this has been a great health hazard in Sri Lanka, there are only a handful of studies conducted to identify the association between dengue and climate variability. The published studies were mainly limited to examining the clinical and epidemiological characteristics of dengue (Pathirana, Kawabata, & Goonatilake, 2009).

Furthermore, there were no known studies that have used the lag effect of several climatic variables on dengue transmission incidence in Sri Lanka. To improve dengue prevention and surveillance, public health officials need to know much more about the patterns of dengue virus transmission and about the factors that underlie these patterns. This would allow the implementation of timely preventative measures.

Dengue is widely distributed throughout tropical and subtropical regions of the world and approximalt 50% of world population live in dengue endemic areas. At the same time many hotspots of dengue fever are also tourists' hotspots, for example Phuket, Rio de Janeiro, Sri Lanka etc. As foreign travel to tropical locations becomes more accessible and popular, dengue fever is becoming a big threat to the tourism industry. This has a serious impact for a country in which the tourism sector contributes greater portion to national GDP. Recently, countries such as the UK have issued dengue fever warning for travellers to areas where the disease in endemic. Moreover, according to current estimates, the annual social cost incurred due to dengue is Rs. 7 billion and, the cost to the government for treating a dengue patient in the Intensive Care Unit is about Rs. 50,000-60,000 a day ("Dengue battle", 2014).

The model developed in this study quantitatively assesses the relationship between climatic factors and dengue outbreaks. This provides time for the allocation of resources to interventions such as preparing health care services for increased number of dengue patients and educating populations to eliminate mosquito breeding sites. Further, because of time lags involved in the climate-disease transmission system lagged observed climate variables could provide some predictive lead for forecasting disease epidemics.

The CEO of Appllo Munich Healthcare claimed dengue care is a good entry point to insurance as dengue is understood by all. He argued selling health insurance can be difficult because general public is mostly reluctant to pay a monthly insurance fee for a benefit they would claim only in the case of illness or accident but dengue fever insurance product would help people to taste insurance. Indonesia has already introduced dengue fever insurance to the public. So the results of this study would benefit for both actuaries and policy makers in the field of finance.

Studies on prevalence of dengue are important not only to assess the problem of dengue in a given region, but also to analyses the effectiveness of strategies for primary and secondary prevention as well as its quality and impact. Economic burden of dengue due to hospitalization, mortality and morbidity costs along with opportunity costs of time and productivity losses due to illness far exceed the cost of vector control. Public health systems are already overburdened in many countries. Thus, the results of this study would benefit for optimizing current dengue surveillance and control programmes.

1.5 Outline of the Thesis

This report consists of eight chapters. Chapter 2 presents a systematic review of literature illustrating the nature of the impact of climate change on health, related factors and research studies with statistical modeling approaches related to climate change and health. It also discusses the methodology used by the previous researchers, identifies research gaps and gives recommendations for the future studies. Chapter 3 gives a brief overview of the two data sets used in the research: epidemiology data and climate data. We also describe the study population and coverage area and data management. This chapter further describes statistical approaches especially the wavelet analysis, change point detection and distributed lag nonlinear modeling approach used in the study. We illustrate a brief overview of the theoretical descriptions of the above methods. In chapter 4, we give a brief overview of the two data sets used in the research: Epidemiological data and climate data. Chapter 5 presents the results of wavelet analysis of each district. Results of wavelet cluster analysis and wavelet coherency analysis also present under this chapter. Chapter 6 presents the results of change point analysis. In chapter 7, we present the results of Poisson regression model combined with distributed lag nonlinear model. Chapter 8 concludes the thesis and describes some of the limitations of the research.

CHAPTER 02

LITERATURE REVIEW

2.1 Overview

The first part of this chapter focuses on dengue fever, its epidemiology, the role of climate in the dengue transmission cycle and previous studies linking climate to dengue worldwide. Section 2.3 is a systematic review of the relationship between climatic factors and dengue incidence around the world and some of the modeling techniques that have been used to find the association between climatic variables and dengue incidence. This review will help to identify and highlight the knowledge needed to develop a successful model for dengue risk based on climate information.

2.2 Dengue

Dengue Fever (DF) is a mosquito-borne disease endemic to tropical and subtropical areas, which is transmitted by mosquitoes *Aedes aegypti* and *Aedes albopictus*. *Aedes aegypti* is the principal vector for DF transmission and is a highly domesticated mosquito. The *Aedes albopictus* is the secondary vector of DF. The hot and humidity with moderate rainfall climate in tropical areas forms an ideal condition for them to be active all year around. Dengue exists in 4 distinct serotypes – DENV 1- 4, within which there is considerable genetic variation (Fansiri et al., 2013).

Dengue fever (DF) is characterized by high fever, severe headache, and vomiting and low blood cell count. Dengue fever has the potential of escalating to DHF and dengue Dengue Shock Syndrome (DSS), which are potentially deadly complications (Lam et al., 2013). These are characterized by high fevers, enlargement of the liver and in worse case situations, circulatory failure (Harris et al., 2000). DF transmission is most common in urban areas due to overcrowding, unplanned urbanization and environment pollution. Transmission occurs when a female mosquito bites and sucks blood containing the dengue virus from infected person which then goes through incubation period of approximately 10 days. At this stage the virus is capable of being transferred to a human host when the mosquito probes the skin. After that, the mosquito remains infective for the rest of its life. As there are no specific antiviral medicines treating or vaccines preventing dengue, the only way to control or prevent the disease is through the management of mosquito populations (Lowe et al., 2011).

2.3 Mosquito Lifecycle

Changes in temperature and precipitation have well-defined roles in the transmission cycle and may thus play a role in changing incidence levels (Johansson, Cummings, & Glass, 2009). The life cycle of a mosquito consists of four stages; egg, larva, pupa and adult. Each of these stages can be easily recognized by their special appearance. Figure 2.1 displays the life cycle of the Aedes mosquito. The lifecycle starts by laying eggs on the surface of the water. The pupa and larval states of the mosquito will take place in the water reservoir where a female adult mosquito lays her eggs. On average, a female Aedes mosquito can lay about 300 eggs during her life span (Banu, 2013). A period of about 48 hours is required for the eggs to hatch into larva but under optimal condition the eggs of an Aedes mosquito can hatch into a larva in less than a day(Banu, 2013). The larva then takes about four days to develop into pupa depending on nutrient levels, temperature and water condition. Then after two days adult mosquito will emerge from pupa. Three days after the mosquito has bitten a person takes in blood, it will lay eggs, and cycle begins again. So it is clear Aedes mosquito as a biological creature needs few climatic factors to complete their life cycle. Therefore, a good understanding of the relationships between climate and dengue cases is needed to facilitate the analyses in the effort to prevent their occurrences.

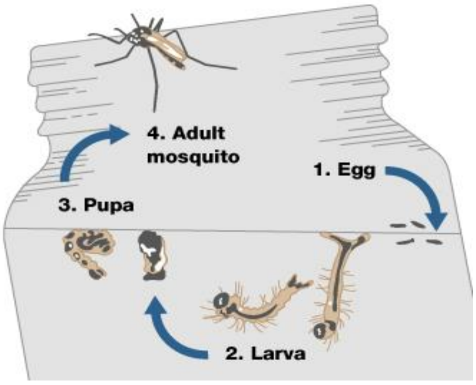


Figure 2.1: Aedes mosquito lifecycle
Source: http://www.nature.com/scitable/topicpage/dengue-transmission-22399758 (assessed on: 1 - 12 - 2014)

2.4 Geographical Distribution of Dengue

Dengue is the most rapidly spreading mosquito-borne viral disease in the world (Alshehri, 2013). The World Health Organization (WHO) ranks dengue among the most important infectious disease with major impact on international public health (Descloux, 2012; Wu et al., 2009). The geographical distribution expanding and the transmission rates are increasing. Today it is estimated that over two fifth (2.5 billion) of the world population live in dengue endemic areas, of whom fifty million are infected annually. Dengue incidence has dramatically increased globally over the last two decades due to population growth, unplanned urbanization, increased travel and transportation of goods, lack of political will and limited resources for implementing effective control measures (Hu, Clements, Williams, & Tong, 2010). The disease is now endemic in more than 100 countries in Africa, the Americas, the Eastern Mediterranean, South-east Asia and Western Pacific (Xiao et al., 2013). South-east Asia and the Western Pacific are the most seriously affected.

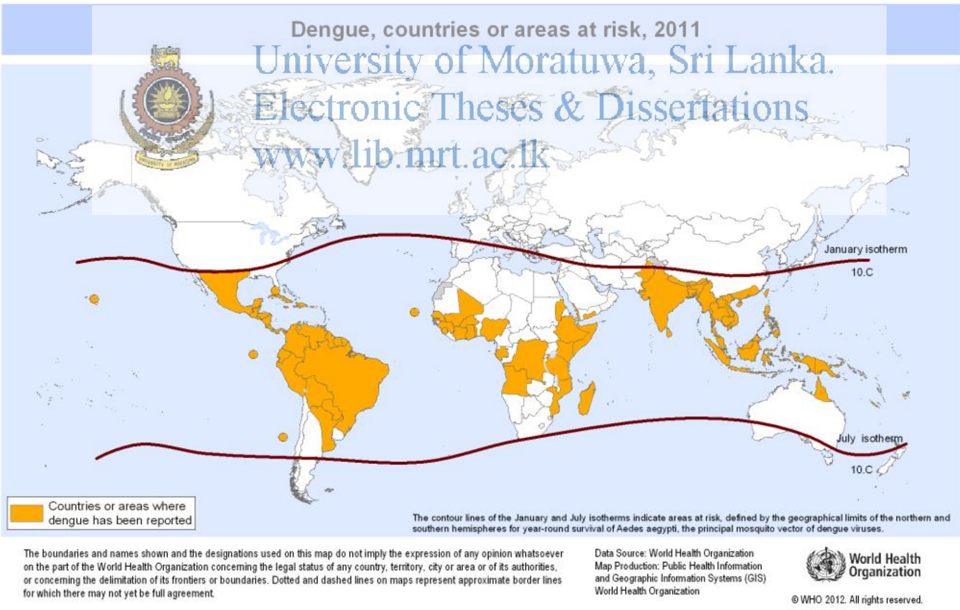


Figure 2.2: Dengue, countries or areas at risk, 2011

Source: http://www.humanosphere.org/2013/08/dengue-fever-spreading-brazil/

(assessed on: 1 – 12- 2014)

2.5 Dengue Epidemiology in Sri Lanka

Sri Lanka has geographic and climatic features that are conducive for the propagation of vectors of dengue fever and its epidemics. All four serotypes of dengue virus have already been identified in Sri Lanka (Messer et al., 2002). Geographical distribution is spreading and transmission rates have increased over the last decades.

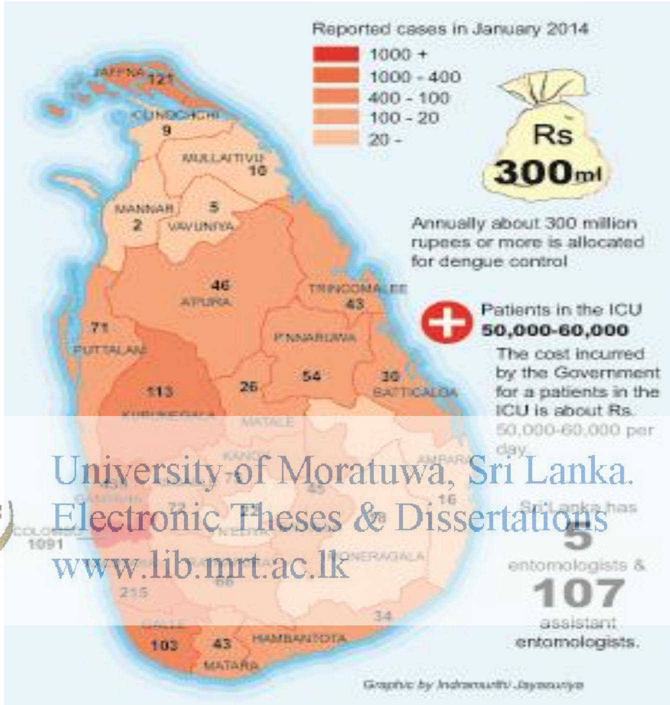


Figure 2.3: Reported dengue cases in January 2014

Source: http://www.sundaytimes.lk/140209/news/dengue-battle-costs-billions-so-why-the-soaring-deaths-85137.html (assessed on: 1 - 12- 2014)

Dengue cases were serologically confirmed in Sri Lanka since 1962. Initially, the disease was mainly spread in the western costal belt and later found in other suburbs as well. In 1965, there was a dengue outbreak throughout the country with 51 cases and 15 deaths. The first epidemic of DHF/DSS occurred during 1989-90 and the etiological agent was DENV-3, which was reported to have a genetic change resulting in increased epidemic potential/ virulence. Since then outbreaks with successive ones being larger in dimension than previous ones have occurred, and currently DF and DHF are endemic to Sri Lanka.

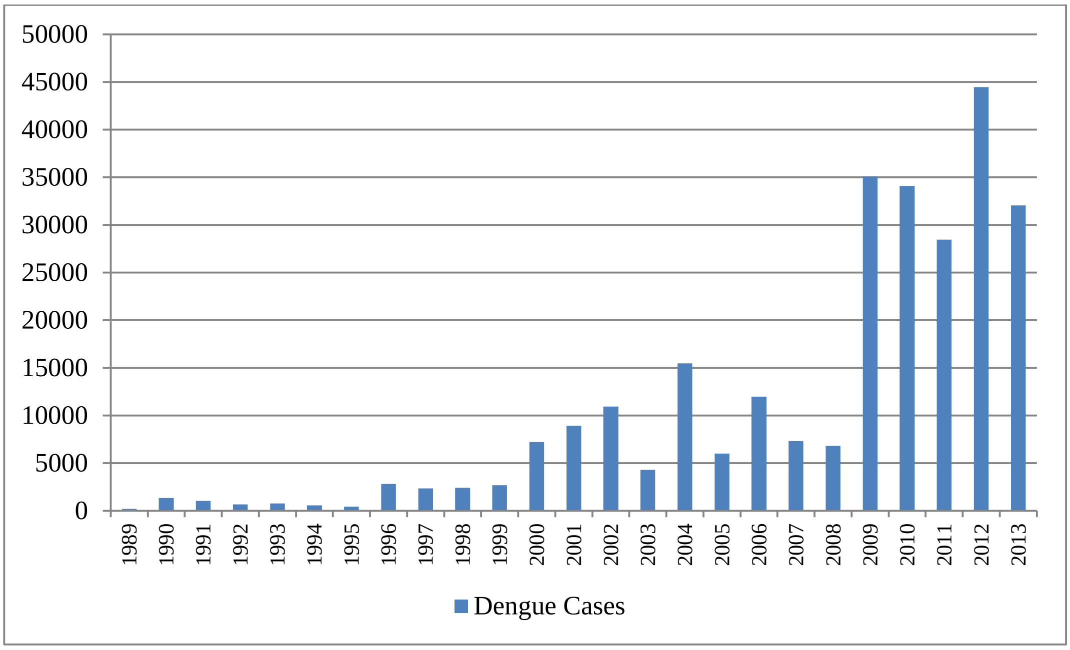


Figure 2.4: Annual number of DF/ DHF cases in Sri Lanka

2.6 Determinants of Dengue Transmission and Modeling Approaches

There are many factors such virus, vector, host, and environment that are involved in the transmission cycle of DF. Numerous human activities such as population growth, unplanned urbanization commonly associated with insufficient waste collection, increased transportation of goods facilitates breeding sites for the mosquito and movement of infected mosquitoes across regions (Cheong, Burkart, Leitao, & Lakes, 2013). Climate is an important determinant of temporal and spatial distribution of DF vector. Rainfall, temperature and relative humidity are thought as important factors attributing towards the growth and dispersion of mosquito vector and potential of DF outbreaks (Banu, 2013).

In light of these biological relationships between climate and transmission potential, several studies have suggested an association between dengue epidemics and climatic factors. Different methods were used to evaluate the association between climatic variables, non-climatic variables and DF incidence or mosquito density. The methods used range in complexity, from simple descriptive analysis to the applications of more sophisticated methods. These modeling techniques can be divided into six categories as; 1) linear regression models, 2) lagged time Poisson regression models, 3) time series models, 4) Bayesian models, 5) Wavelet analysis and 6) Spatial Analysis. Weather and climate variables generally included temperature, rainfall, humidity, and an El Ni˜no index (Hu et al., 2010; Cheong et al., 2013; Tissera., 2011). Most of the studies used reported cases and some used laboratory confirmed data as response variable.

2.6.1 Linear regression models

Colon – Gonzalez, Lake, and Bentham (2011) used multiple linear regressions to explore the relationship between climate variability and dengue incidence in Mexico from 1985 to 2007. They found that the incidence was higher during El-Nino events and in the warm and wet season, especially during the cool and dry. Similarly, Nakhapakorn and Tripathi (2005) explored the empirical relationship between climatic factors and dengue incidence in Thailand using multiple linear regression approach. Authors found that dengue incidence generally occurred when average temperature increased above normal and rainfall was comparatively lower and humidity was higher. But in this model the response variable is counts. Further these models were not able to capture the nonlinear effect of response variables.

2.6.2 Lagged time Poisson regression models

Lagged time Poisson regression has been widely used technique to identify the association between dengue incidence and weather variables (Chen et al., 2010; Fairos, Azaki, Alias, & Wah, 2010; Pham et al., 2011). Hii (2013) examined the relationship between climate and dengue incidence in Singapore with the aim of developing early warning system to forecast dengue outbreaks. To analyze the relationship between dengue incidence and temperature and rainfall, a Poisson regression model was developed using weekly data from 2000 – 2010. Quasi Poisson was applied to allow for over – dispersion of the data. This study suggested that the optimal time for dengue incidence forecast was at least three months. Further results showed that the higher risk occurred at a lag of 3 and 4 months subsequent to mean temperature and cumulative rainfall. Author mentioned risk factors such as population, climate and human behavior can be unique to different study areas hence dengue forecasting models needs to study area specific. Dengue fever has become a major health concern in the tropical countries. Similarly, Fairos et al. (2010) conducted a study in Malaysia using weekly climate data. The dependent variable used is the number of dengue cases while the explanatory variables were daily cloudiness, daily relative humidity, daily rainfall, maximum daily temperature, minimum daily temperature and daily wind speed. In addition to Poisson regression model, they used Negative binomial regression model since the variation of data is higher than the mean. They conclude lagged operator of 14 and 21 days climate significantly influenced the climate break.

Chen et al. (2010) conducted a study in Taiwan using weekly confirmed cases from January 1998 to October 2008 and weekly meteorological data to identify link between meteorological data and mosquito abundance to dengue fever dynamics. A Poisson regression analysis was performed by using a generalized estimating equations (GEE) approach. Their study was done in two areas Taipei and Kaohsing, where major dengue outbreaks occurred in southern Taiwan. Based on the cross – correlation analysis, 1 – month lag of rainfall, 1 – month lag of minimum temperature and 4 – month lag of relative humidity selected as independent variables for Taipei while for Kaohsing, 3 – month lag of rainfall, 3 – month lag of minimum temperatures, 3 – month lag of relative humidity and 1 – month lag of Breteau index level was chosen. Authors suggested that warmer temperature with a 3 – month lag and elevated humidity increased transmission rate of dengue fever.

However in all the above models the response variable may be correlated with the adjacent point in time so it is necessary to embody autocorrelation of the response variable when modeling. But all the above models described how the response variable is related to explanatory variables without considering how response can be correlated with its past values. In addition, when estimating parameters autocorrelation causes trouble because GLM and GAM essentially requires each observation to be independently distributed. Violation of this assumption can lead to problematic estimates. In order to avoid above problems Yang et al. (2012) introduced

GAM with Autoregressive terms (GAMAR) which is derived from Generalized Autoregressive Moving Average models to study the effect of daily temperature on mortality. Authors stated GAMAR has two advantages over GAM: 1) It is a model for generalized time series analysis rather than a probabilistic model like GAM; 2) the AR part of the GAMAR can explain the autocorrelation structure of observations. Briet, Amerasinghe, and Vounatsou (2013) extended GARMA to generalized seasonal autoregressive integrated moving average (GSARIMA) to model monthly malaria cases in Sri Lanka. Model fit was carried out using full Bayesian Inference. This approach is effective in modeling non Gaussian, non stationary and/ or seasonal time series of count data.

2.6.3 Time series models

Time series modeling approaches have been extensively used to identify the impact of climatic variables on dengue incidence (Cazelles et al., 2005; Gharbi et al., 2011; Hu et al., 2010; Pinto, Coelho, Oliver, & Massad, 2011; Thai et al., 2010). Out of different Box – Jenkins models SARIMA models are potentially useful when forecasting dengue incidence (Chaves & Koenraadt, 2010; Martinez & Silva, 2011). Gharbi et al. (2009) used seasonal autoregressive integrated moving average (SARIMA) model to predict the occurrence of dengue epidemics in French West Indies. Weekly laboratory confirmed cases from 2000 – 2007 were used for the study. They found temperature improves dengue outbreaks forecasts better than humidity and rainfall. Their results are results consistent with those of other studies dealing with the effect of climate on dengue incidence (Focks et al., 2006; Luz et al.,2011; Serfling, 1963; Wu et al., 2007). Similarly, Hu et al. (2010) fitted a SARIMA model to examine the impact of El – Nino on the occurrence of dengue in Queensland, Australia for the period 1993 – 2005.

SARIMA models have been successively used in epidemiology studies to predict other infectious diseases such as Malaria, Cryptosporidiosis, etc. (Hu, Tong, Mengersen & Connell, 2007; Yang et al., 2012]. For example, with the aim of developing a forecasting system in Sri Lanka, Briet et al. (2013) used SARIMA model to forecast malaria incidence in Sri Lanka. The addition of covariates such as the number of malaria cases in neighbouring districts, rainfall improves the prediction of models. One main advantage in this method is it allows the integration of external factors that may lead to increase the predictive power.

But there are some several drawbacks in these models. Mainly, these models were not sufficient to capture the non – linear relationship between dengue incidence and climatic variables.

2.6.4 Bayesian models

Bayesian modeling approach has been often used in epidemiological studies to understand the spatial and temporal pattern of infectious diseases (Castillo, Korbl, Stewart, Gonzalez and Ponce, 2011). Zacarias et al. (2010) used Bayesian modeling approach to analyze the spatial and temporal pattern of malaria and which climatic variables influence the distribution of malaria incidence in Mozambique, for the period 1999 – 2008. Prates, Dey, and Lachos (2012) developed novel approach to capture effects of skewness and heavy tail behavior of data while maintaining the conditional autoregressive structure. Bayesian hierarchical method was used to fit the model. Appropriateness of the model was tested by using dengue fever infection in the state of Rio de Janeiro.

2.6.5 Wavelet analysis

Among the various approaches developed to study nonstationary data, wavelet analysis is probably the most efficient (Fairos et al., 2010; Pham et al., 2011). Wavelet analysis is now frequently used to extract information from ecological and epidemic time series (Cazelles and Chavez, 2014). Wavelet analysis provides the possibility of investigating the quantifying the temporal evolution of time series with different rhythmic components. In addition, wavelet analysis allows detection of changes in periodicity in time. Wavelet time series models have been applied in determining the relationship between climate variables and dengue incidence in Puerto Rico, Mexico, and Thailand particularly, with the aim of identifying time and frequency specific association (Johansson et al., 2009). Cazelles and Chavez (2014) used wavelet time series analysis to demonstrate association between dengue incidence and El-Nino in Thailand from 1986 to 1992. Different transformation techniques on dengue incidence time series were used before analysis to reduce skewing and standardized the amplitude. (Descloux et al., 2012; Pham et al., 2011). Study conducted by Thai et al, (2010) trend was suppressed before analysis by removing the periodic components with period components greater than 8 years by using a classical low pass filter.

Unlike conventional statistical methods (i.e. spectral density analysis), wavelet coherence measures the cross correlation between two time series as a function of their frequencies, providing information about those periods where two nonstationary signals are linearly correlated with each other (Cazelles et al., 2014). More specifically, wavelet coherence analysis determines if the presence of a particular frequency in a disease series at a specific time is related to the same frequency and at the same time in a given covariate.

Thai et al. (2010) investigated dengue transmission dynamics in nine districts in Binh Thuan province, southern Vietnam over the period 1994 – 2009. Wavelet analyses were performed on time series of monthly notified dengue cases to detect and quantify dengue periodicity, to describe synchrony patterns in both time and space and to investigate the spatio-temporal waves. Wavelet coherency analysis was used to estimate the relationship between dengue incidence and El Nino-Southern Oscillation (ENSO) indices. Wavelet analyses of time series data from nine districts of Binh Thuan province displayed periodicity for all districts. More specifically, periodicities were detected in the 1-year and the 2-3 year bands. Further dengue dynamics showed different evolutions across the nine time series which can be divided into three groups based on wavelet cluster analysis. The first group consists of three districts in which a multi-annual cycle was predominant and the annual cycle was week. Second group consist three districts in which the annual cycle was predominant and the last group consists of districts in which both annual and muti-annual cycle were present. Wavelet coherence revealed a strong non-stationary association between ENSO indices and climate variables. This study revealed interesting information on dengue transmission dynamics in Binh Thuan province. However, there was a limitation; dengue data used in this study were based on notified clinically-suspected dengue cases from hospitals or clinics without laboratory confirmation. These numbers may be an underestimation of the true incidence.

Cazelles et al. (2005) estimated associations between severe dengue (henceforth dengue) incidence in Bangkok and the averaged incidence for the rest of Thailand, and the Ni˜no-3 index, the Southern Oscillation Index, and average monthly temperature and precipitation over the period 1983–1997. Wavelet analysis was selected because, as previously explained, it allows the quantification of the temporal evolution of a time series with different cyclic components (Cazelles et al., 2007). Statistical relationships between the dengue and climatic time series were estimated using wavelet coherence analysis. The dengue series showed strong seasonal oscillations, indicating a strong influence of the annual cycle on dengue dynamics. The El Ni˜no series on the other hand, was dominated by cycles of about 4–6 years. Both dengue series have in-phase cycles of about 2–3 years (with a mean delay of three months in the rest of Thailand with respect to Bangkok) only over the period 1984–1992 where there is high coherence with El Nino cycles. Over the periods 1983–1986 and 1991–1997 the annual oscillations are dominant, showing a mean delay of one month in Bangkok with respect to the rest of Thailand. Dengue and precipitation were significantly associated with each other at the annual scale. Both series are in-phase in most of the country; however, dengue incidence in Bangkok follows the seasonal peak of precipitation after a short lag time (length not specified by the authors). Over the period 1986–1991, dengue and precipitation were significantly associated for cycles of about 2–3 years. Similar but weaker patterns of oscillation were observed for temperature in both series.

2.6.6 Spatial analysis

Seng, Chong, and Moore (2005) conducted a research to analyse the spatial pattern and diffusion of dengue fever in Malaysia by incorporating epidemiological and statistical techniques into a Geographical Information System (GIS). It has been widely used in disease monitoring and surveillance and identification of high – risk areas and population at risk (Seng et al., 2005). All suspected and indeterminate cases of dengue fever reported in the Johar State for 2004 were used in the study. With the aim of implementing effective vector control programs space – time cluster analysis was used and it identified a total of 31 clusters in the Johor State. Geographical weighted regression (GWR) analysis has been utilized in this study to identify association between dengue fever prevalence, population distribution and meteorological factors and characteristics of space time clusters in the Johor State. GWR analysis illustrates that 10 to 14 days of accumulative rainfall is sufficient to support mosquito breeding cycle and the dengue virus incubation period in the Johor Bahru district is 15 days. Jeefoo (2012) used GIS to analyze the spatial factors related to dengue fever, dengue hemorrhagic fever and dengue shock syndrome epidemics in Thailand. Spatial autocorrelation statistics and kernel-density estimation was employed by the author. Spatial autocorrelation is a valuable technique to study how spatial patterns change over time. Finally they developed a risk zone map for the incidence. Similarly, Wu et al. (2009) used GIS to illustrate the spatial patterns of dengue fever incidence, climate and non-climatic factors of the 358 townships in Taiwan. They obtained daily data from 80 monitoring stations with complete temperature records and 300 monitoring stations with complete rainfall records from 1998 to 2002. Further daily notification of dengue fever cases for the period of 1998 – 2006, including age, gender, township of residence, and the time of disease on set for each case were used for the study. In addition in this research they used several non-climatic factors such as population density, income, percentage of service and agriculture occupancy, home ownership and number of clinics. Number of months with average temperature higher than 18^0C per year and degree of urbanization were found to be associated with increasing risk of dengue fever at township level.

2.6.7 Distributed log nonlinear modeling approach

Horta et al. (2003) applied distributed lag nonlinear modeling framework to determine the time-lag effect of meteorological factors on the relative risk of dengue incidence in Coronel Fabriciano city, Brazil. The weekly number of notified dengue cases during the period 2004-2010 was used for analysis. They found when considering the rainfall, the highest RR (1.2) was observed for lag 10. Further authors have shown that DF incidence was associated with weekly cumulative precipitation at lag 5-8 and 9-12. Weekly precipitation was associated with dengue incidence at lag of 7-12 weeks. Increasing weekly cumulative precipitation posed increasing risk on dengue outbreaks until time lag of 14 weeks, whereas highest RR for weeks after rainfall peaked at time lag 10. In addition to above discussed methods Yusof and Mustaffa (2011) used least square support vector machine approach to predict dengue outbreaks in Malaysia. Support vector machine is efficient approach for solving problems in nonlinear classification and regression.

In summary, this review indicates that climate change likely to affect the pattern of dengue incidence. The quantitative models employed for evaluating the relationship between climate variables and dengue incidence have been typically different with respect to nature of the relationship (linear or nonlinear), distributional assumptions (normal or poisson), spatial dynamics. These studies have highlighted that many climatic variables play a key role in dengue transmission and its distribution. The most important predictor variables in the model were temperature, humidity, rainfall and urbanization. Many of the studies highlighted the importance of delayed effect of climatic variables on dengue incidence.

CHAPTER 03

METHODOLOGY

3.1 Overview

This chapter describes in detail the procedures employed in achieving the aims and objectives of this research. The chapter is organized as follows: Sections 3.2, 3.3 discuss the study area and description of data used in the study. Section 3.4 is devoted to the establishing of theoretical background of wavelet analysis. In section 3.5 we give an overview of change point analysis of variation by using PELT segmentation. Detail explanation distributed non linear lag models is given in sections 3.6.

3.2 Study Area

Sri Lanka is an island located in southeastern tip of India (7^0N, 81^0E) with a total area of 65610km^2 with 64740km^2 of land and 870km^2 of water. It is primarily a tropical country with high humidity and warm temperature throughout the year. This climate condition plays an important role in conducive for transmission of dengue fever. The topography of the country is divided into three distinct areas namely; plains, the coastal belt and the central highlands. The average yearly temperature for the whole country ranges from 28 to 30^0C. The mean temperature in central highland is 15.9^0C. The coldest month with respect to mean temperature is January while the warmest months are April and August. The rainfall pattern in Sri Lanka is influenced by the monsoon winds. According to the to the climate characteristics of 12 month the island can be divided into 4 climate seasons as; first monsoon (March - April), southwest monsoon (May – September), second inter monsoon (October - November), Northeast monsoon (December - February). Relative humidity ranges from 60% to 90% during different seasons and areas of the country.

The association between dengue incidence and climatic factors were studied in the Colombo District, where there is a marked increase of dengue cases evidenced during the last few years. It is located in the southwest of Sri Lanka and has an area of

699km^2. Colombo district is the most urbanized and density populated region of Sri Lanka and has a number of urban centres including Colombo, the capital (Figure 3.1). The main features of the climate are the relatively stable temperature and relative humidity year-round, forming an ideal condition for the growth of the vector of dengue fever mosquito.

Figure 3.1 Study Area

Source:

https://www.google.lk/maps/place/Sri+Lanka/data=!4m2!3m1!1s0x3ae2593cf65a1e9d:0xe13da4b400e2d38c?sa=X&ei=eLoOVeWqM5CiugT4uYHYAg&sqi=2&ved=0CBsQ8gEwAA (assessed on: 2 – 2 - 2015)

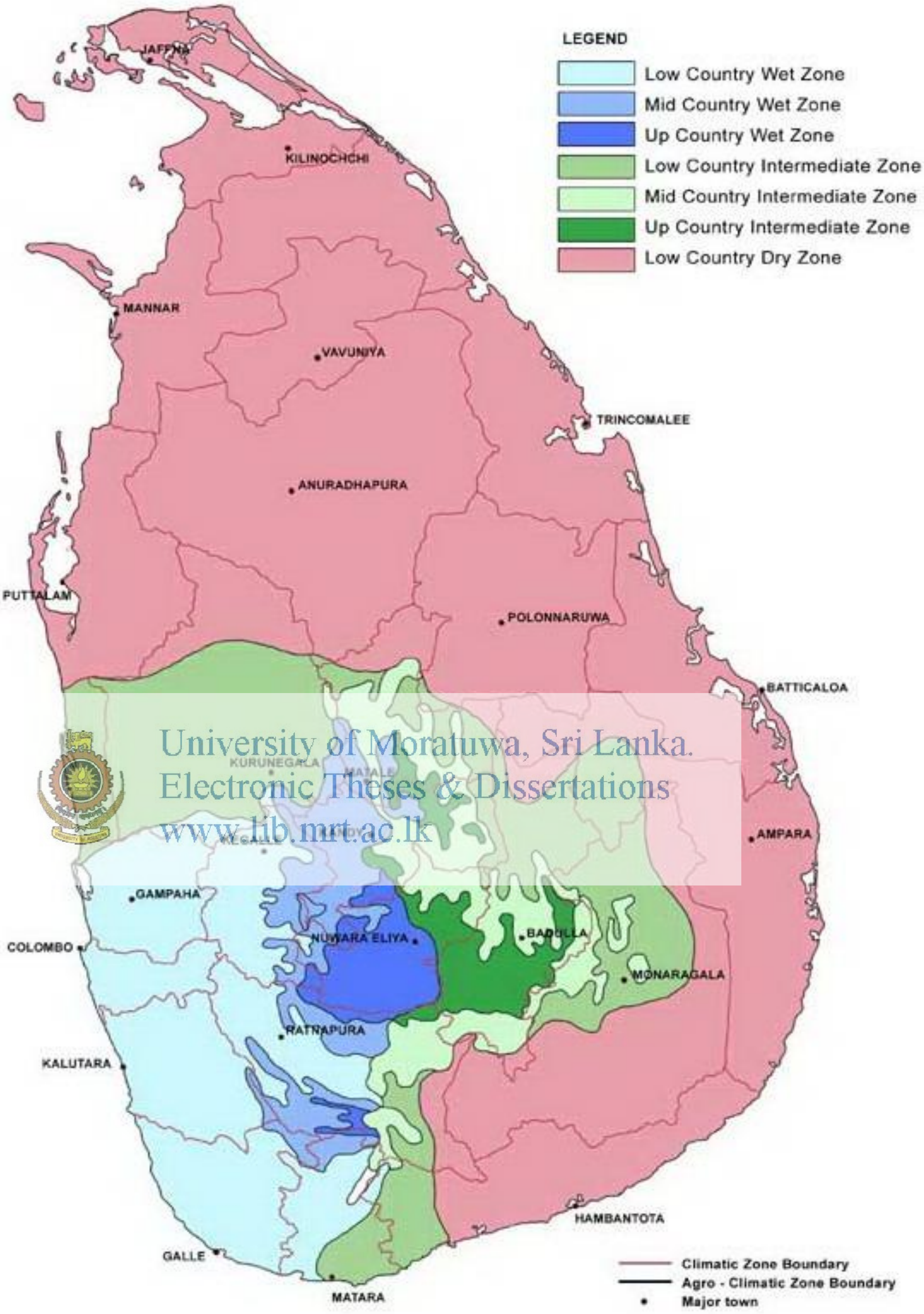


Figure 3.2: Climatic zones of Sri Lanka

(Source: http://jayaneththi.blogspot.com/2011/03/trunk-of-rubber-tree.html, assessed on: 2 - 2 - 2015)

3.3 Data Description

The data used in this study can be divided into two parts; (i) epidemiological data and (ii) climatic factors. Section 3.3.1 gives the brief description of the epidemiological data used in the study while section 3.3.2 illustrates the meteorological factors.

3.3.1 Epidemiological data

Dengue incidence is reported in Sri Lanka through a national network that covers the whole country. These dengue data includes records from health posts and centres, and hospitals complied at district level. It includes both microscopically and clinically confirmed cases. These counts are registered daily and used to generate Weekly Epidemiology Bulletin. They are collected and summarized by each district health department and reported to provincial health Officers' monthly. These values are published as weekly epidemiological reports (WERs) by the Epidemiology Unit, Ministry of Health, Sri Lanka.

Weekly notified dengue cases in 25 districts in Sri Lanka were obtained from weekly epidemiological reports published by the Epidemiology Unit, Ministry of Health, Sri Lanka. Data include cases from 52nd week of (December) 2008 through 36th week (September) of 2014.

3.3.2 Climatic data

Daily climate data were obtained from an online source (www.tutiempo.net/en/). The data from this source was obtained directly from the local weather station in Colombo. Daily mean, minimum and maximum temperatures, mean visibility, mean wind speed, maximum sustained wind speed, relative humidity and precipitation for the years 52nd week of 2008 to 36th week of 2014 were obtained. The daily values were used to obtain weekly averages.

Table 3.1: Climate Variables, Variable Label and Unit of Measurement

Climate Variable	Variable Label	Unit of Measurements
Mean Temperature	TEM	^0C
Maximum temperature	TM	^0C
Minimum temperature	Tm	^0C
Mean humidity	H	%
Precipitation amount	PP	mm
Mean visibility	VV	km
Mean wind speed	V	km/h
Maximum sustained wind speed	VM	km/h

3.4 Data Analysis

3.4.1 Exploratory data analysis

In the initial stage of the quantitative data analysis descriptive statistics were performed. Descriptive analysis and graphical analysis were useful to gain insights into data. They also highlighted errors in the data entry. Since there were no missing in dengue cases, no substitution were made. But in climate data there were some missing values. Those missing values were imputed from nearest neighboring station data values.

3.4.2 Determining dengue periodicity: Wavelet analysis

According to the exploratory data analysis it reveals time series of dengue incidence are characterized by non stationary, non linear dynamics with strong seasonality and various oscillations. Therefore, conventional methods such as Fourier analysis, generalized linear models (GLM), Box Jenkins time series are inadequate to capture those effects. According to Cazelles et al. (2005) among the different approaches of studying non stationary data wavelet analysis is probably the most efficient. In this research we applied wavelet analysis on time series of dengue cases in each district to explore the periodicity in the dengue incidence and how periodicity change with time. In contrast to Fourier analysis, wavelet analysis is well suited for the study of signals whose spectra change with time. This time-frequency analysis of the signal provides information on the different frequencies as time progresses.

To explore the periodicity in the dengue incidence time series continuous wavelet transform was performed which decomposes the time series into time and frequency components. Wavelet power spectrum quantifies the distribution of the variance of the time series in the time – frequency domain. Wavelet coherency analysis was performed to identify association between dengue cases and climate conditions. Coherence is similar to some classical correlation, but it pertains to the oscillating in a given frequency mode. Wavelet coherence generalizes the possibilities of wavelets for quantifying the dependencies between two signals.

3.4.2.1 Computing environment

All analyses were performed using the statistical package R (verion 3.1.2 and version 3.1.3). Much of the code was adapted from MATLAB code by Torrence and Compo (1998) and Grinsted, Moore and Jevrejeva (2004). The wavelet analysis was based on the results of the R package “biwavelet”.

3.4.2.2 Concept of wavelet analysis

The wavelet transform is a relatively new integral transform, having been developed by Morlet and Grossman in the early 1980s. The concept of integral transformation goes back to the 18th century, in work by Fourier and others. In general, an integral transformation can be expressed as follows:

$$Tf(\omega) = \int_{t_1}^{t_2} K(t, \omega) f(t) dt$$

By multiplying the original function, f, by a kernal function, K, and integrating, a new function, Tf, is produced. Depending on the properties of the kernal function chosen, the output function may be a unique representation of the data within a new domain on the variable ω. The wavelet transformation constitutes a set of criteria which the kernal function must satisfy. The intention of the wavelet transformation is to represent the function in both frequency and spatial domains, such as position or time, simultaneously. By using wavelet analysis we can identify which frequencies dominate, and where in space or time they occur.

3.4.2.3 The wavelet transform

wavelet is a wave-like oscillation with an amplitude that begins at zero, increases, and then decreases back to zero (An and Rocklov, 2014). Wavelets are quite literally ‘mini waves’. Rather than being a wave that goes on forever, like sin() or cos(), wavelets are a short ‘burst’ of waves that quickly die away, like the figure below:

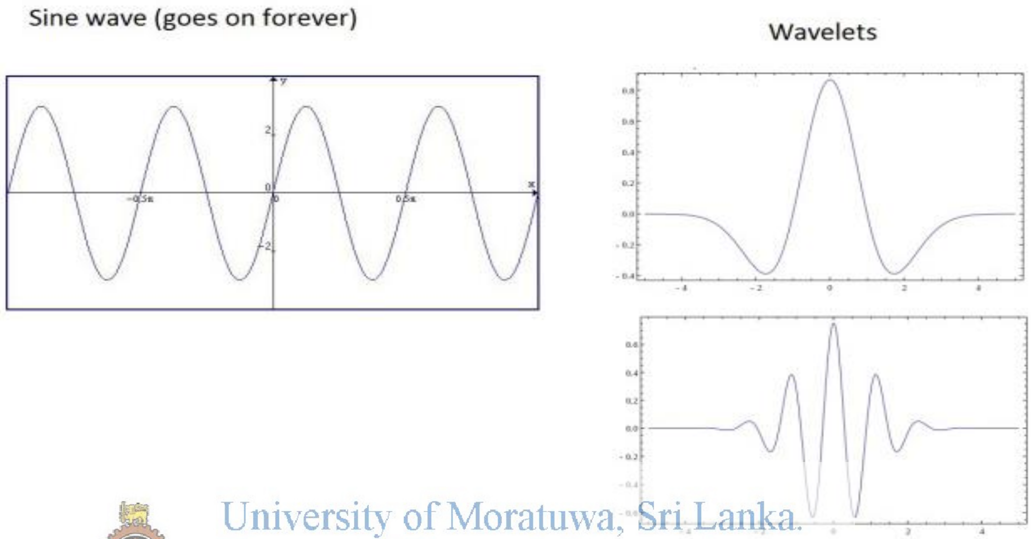


Figure 3.3: Comparison of sine wave and wavelets

(Source:http://georgemdallas.wordpress.com/2014/05/14/wavelets-4-dummies-signal-processing-fourier-transforms-and-heisenberg/)

3.4.2.4 Continuous Wavelet Transformation (CWT)

Wavelets are defined as $\varphi_{a,\tau}$ (t) = $\frac{1}{\sqrt{a}}\varphi\left(\frac{t-\tau}{a}\right)$.

where a – scale of the wavelets

τ – time position

The wavelet transform of a continuous signal of infinite duration with mother function φ (t) is:

$$W_x\,(a,\tau) = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} x(t)\varphi^*\left(\frac{t-\tau}{a}\right)dt = \int_{-\infty}^{\infty} x(t)\varphi_{a,\tau}^*\,(t)dt \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

Where * denotes the complex conjugate form. The wavelet coefficients, W_x(a,τ), represent the contribution of the scales (the a values) to the signal at different time positions (the τ vallues). The wavelet transformation can be thought as a cross correlation of signal $x(t)$ with a set of wavelets of various "widths" or "scales" a, at different time positions τ.

3.4.2.5 Selection of a basis function for the wavelet transformation: The Morlet Wavelet

The Morlet wavelet was used, in all analysis. It is a complex sine wave localized by a Gaussian distribution,

$\Psi_0(\eta) = \pi^{-1/4} e^{i\omega_0 \eta} e^{-\eta^2/2}$……………….(2)

where η is a scaled time unit and ω_0 describes the relative frequency of the sine wave ($\omega_0 = 6$ here to satisfy admission criteria). Because it is a localized periodic function, it is ideal for analyzing periodic behavior such as multiyear climatic variables or seasonal dengue variation.

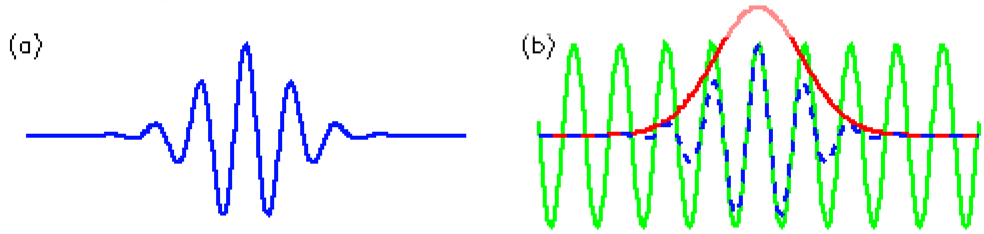


Figure 3.4: (a) Morlet wavelet of arbitrary width and amplitude, with time along the x- axis. (b) Construction of Morlet wavelet (blue dashed) as a Sine curve (green) modulated by a Gaussian (red).

3.4.2.6 The continuous wavelet transform of a discrete sequence

As seen in the definition of the CWT, the transformation of the analysisng signal with a dilated and translated wavelet function and assumes a continuous signal as input. However, in empirical applications, data are recorded discretely with time steps denoted by δt. Therefore, a discrete computation of the CWT need to be performed. The continuous wavelet transform of a discrete sequence is the convolution of the series x_n and the wavelet Ψ_0 at time t and scale s, where x_n is a series of observations x_0, x_1,…,x_{N-1} equally spaced in time by δ_t . This is defined as

$$W_{n,s} = \sum_{n'=0}^{N-1} x_{n'} \Psi^* \left(\frac{\delta_t(n'-n)}{s}\right) \text{……………….. (3)}$$

where Ψ^* is the complex conjugate. By varying the wavelet scale s and translating along the localized time index n, one can construct a picture showing both the amplitude of any features versus the scale and how this amplitude varies with time. To ensure that the wavelet transforms at each scale s are directly comparable to each other and to the transforms of other time series, the wavelet function at each scale s is normalized to have unit energy. In convolution formula (2), the normalization is

$$\Psi\left[\frac{(n'-n)\delta t}{s}\right] = \left(\frac{\delta t}{s}\right)^{1/2} \Psi_0 \left[\frac{(n'-n)\delta t}{s}\right]$$

where $\Psi_o(\eta)$ is normalized to have unit energy.

The power, $|W_{n,s}|^2$, indicates the strength of the wavelet – like behavior at every point and is presented in the power spectrum of each transformation.

3.4.2.7 Wavelet coherence analyses

To identify the dependencies between dengue incidence in Colombo district and climatic factors wavelet coherence analyses was performed. In addition, it allows checking whether various periodic modes of various climatic factors and dengue incidence tend to oscillate simultaneously, falling and rising together and quantifying the synchrony of these two time series. In addition phase analysis was calculated between climatic factors and dengue incidence. It provides an information on the sign of the relationship such as in phase, out of phase, lead by $\pi/2$. The details of the method can be found in 'a practical guide to wavelet analysis' (Torrence & Compo, 1998).

3.4.2.8 Significance of the wavelet power spectrum

Significance of the wavelet power spectrum is assessed by comparison with simulated or theoretical spectra representing a null hypothesis: the variability of the observed time-series is equivalent to the expected variability of a random process with similar first-order autocorrelation. “biwavelet” package in R estimate the first-order autocorrelation of the time series to be analyzed and create a theoretical Fourier power spectrum of a Gaussian process with equivalent first-order autocorrelation and χ^2 estimator was used to establish 95% confidence bounds for the null hypothesis. In order to test the significance of coherence Monte Carlo simulations was used. The details of the method can be found elsewhere (Castillo et al., 2011; Cazelles et al. 2005; Cazelles et al., 2014; Torrence & Compo, 1998).

3.4.3 Change point detection in variance: the PELT – TREE method

Change point analysis was performed with statistical software R (version 3.1.2) package “changepoint”. This package includes three multiple change point algorithms 1) binary segmentation, 2) sequent neighbourhoods and 3) proposed pruned exact linear time (PELT). In our analysis we used PELT algorithm, it is recently proposed by Killick and Eckley (2011). PELT algorithm is similar to segment neighbourhood algorithm but it is more computationally efficient, due to its use of dynamic programming. The mean assumption is that the number of changepoints increased linearly as the data set grows, controls the computational time. Graphical inspection of the dengue time series indicates that there is a change in the mean constantly throughout the study period. Hence our study focused on changes in variance.

Suppose we have an ordered sequence of data, $y_{1:n} = (y_1, \ldots, y_n)$. Changepoint, is said to occur within this set when there exists a time, $\tau \in$ {1,…,n-1}, such that the statistical properties of $\{y_1 \ldots y_\tau\}$ and $\{y_{\tau+1} \ldots y_n\}$ are different in some way.

The most common approach to identify multiple changepoints in the literature is to minimize

$$\sum_{i=1}^{m+1}[C(y_{(\tau_{i-1}+1):\tau_i})] + \beta f(m)$$

where C is a cost function for a segment e.g., negative log-likelihood and $\beta f(m)$ is a penalty to guard against over fitting (a multiple changepoint version of the threshold c). In PELT algorithm cost function is minimized by dynamic programming technique.

3.4.4 Distributed Lag Non-linear Models

A Poisson regression model combined with distributed lag non-linear model (DLNM) was used to examine the effects of climate variables on dengue incidence. The objective of developing the DLNM model are to justify the impact of lag effect of climate on dengue incidence and to identify the structure of the lag-period for different climate variables and to capture the nonlinear nature of the data by introducing appropriate smoothing techniques.

DLNM, was proposed recently by Gasparrini et al. (2010) is a flexible model to describe simultaneously a non-linear and delayed effect of climate change on dengue incidence. This model used a "cross-basis" function that examine a two dimensional relationship along the dimensions of climate change and lag weeks. The cross-basis is specified by the choice of two basis, one for each dimension, among a set of possible options such as splines, polynomials, or step functions. In our study, the choice of lag period is varies for various meteorological factors. We decided the lag period based on the literature review and provided the maximum plausible weeks as the lag for all the variables to improve the precision of the DLNM model. Table 3.2 summarizes the choice of lag period, variable basis and basis for lag for each climatic variable. Except for precipitation, in this study, we used natural spline (ns) basis for all the variables used in the model. B-spline function was used as the basis function for precipitation while polynomial function was used as the basis for lag. The degree of freedom for all variable basis and lag basis are based on the results of exploratory data analysis, previous studies from literature and also judging by the AIC/ BIC results tested under various values of degree of freedom. In this analysis we placed the knots of variables at equally spaced values on the log scale of lags.

Table 3.2 Choice of lag period, variable basis and lag basis

Variable	Lag Period (weeks)	Basis for Variable	Basis for Lag
Mean Temperature	30	ns with degree 1	ns with lagnots
Maximum Temperature	30	ns with degree 1	ns with lagnots
Precipitation	25	B-spline with degree 4 and 5 df	Polynomial with degree 3
Humidity	20	ns with degree 2	ns with lagnots
Maximum sustained wind speed	20	ns with degree 2	ns with lagnots
Visibility	20	ns with degree 2	ns with lagnots

The applied poisson model can be written as follows.

$$Ln(E(Y_t)) = \alpha + \beta_1 TEM_{t,l} + \beta_2 TMAX_{t,l} + \beta_3 PP_{t,l} + \beta_4 H_{t,l} + \beta_5 VM_{t,l} + \mu_j week_j + \gamma_k year_k$$

Where t refers to the week of the observation; (Y_t) denotes the observed weekly dengue counts on week t; α is the model intercept. $TEM_{t,l}$, $TMAX_{t,l}$, $PP_{t,l}$, $H_{t,l}$, and $VM_{t,l}$ are the cross basis matrix obtained to mean temperature, maximum temperature, precipitation, humidity and maximum sustained wind speed respectively. β_i's represent the vector of coefficients for corresponding cross basis and l is the lag weeks. $Week_j$ (j= 1, 2, 3, ….52) denotes week effects that were controlled by a categorical variable $year_k$ denotes the year (k=2009, 2010, 2011, 2012, 2013, 2014).

Since the study population was relatively stationary during the time period from 2009 – 2014 with annual growth rate below 1% the trend of incidence during the study period could be similarly prescribed by the trend of disease counts. (According to 2001 census Colombo district population 2251300, 2012 census population in Colombo district equals 2310100, population growth from 2001 to 2012 is 2.61%) Hence we used the dengue counts as the response variable in our model. Finally the residuals were checked to evaluate the adequacy of the model. Sensitivity analyses were performed by varying the degrees of freedom (df). All statistical analyses related to DLNM were performed with R software version 3.1.3 using the package dlnm.

CHAPTER 04

EXPLORATORY DATA ANALYYSIS

4.1 Overview

In recent years dengue has become the number one killer mosquito borne infection in Sri Lanka. The number of cases of dengue appears to be rising each year. Earlier the disease was mainly restricted to urban and semi urban areas of the country. However, over the years DF and DHF has been found in all provinces in Sri Lanka due to population movement through transport development, economic activities and change in climatic factors. This chapter includes the presentation of dengue incidence in Sri Lanka from 2009 to 36th week of 2014. Initial examination of the data is presented in descriptive manner.

4.2 Descriptive Statistics of Dengue Cases

4.2.1 Western province

"Over 260,000 suspected dengue cases have been reported to the Epidemiology Unit from all over the island during the last 8 months of this year. Approximately 57.85 percent of dengue cases were reported from the Western province, Ministry of Health revealed."

http://www.news.lk/news/sri-lanka/item/2350-57-85-dengue-cases-reported-from-western-province

(Accessed on 14 – 9 - 2014)

Dengue infection is predominant in Western province where majority of the country's population live. The disease keeps on increasing year by year. The Western Province, consisting of Colombo, Gampaha and Kalutara Districts, is the most socio-economically developed part in Sri Lanka. It contributes more than fifty percent to the Gross Domestic Product (GDP). Population of Western province in Sri Lanka is 5.72 million and the total extent of area is 3,709 km^2.

4.2.1.1 Colombo district

Colombo District, Sri Lanka where there is a marked increase of dengue cases evidenced during the last few years. Colombo district is the most urbanized and density populated region of Sri Lanka and has a number of urban centers including Colombo, the capital. The main features of the climate are the relatively stable temperature and relative humidity year-round, forming an ideal condition for the growth of the vector of dengue fever mosquito. In the total 298 weeks of the study period, there were 36949 dengue cases (including Dengue and dengue hemorrhagic fever) reported in Colombo District. Table 4.1 shows the summary statistics of weekly dengue cases from 2009 to 2014. The highest mean weekly cases occurred in 2014 followed by 2011. During the study period, the weekly mean dengue cases were 125. There was a small decline in mean number of dengue incidence in 2012. Even though the year 2014 consists data from 36 weeks total number of cases in that year was highest than other years.

Table 4.1: Descriptive Statistics of Dengue Cases – Colombo District

Year	Dengue Cases					
	Minimum	Median	Mean	SD	Maximum	Total
2009	20	62.5	80.06	56.31	288	4163
2010	8	63	95.6	81.5	334	4971
2011	25	114	145.3	98.6	475	7557
2012	0	99	108.25	70.36	297	5629
2013	41	127	138.71	64.74	329	6797
2014*	42	143	217.1	133	491	7817
Overall	42	171	125.68	93.88	491	36949

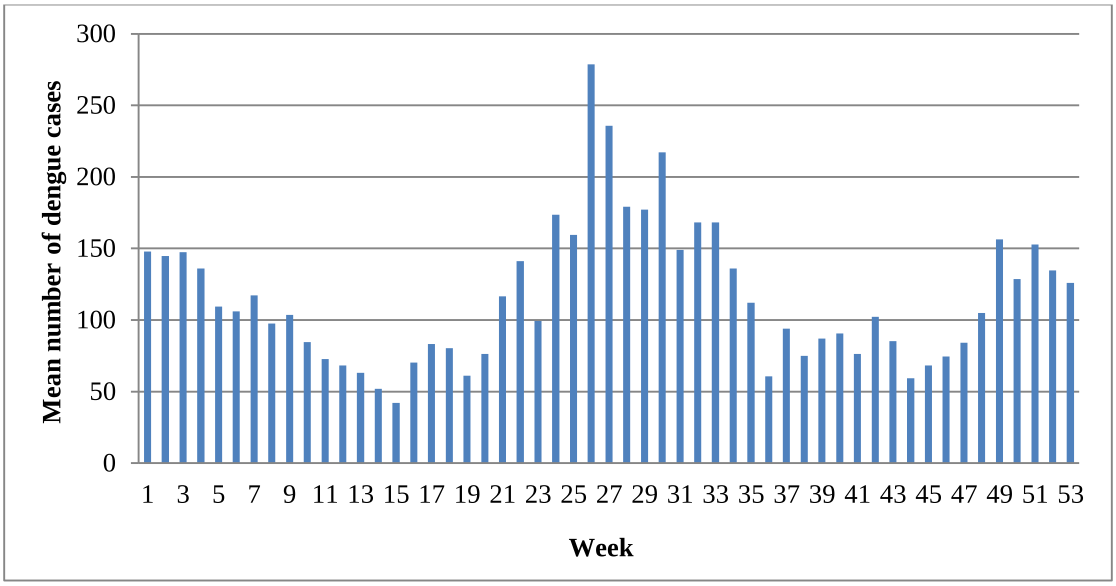


Figure 4.1 : Distribution of weekly mean number of dengue cases – Colombo District

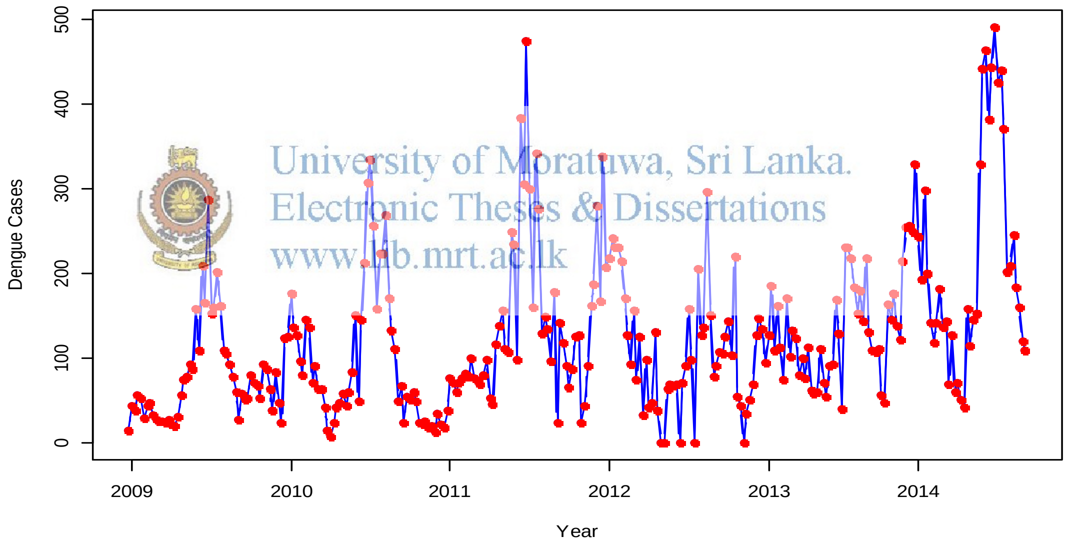


Figure 4.2: Weekly distribution of confirmed dengue cases in Colombo district

Figure 4.1 shows that a high number of dengue cases generally occurred from week 18 to week 36 that is from May to October. The highest number of dengue cases were reported during the twenty sixth week. Interestingly, disease pattern indicate that the critical months of incidence were during the May to September, which is the rainy season. Again there Figure 4.2 tend to exhibit repetitive behavior, with regular seasonal that are easily visible. According to figure 4.2 drastic downward trend in the end of 2010 was partially due to the effectiveness of strengthened vector control programs. But a drastic upward trend can be observed in the middle of 2011. The worst incidence noted was in July 2011 with more than 300 cases.

4.2.1.2 Gampaha district

Gampaha District is located in the west of Sri Lanka and has an area of 1,387 square kilometres (536 sq mi). It is bounded by Kurunegala and Puttalam districts from north, Kegalle District from east, Colombo District from south and by the Indian Ocean from west. The descriptive statistics of dengue cases for the study period (2009 to 36th week of 2014) in Gampaha district is given in table 4.4.

Table 4.2: Descriptive Statistics of Dengue Cases – Gampaha District

Year	**Dengue Cases**					
	Minimum	Median	Mean	SD	Maximum	Total
2009	4	46	61.5	50.53	194	3198
2010	5	33.5	48.87	42.08	181	2541
2011	8	44.5	56.46	38.55	201	2936
2012	0	57.5	66.87	49.14	256	3477
2013	9	44	49.37	21.74	110	2419
2014*	8	67.5	80.69	59.74	296	2905
Overall	0	49.5	59.47	45.27	296	17483

The distribution of DF/ DHF incidence in years 2009 - 2014; Week 36 is shown in figure 4.3. Interestingly, disease patterns indicate that the critical months of incidence were during May to September, which is in the Southwest monsoon season. According to figure 4.4 the worst incidence noted was in 3rd week of 2012 with more than 250 cases. But a drastic downward trend can be seen within the same year from May to June.

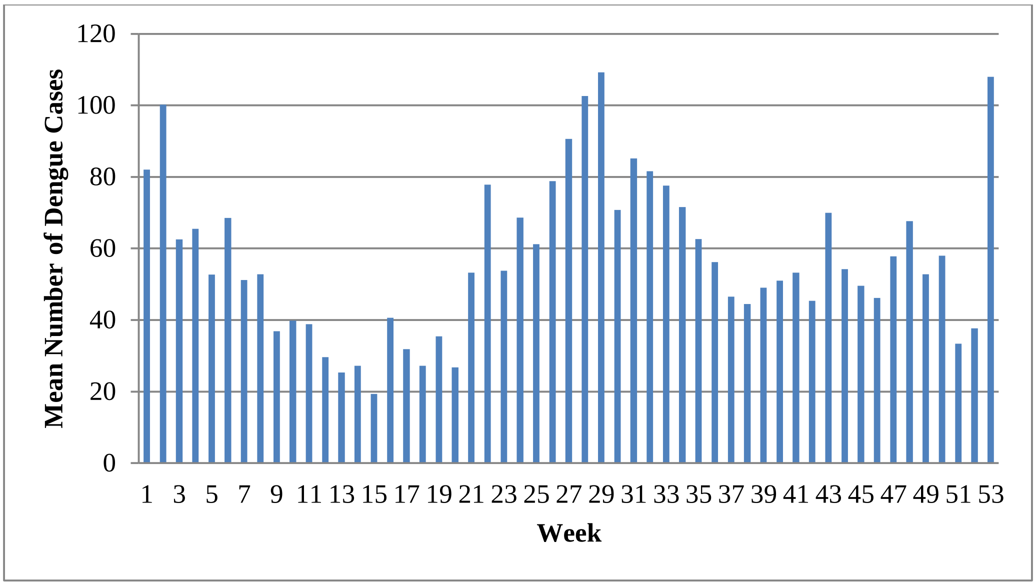


Figure 4.3: Distribution of weekly mean number of dengue cases – Gampaha District

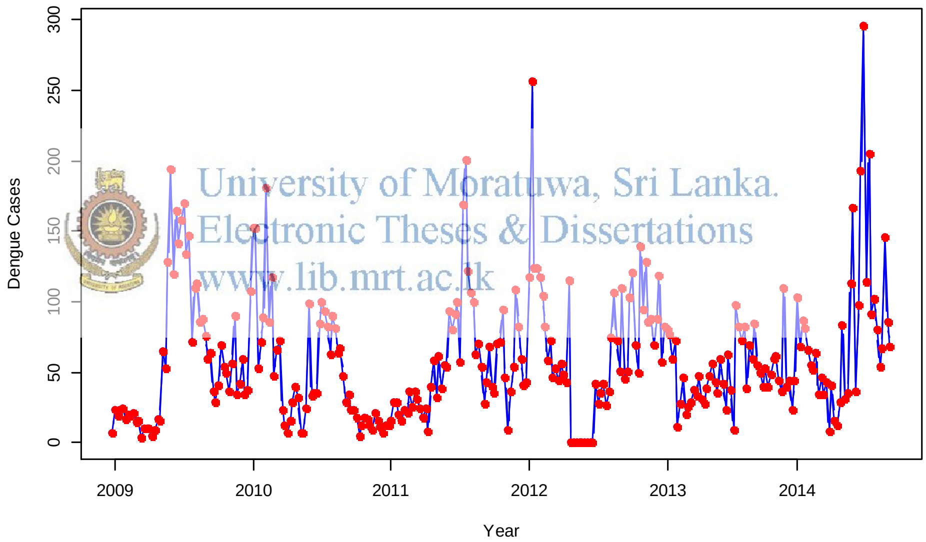


Figure 4.4: Weekly distribution of confirmed dengue cases in Gampaha district

4.2.1.3 Kalutara district

Kalutara District is located in the south west of Sri Lanka and has an area of 1,598 square kilometres (617 sq m). Kalutara District is bordered by the sea to the west, Ratnapura District to the East, Galle District to the South and Colombo District to the North. Kalutara District is in the wet zone and the main characteristics of the climate are low rainfall, high temperature and high humidity throughout the year. The monsoon seasons extending from May to August and October to January include heavy rains, slightly lower temperatures periods of lower humidity.

Table 4.3: Descriptive Statistics of Dengue Cases – Kalutara District

Year	**Dengue Cases**					
	Minimum	Median	Mean	SD	Maximum	Total
2009	3	11.5	16.4	13.32	75	853
2010	2	20	22.96	18.23	66	1194
2011	1	19	20.15	12.54	60	1048
2012	0	23.5	23.5	18.42	67	1222
2013	6	26	27.51	10.05	49	1348
2014*	9	37.5	44.42	26.11	101	1599
Overall	0	22	24.71	18.46	101	7265

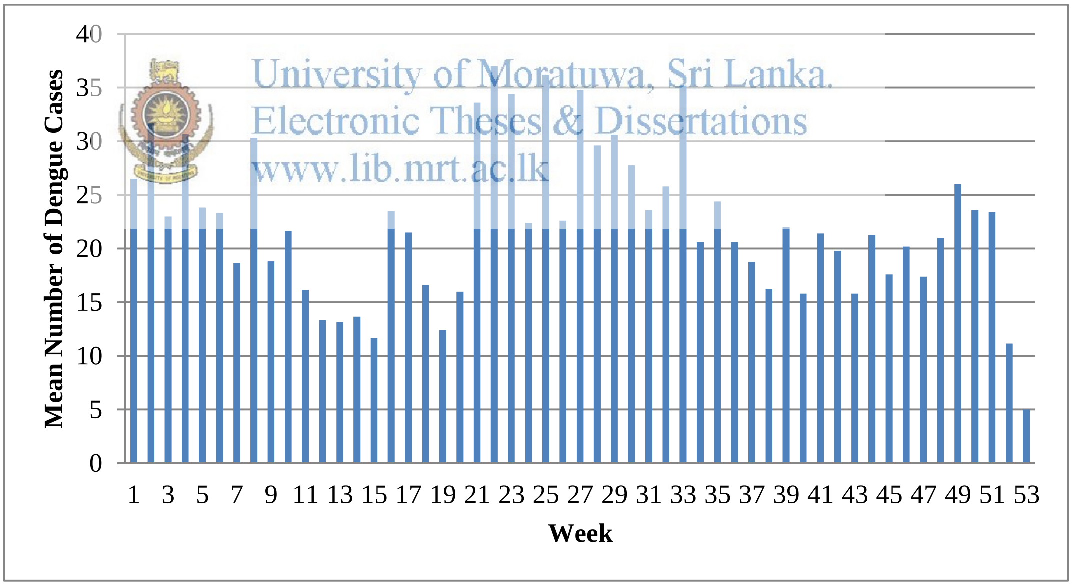


Figure 4.5: Distribution of weekly mean number of dengue cases – Kalutara District

According to figure 4.5 the highest number of dengue cases were reported between week 21 to week 31. As shown in figure 4.6, weekly dengue cases peaked in the June, 2009 and plunged to a low in August, 2009. Again a dramatic upward trend can be seen during the period of May to September in 2010 and 2011. At that time, the epidemic took approximately 20 weeks starting on May. The largest outbreak of dengue cases was observed in the year of 2014.

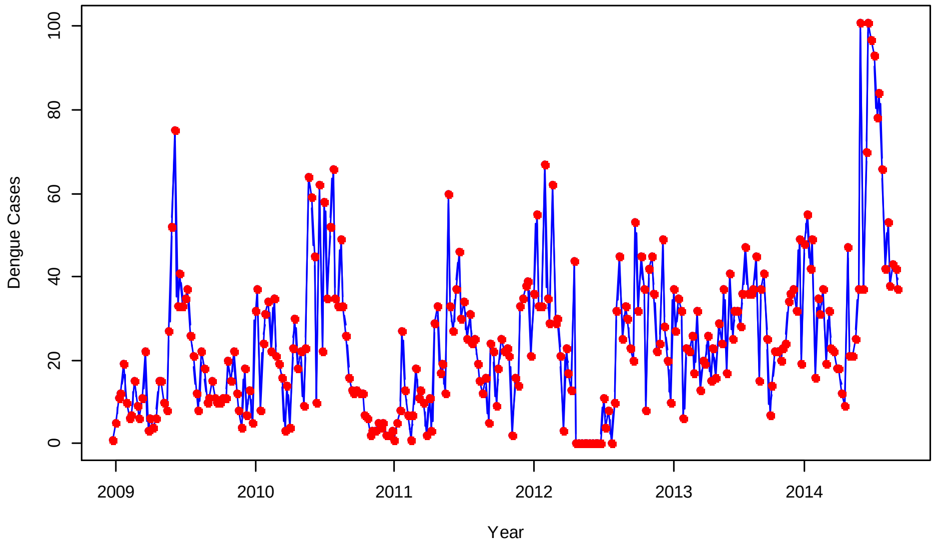


Figure 4.6: Weekly distribution of confirmed dengue cases in Kalutara district

Further, according to 4.6 the disease has a seasonal trend, where two peaks of dengue occur following monsoon rains in June-July and October – December. The DF/ DHF distribution in Gampaha District and Kalutara District had a similar pattern over the study period. Further, DF and DHF distribution in the whole province having its highest incidence in rainy season and had a similar trend for every year.

4.2.2 Central province

The central province consists of three administrative districts, namely, Kandy, Matale and Nuwara Eliya. The climate is cool, and many areas about 1500 meters. The western slopes are very wet, some places having almost 7000 mm of rain per year. The eastern slopes are parts of the mid-dry zone as it is receiving rain only from North-Eastern monsoon. The Temperatures range from 24°C at Kandy to just 16°C in Nuwara Eliya, which is located 1,889 m above sea level. The highest mountains in Sri Lanka are located in the Central Province.

4.2.2.1 Kandy district

It has an area of 1906.3 km². Kandy city is the second largest city in the country after Colombo. With Kandy located in the centre of the island and in a high elevation, the city has relatively wetter and cooler temperatures than that of the tropical climate of the rest of the country, especially the coastal regions. Nuwara Eliya is south to it and has a cooler climate due to its higher elevation. The city has its dry season from December through to April. From May through to July and December to January the region experiences its monsoon season, during this time the weather is rough and unstable. The island being in the northern hemisphere gives Kandy it coldest month in January and its hottest in July. From March through the middle of May is the inter monsoonal period, during this time there is light rain and strong humidity.

Over the study period, a total of 9287 cases of dengue were reported to the epidemiology unit of Sri Lanka. The worst incidence noted was in June – July, 2009 with more than 200 cases. According to the figure 4.8 it is clear that the dengue has a decreasing trend in first 21 weeks of 2014 which is due to the certain administrative plans by the local administration.

Table 4.4: Descriptive statistics of Dengue Cases – Kandy District

Year	Dengue Cases					
	Minimum	Median	Mean	SD	Maximum	Total
2009	5	38	59.06	50.82	217	3071
2010	1	20	23.69	19.21	69	1232
2011	0	23	29.10	23.12	94	1513
2012	0	28	25.56	18.29	66	1329
2013	0	25	24.22	13.42	60	1187
2014*	3	16	26.22	20.31	75	944
Overall	0	26.50	31.59	30.17	217	9287

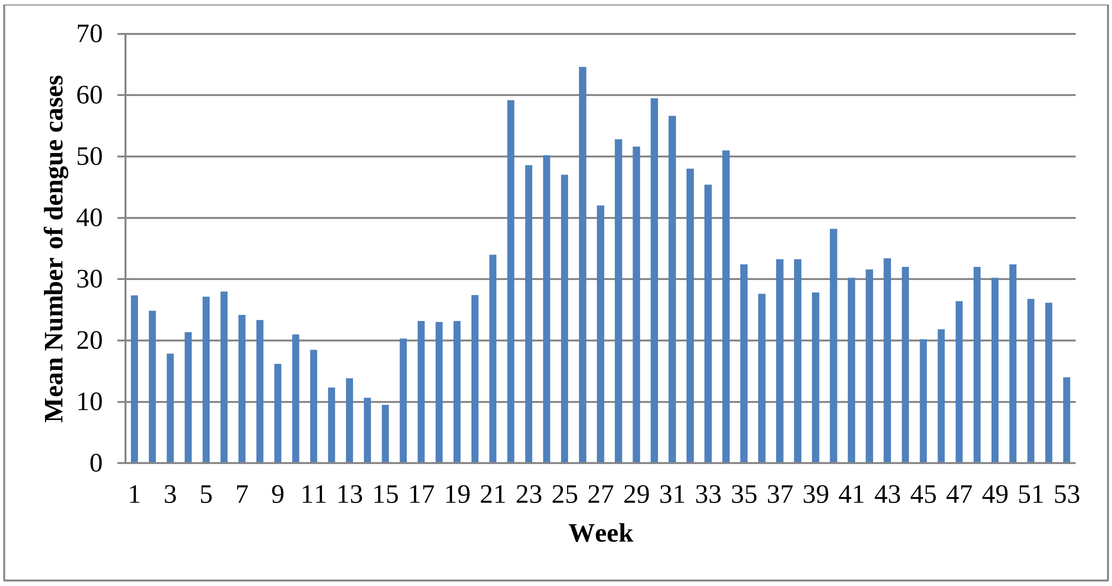


Figure 4.7: Distribution of weekly mean number of dengue cases – Kandy District

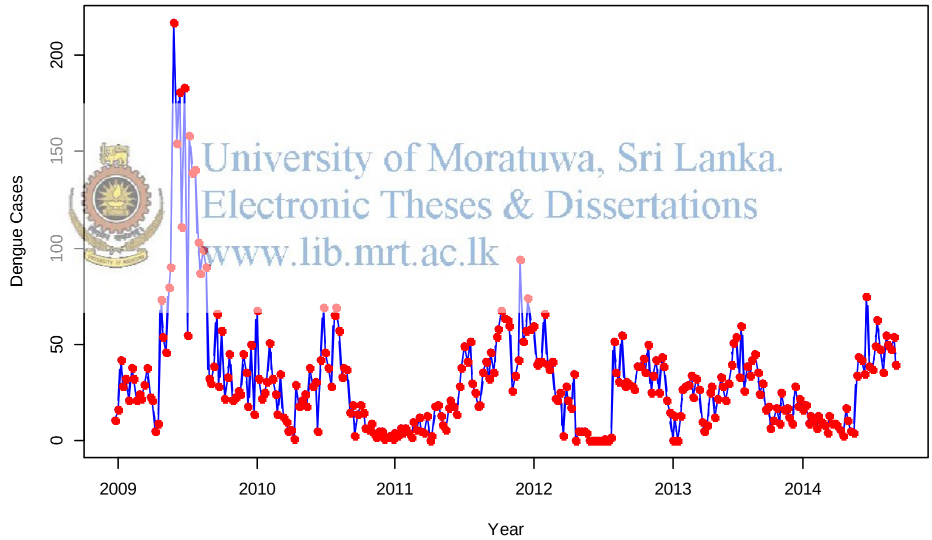


Figure 4.8: Weekly distribution of confirmed dengue cases in Kandy district

4.2.2.2 Matale district

Matale District is located in Central, with a population of 445866 habitants. The estimate terrain elevation above sea level is 213 meters. The descriptive statistics of reported number of dengue cases for the study period is given in table 4.5. During the year 2009 one of the highest outbreak year, 1852 patients were suspected with DF/

DHF. According to figure 4.9 significant numbers of cases were reported in the month of July are reaching a peak in August and gradually decrease.

Table 4.5: Descriptive Statistics of Dengue Cases – Matale District

Year	**Dengue Cases**					
	Minimum	Median	Mean	SD	Maximum	Total
2009	3	20.5	35.62	31.43	130	1852
2010	0	7	9.40	8.03	44	469
2011	0	5	6.481	4.52	19	337
2012	0	6	6.538	5.66	21	340
2013	0	6	6.341	4.18	20	311
2014*	1	5	7.06	6.67	34	254
Overall	0	7	12.20	17.89	130	3587

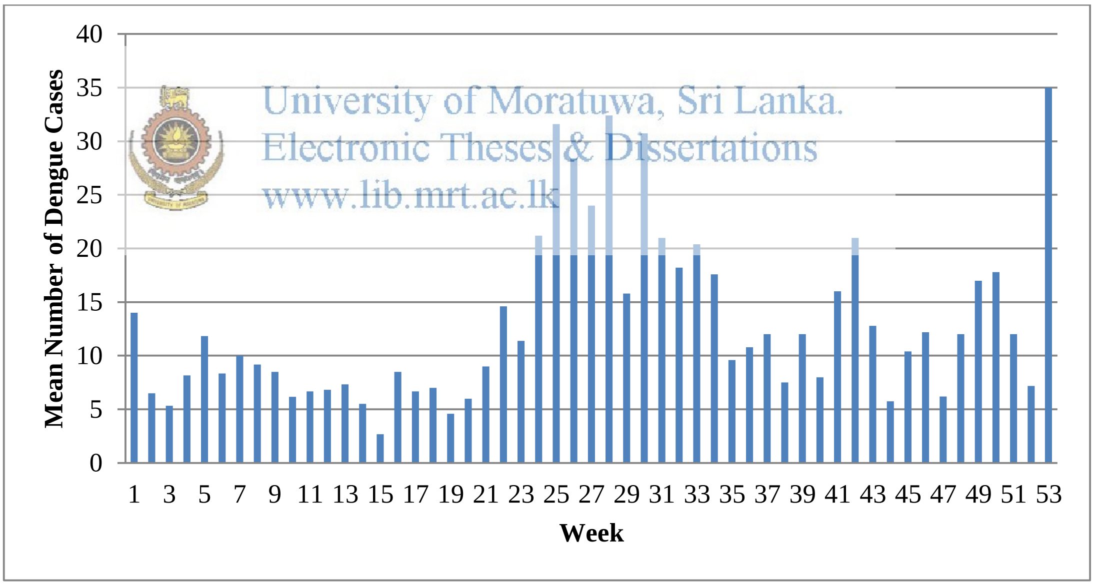


Figure 4.9: Distribution of weekly mean number of dengue cases – Matale District

According to figure 4.10 the number of reported dengue cases varied by year. Over the study period, highest cases of dengue were reported in 2009 and lowest in the following three years. The worst incidence noted was in June – July , 2009 with more than 100 cases.

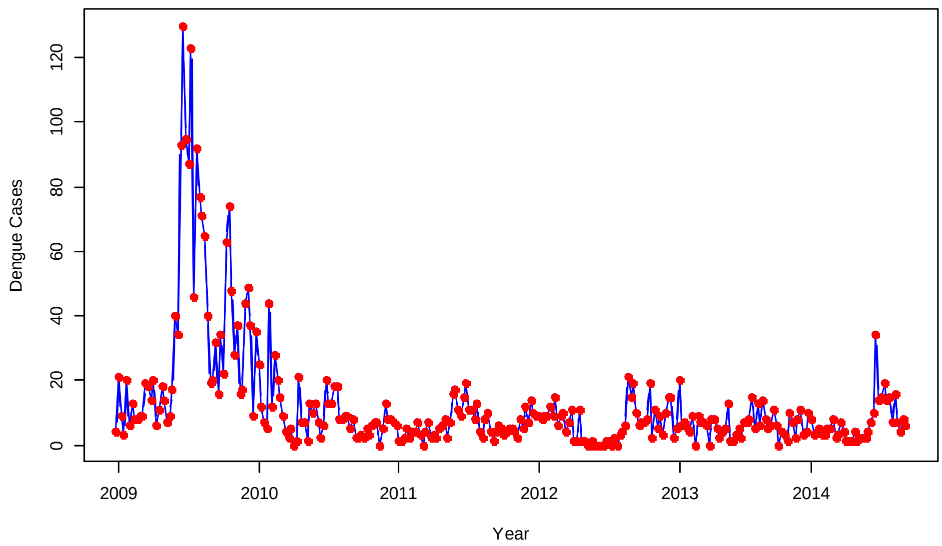


Figure 4.10: Weekly distribution of confirmed dengue cases – Matale District

4.2.2.3 Nuwara Eliya district

Due to its high altitude, it has a sub tropical highland climate. The average annual temperature varies between 11-20 C° and the recorded lowest temperature is 0.4 C° and the recorded highest temperature is 27.7 C°. Monthly rainfall varies between 70-225 mm and has an average annual rainfall figure or precipitation of 1900 mm. The maximum rainfall is generally in October and the minimum rainfall is in March. During the year it has a relative humidity between 65%-87%.

Table 4.6: Descriptive Statistics of Dengue Cases – Nuwara Eliya District

Year	Dengue Cases					
	Minimum	Median	Mean	SD	Maximum	Total
2009	0	4	5.346	5.753	24	278
2010	0	3	3.865	4	15	201
2011	0	3	4.135	4.005	20	215
2012	0	4	3.923	3.486	14	204
2013	0	4	3.959	2.661	12	194
2014*	1	3.5	4.917	3.872	14	177
Overall	1	3	4.316	4.098	24	1269

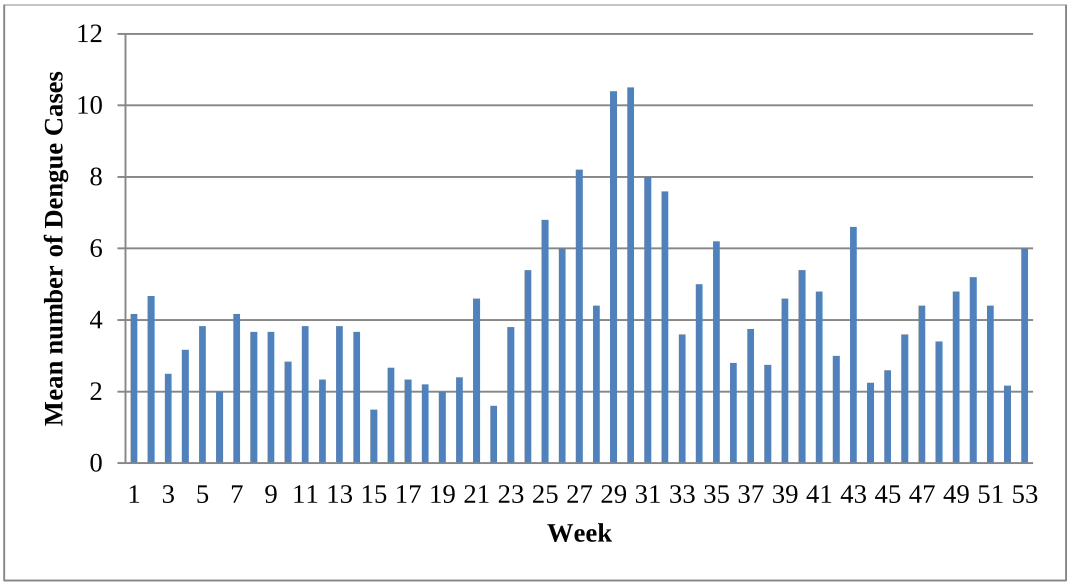


Figure 4.11: Distribution of weekly mean number of dengue cases – Nuwara Eliya District

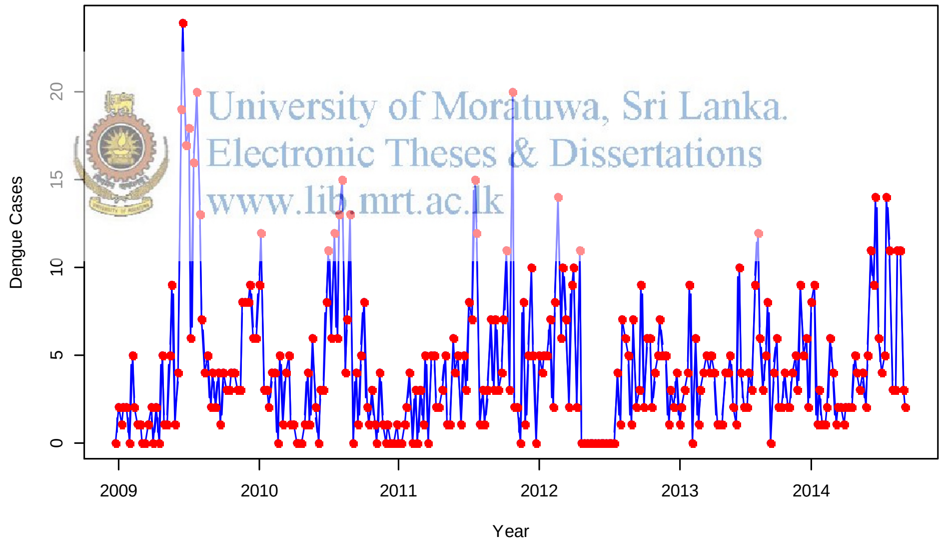


Figure 4.12: Weekly distribution of confirmed dengue cases in Nuwara Eliya District

Similar to Kandy District and Matale District the highest number of dengue cases was reported in the year of 2009. It has reached to peak during the twenty sixth week of 2009 and gradually decreased. Again in the middle of 2010 it has reached to a peak of 15 cases. Figure 4.12 tend to exhibits multiple repetitive behaviors. Seasonal pattern is similar to the pattern of Colombo District.

4.2.3 Southern province

Southern Province is the 7th largest province by area and is home to 2.5 million people, the 3rd most populated province. The Southern Province is a small geographic area consisting of the districts of Galle, Matara and Hambantota

4.2.3.1 Galle district

Galle features a tropical rainforest climate. The city has no true dry season, though it is noticeably drier in the months of January and February. As is commonplace with many cities with this type of climate, temperatures show little variation throughout the course of the year, with average temperatures hovering at around 26 degrees Celsius throughout. During 2009 to 36th week of 2014 a total of 4132 cases were reported.

Table 4.7: Descriptive statistics of dengue cases – Galle District

Year	Dengue Cases					
	Minimum	Median	Mean	SD	Maximum	Total
2009	0	8	11.81	12.7	63	614
2010	0	15	18.37	14.92	70	955
2011	0	10	12.52	10.57	51	651
2012	0	12	13.79	10.68	39	717
2013	1	13	13.76	6.97	30	674
2014*	0	11	14.47	13.02	46	521
Overall	0	11	14.10	11.81	70	4132

According to the table 4.7 highest number of cases were reported in the year of 2010. According to figure 4.14 the highest number of dengue cases were reported from June to September.

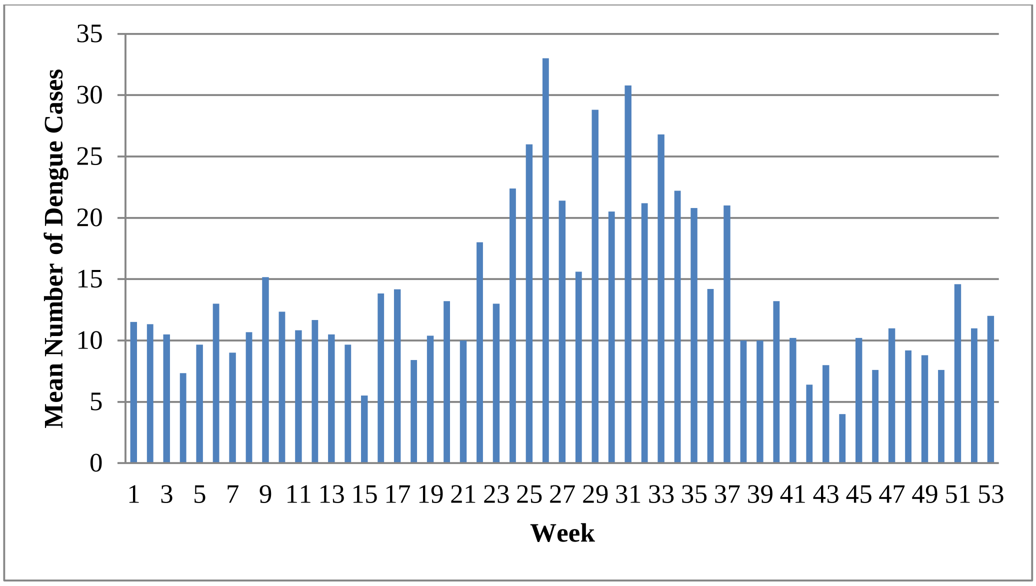


Figure 4.13: Distribution of weekly mean number of dengue cases – Galle District

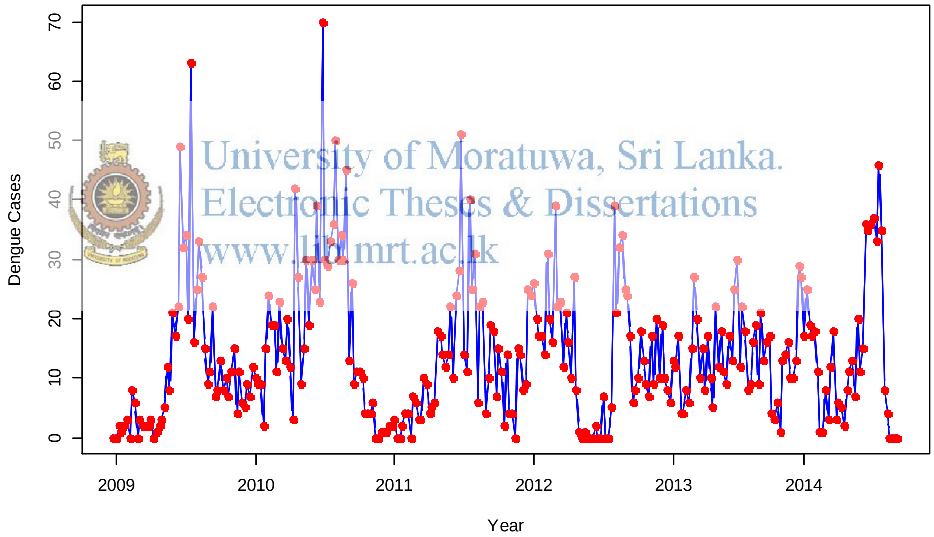


Figure 4.14: Weekly incidence rate of confirmed dengue cases in Galle District

Figure 4.14 tend to exhibit repetitive behavior, with regular cycles that are easily visible. Except the year 2012 the number of dengue cases reached to a peak during the month of July. Significant peak can be observed in 2009, 2010 and 2012. The data show that the dengue fever case has a decreasing trend since end of 2012 due to vector control programs implemented by the administration.

4.2.3.2 Hambantota district

The highest number of dengue cases were reported in the year of 2009. The worst incidence was also in 2009 with more than 85 cases. The year 2013 had comparatively lower number of dengue cases. In Hambantota District also peak dengue incidence was between July and September, corresponding with peak rainfall. According to Figure 4.16 since mid 2012 number of dengue cases gradually decrease. But there has been a drastic upward trend in the year of 2014.

Table 4.8: Descriptive statistics of Dengue Cases – Hambantota District

Year	**Dengue Cases**					
	Minimum	Median	Mean	SD	Maximum	Total
2009	0	10.5	16.96	18.07	87	882
2010	0	8.5	12.65	10.96	40	658
2011	0	5	6.40	6.24	35	333
2012	0	7	7.44	5.65	20	387
2013	0	5	5.27	2.64	14	258
2014*	0	5	10.33	12.28	64	372
Overall	0	6	9.86	11.26	87	2890

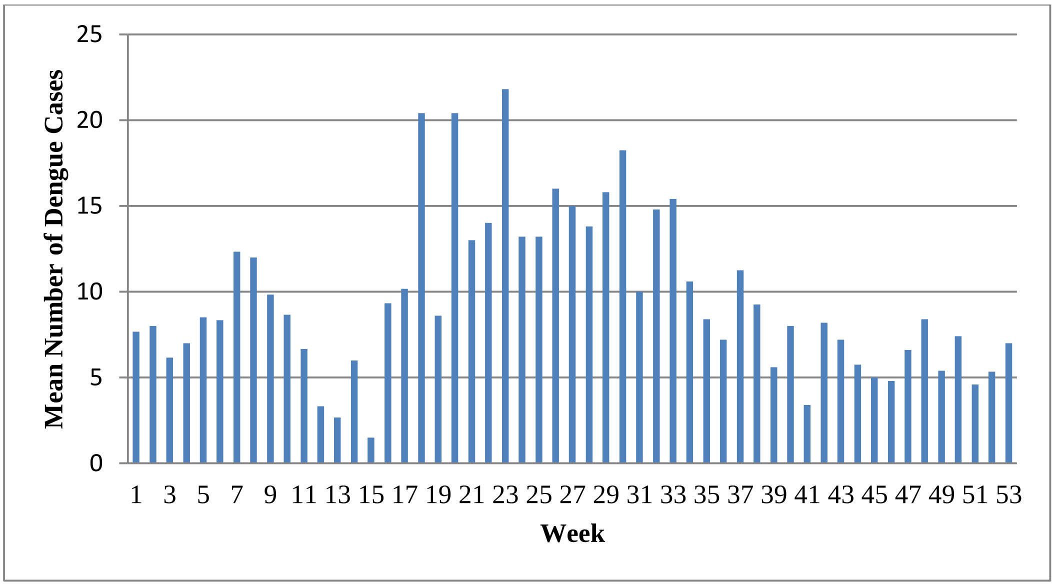


Figure 4.15: Distribution of weekly mean number of dengue cases – Hambantota District

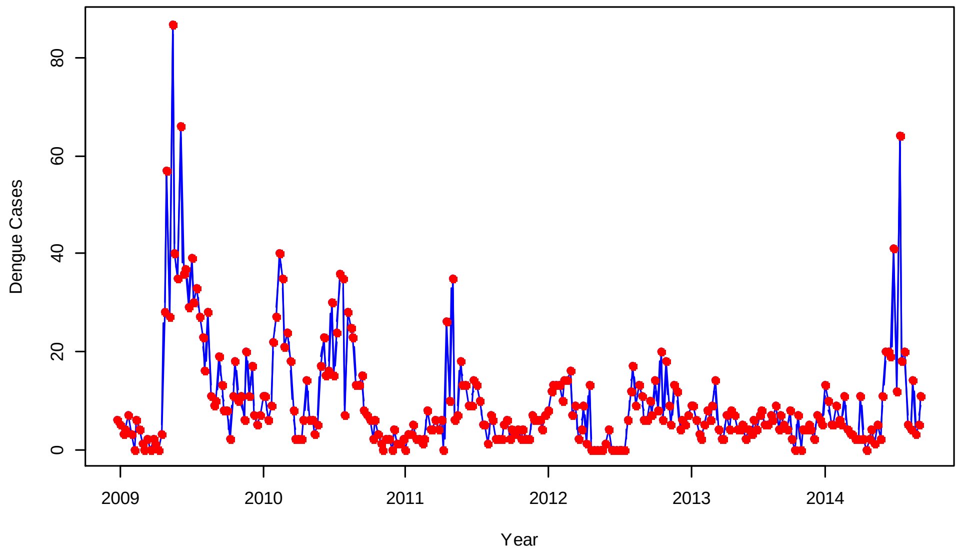


Figure 4.16: Weekly distribution of confirmed dengue cases in Hambantota District

4.2.3.3 Matara district

Significant number of cases was reported in the year of 2012. But the highest peak was recorded in the year of 2009 which is more than 75. Number of dengue counts reported in 2009 and 2012 are twice as much as the number of dengue counts in other districts. Similar to other two districts in Southern Province most of the cases were reported during monsoon in each year except in the year 2012. Since the beginning of 2013 number of dengue cases were gradually decrease. Seasonal pattern is evident from the figure 4.18. This seasonal pattern is similar to pattern that was appeared in Galle District.

Table 4.9: Descriptive Statistics of Dengue Cases – Matara District

Year	**Dengue Cases**					
	Minimum	Median	Mean	SD	Maximum	Total
2009	1	14	20.23	19.38	76	1052
2010	0	8	10.69	9.84	45	556
2011	1	11.5	13.31	11.02	51	692
2012	0	28	24.90	18.21	58	1295
2013	2	8	8.31	4.50	27	407
2014*	0	8.5	11.25	8.43	32	405
Overall	0	10	15.04	14.46	76	4407

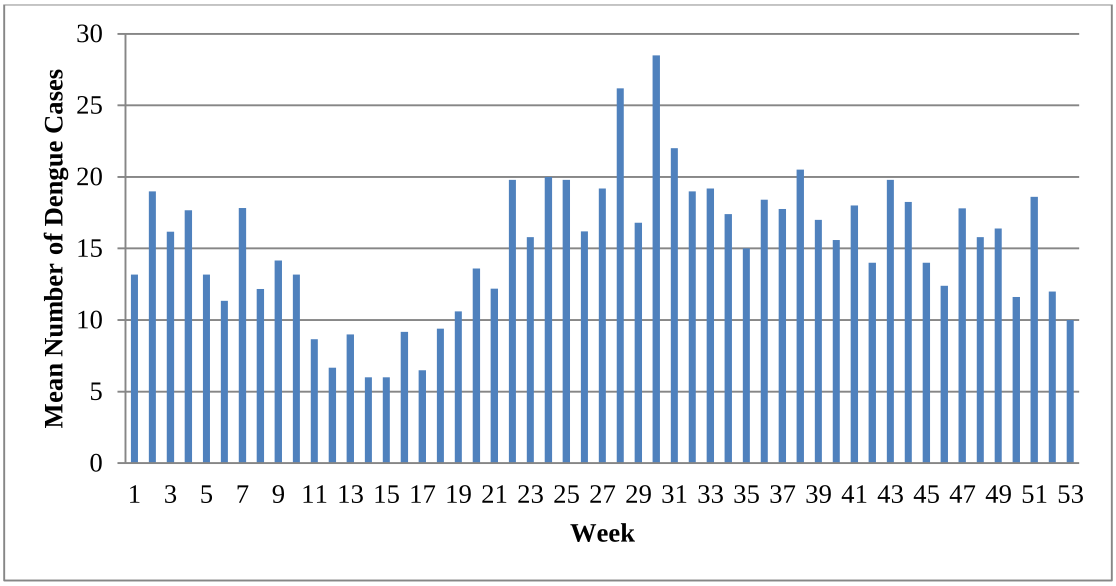


Figure 4.17: Distribution of weekly mean number of dengue cases – Matara District

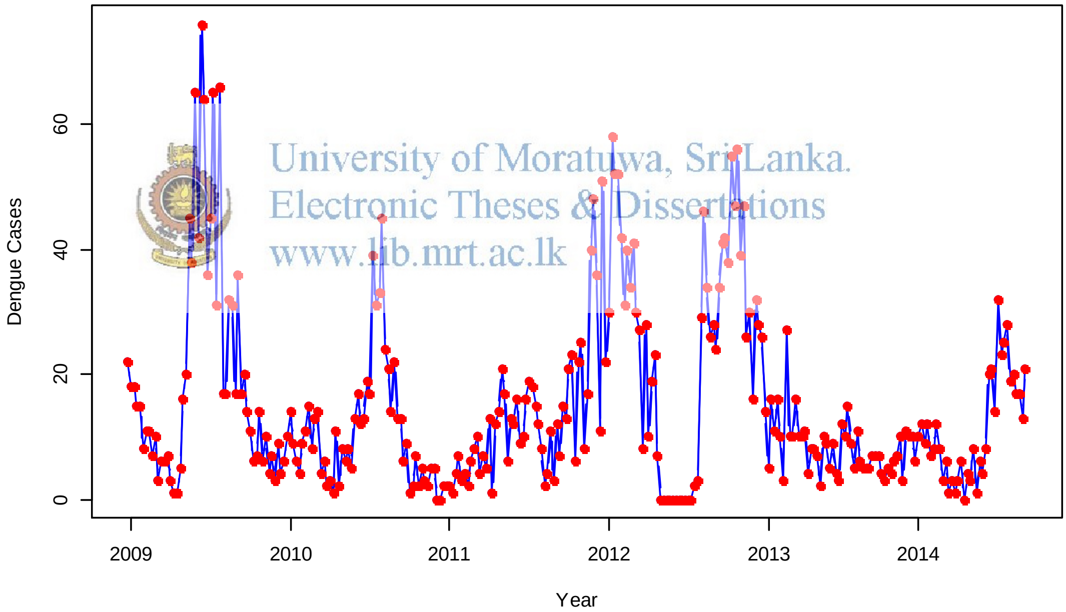


Figure 4.18: Weekly distribution of confirmed dengue cases in Matara District

4.2.4 Nothern province

The Sri Lankan 30 year civil war had its roots in this province. Northern Province is located in the north of Sri Lanka and is just 22 miles (35 km) from India. Northern

Province is covered in tropical forests, with numerous rivers flowing through them and this province has a number of lagoons.

4.2.4.1 Jaffna district

Jaffna District is the capital of Nothern Province. The number of dengue cases reached to a peak in the year of 2010. The reason might be 30 year war was ended in year 2009 and due to the re-habitat programs and infrastructure development projects.

Table 4.10: Descriptive statistics of Dengue Cases – Jaffna District

Year	**Dengue Cases**					
	Minimum	Median	Mean	SD	Maximum	Total
2009	0	0	3.65	15.88	112	190
2010	0	18	35.19	54.68	329	1830
2011	0	5	6.29	4.80	26	327
2012	0	7	14.60	18.48	94	759
2013	4	11	13.88	8.55	37	680
2014*	4	19	20.33	10.42	52	732
Overall	0	9	15.42	27.7	329	4518

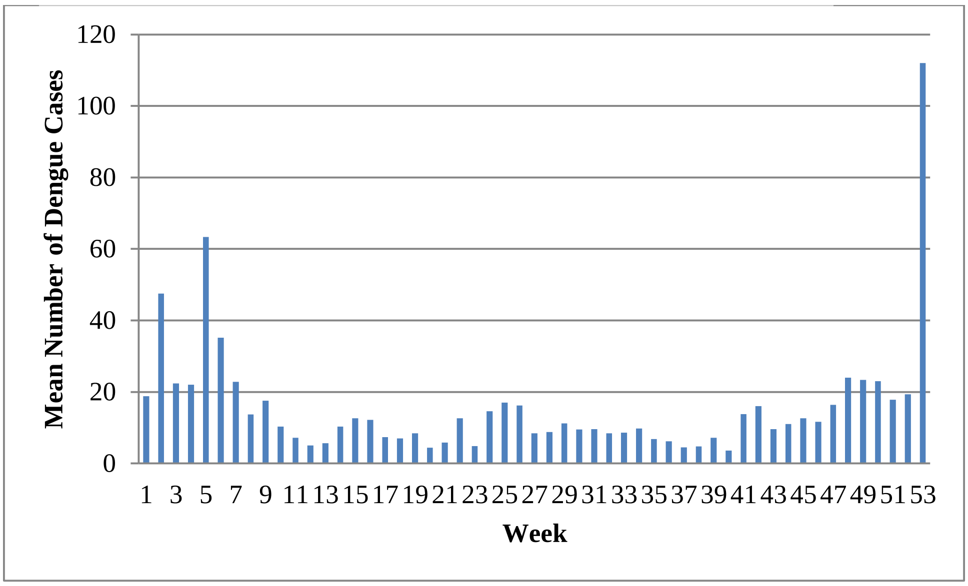


Figure 4.19: Distribution of weekly mean number of dengue cases – Jaffna District

According to figure 4.20 it is clear that the worst outbreak was happened in the year of 2010 due to the unplanned urbanization, infrastructure development and migration.

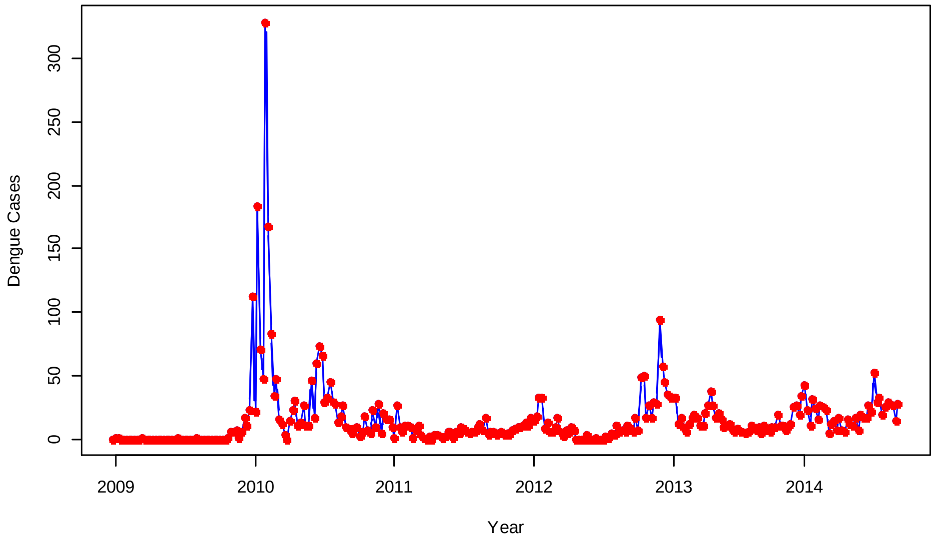


Figure 4.20: Weekly distribution of confirmed dengue cases in Jaffna District

4.2.4.2 Killinochchi district

The climatically condition of Killinochchi district is dry, humid and tropical. Rainfall receives during the period from September to December by North – East monsoon periodical wind. The remaining period other than afore said of the year is dry and warm. According to the figure 4.22 there was a sharp rise in dengue cases from mid 2010. The larges outbreak was recorded in the year of 2010.

Table 4.11: Descriptive statistics of Dengue Cases – Killinochchie District

Year	**Dengue Cases**					
	Minimum	Median	Mean	SD	Maximum	Total
2009	0	0	0	0	0	0
2010	0	0	0.88	1.72	9	46
2011	0	0	0.60	1.17	6	31
2012	0	0	0.46	1.01	6	24
2013	0	0	0.63	1.17	6	31
2014*	0	0	0.61	0.96	4	22
Overall	0	0	0.52	1.16	9	154

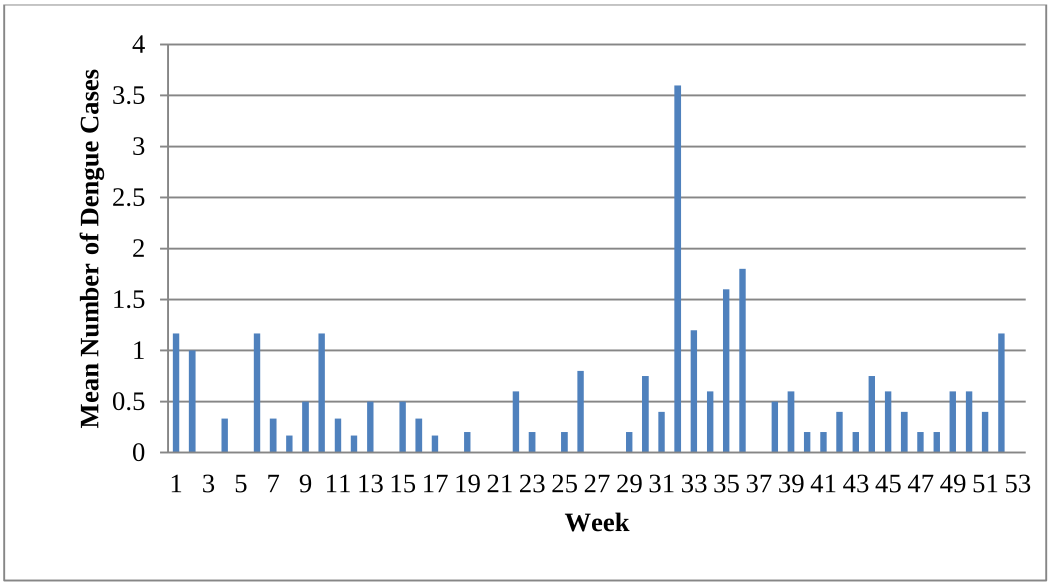


Figure 4.21: Distribution of weekly mean number of dengue cases – Killinochchie District

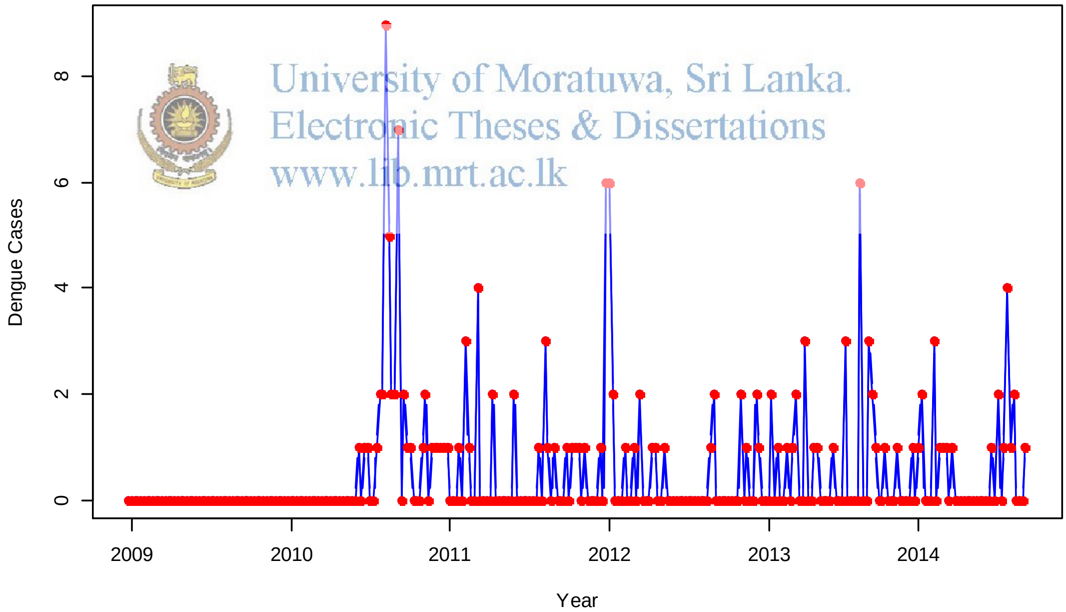


Figure 4.22: Weekly distribution of confirmed dengue cases in Killinochchie District

4.2.4.3 Mannar district

Mannar district is located in northwestern Sri Lanka. Low rainfall and high temperatures characterize the climate. According to figure 4.24 we have seen a dramatic rise in the number of dengue cases in the year of 2010. The next highest outbreak was recorded in the year of 2011. According to figure 4.23 there were two peaks per year. First peak occurred during weeks 31 -33 while the next peak occurred in week 49 – week 3 of the next year.

Table 4.12: Descriptive statistics of Dengue Cases – Mannar District

Year	Dengue Cases					
	Minimum	Median	Mean	SD	Maximum	Total
2009	0	0	0.288	0.92	5	15
2010	0	5	9.06	13.66	84	471
2011	0	1	1.81	3.93	19	94
2012	0	1	2.42	3.39	15	126
2013	0	1	1.25	1.84	10	61
2014*	0	0	1.17	1.91	8	42
Overall	0	1	2.76	6.89	84	809

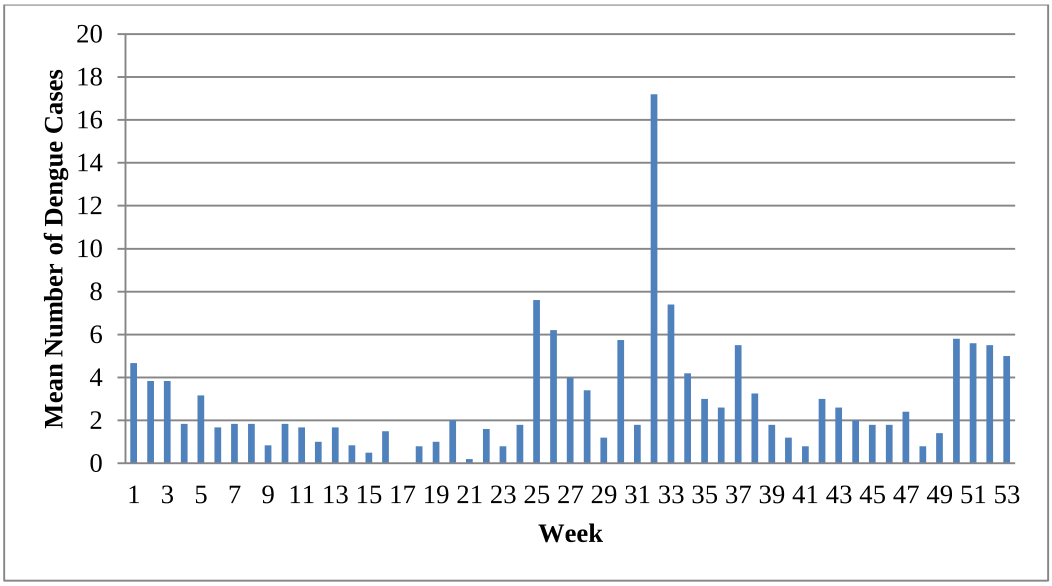


Figure 4.23: Distribution of weekly mean number of dengue cases – Mannar District

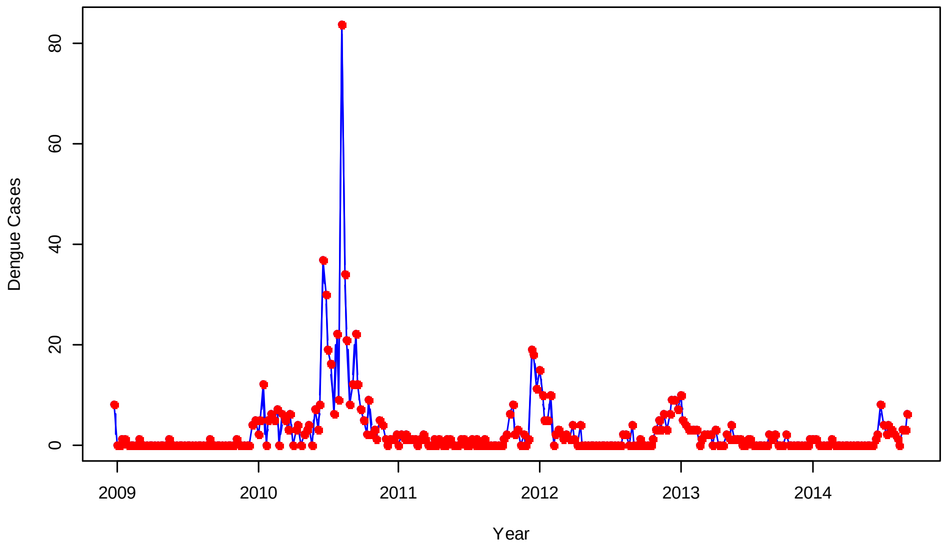


Figure 4.24: Weekly distribution of confirmed dengue cases in Mannar District

4.2.4.4 Vavuniya district

Vavuniya district is located in the North of Sri Lanka. The district is categorized under the area's dry zone of Sri Lanka. According to figure 4.26 there was a sharp rise in the dengue incidence at the end of the each year. Similar to other districts in North of Sri Lanka Vavuniya district shows a sharp rise in the year of 2009, from week 50 - 53.

Table 4.13: Descriptive statistics of Dengue Cases – Vavuniya District

Year	**Dengue Cases**					
	Minimum	Median	Mean	SD	Maximum	Total
2009	0	0	20.81	48.17	209	1082
2010	0	2	10.35	27.13	174	538
2011	0	1	1.35	1.67	10	70
2012	0	1	1.81	2.61	10	94
2013	0	1	1.10	1.14	5	54
2014*	0	1	1.94	3.07	12	70
Overall	0	1	6.51	24.33	209	1908

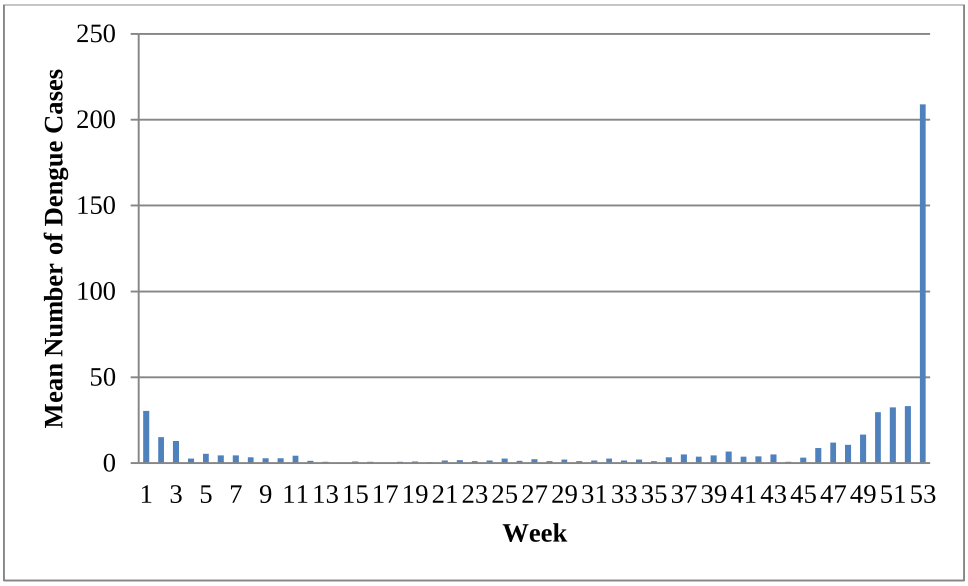


Figure 4.25: Distribution of weekly mean number of dengue cases – Vavuniya District

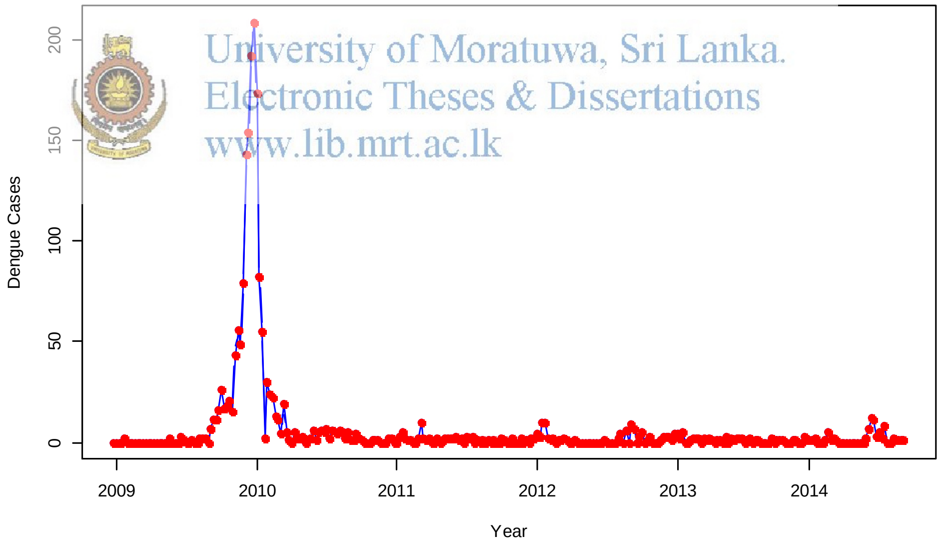


Figure 4.26: Weekly distribution of confirmed dengue cases in Vavuniya District

4.2.4.5 Mulative district

Mulative District is located on the eastern coast of Sri Lanka. Dengue incidence pattern in Mulative district is similar to dengue incidence pattern in Killinochchie district. The number of cases are too low before mid of 2010 for any clear pattern to be visible. We have seen a dramatic rise in the number of dengue cases after 2010. There was a significant increase in the total number of dengue cases in year 2013.

Table 4.14: Descriptive statistics of Dengue Cases – Mulative District

Year	Dengue Cases					
	Minimum	Median	Mean	SD	Maximum	Total
2009	0	0	0	0	0	0
2010	0	0	0.21	0.70	4	11
2011	0	0	0.27	0.69	3	14
2012	0	0	0.40	0.10	4	21
2013	0	1	1.61	1.90	8	79
2014*	0	0.5	1.22	1.59	6	44
Overall	0	0	0.58	1.25	8	169

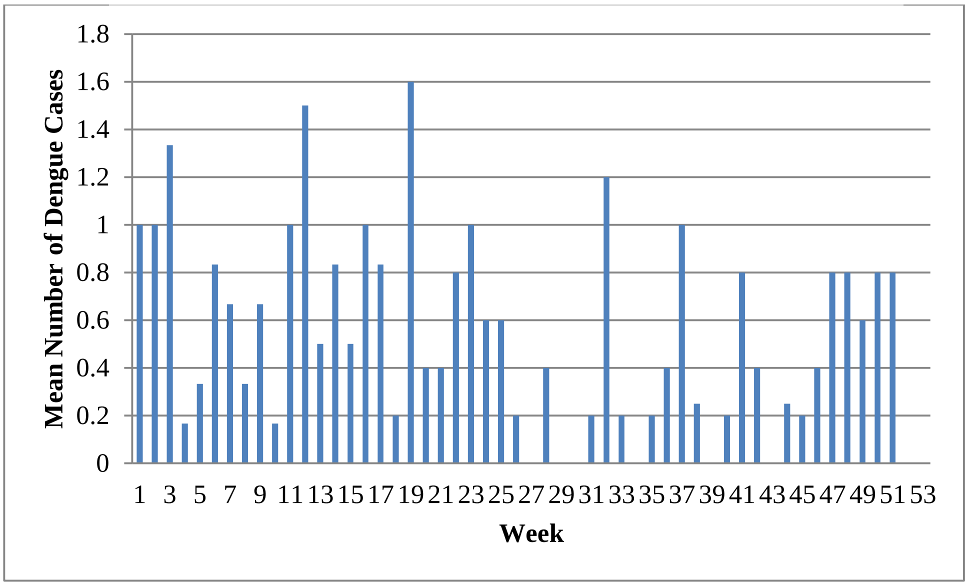


Figure 4.27: Distribution of weekly mean number of dengue cases – Mulative District

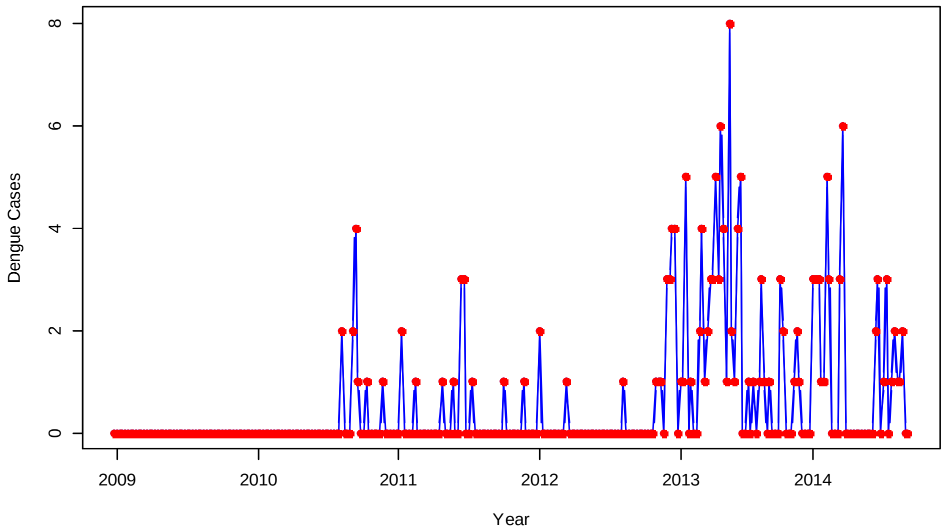


Figure 4.28: Weekly distribution of confirmed dengue cases in Mulative District

4.2.5 Eastern province

4.2.5.1 Batticalo district

Batticalo district is located in the Eastern province of Sri Lanka. Batticaloa has a tropical wet and dry climate. During the monsoon season from November to February heavy rains are recorded, with average temperature of 25^{0}C. According to figure 4.29 there are two peaks per year, at the beginning of the year and at the end of the year. According to figure 4.30 in the year of 2010 there was a sharp rise in dengue incidence. The highest peak of 134 cases was recorded in January 2012. The period which shows large increase in dengue incidence coincide with the monsoon season from November to February.

Table 4.15: Descriptive statistics of Dengue Cases – Batticalo District

Year	**Dengue Cases**					
	Minimum	Median	Mean	SD	Maximum	Total
2009	0	9	11.13	10.12	49	579
2010	0	9.5	17.88	21.16	78	930
2011	0	15.5	26.85	31.40	134	1396
2012	0	5.5	10.83	13.76	62	563
2013	0	7	8.02	6.14	28	393
2014*	1	14	15.42	10.18	47	555
Overall	0	9	15.07	18.98	134	4416

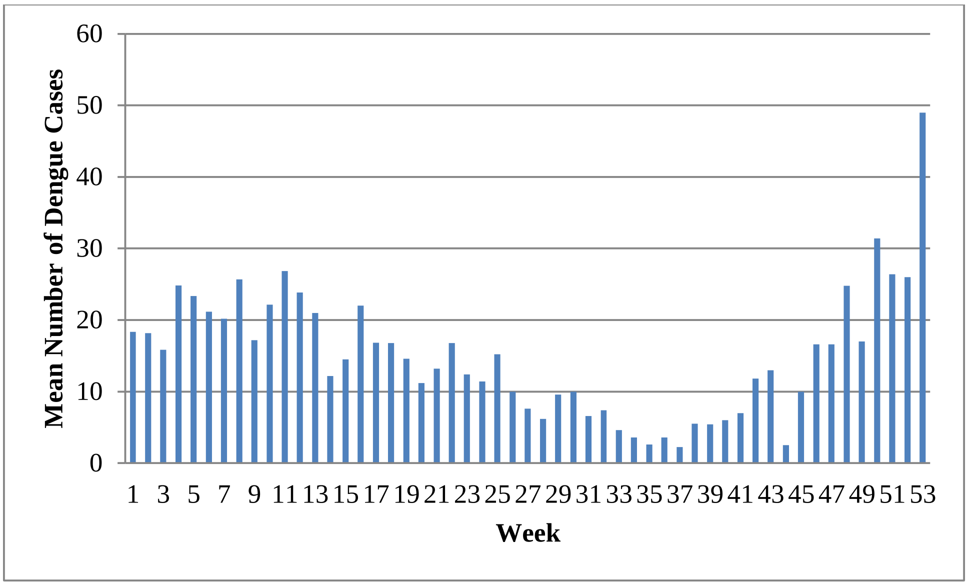


Figure 4.29: Distribution of weekly mean number of dengue cases – Batticalo District

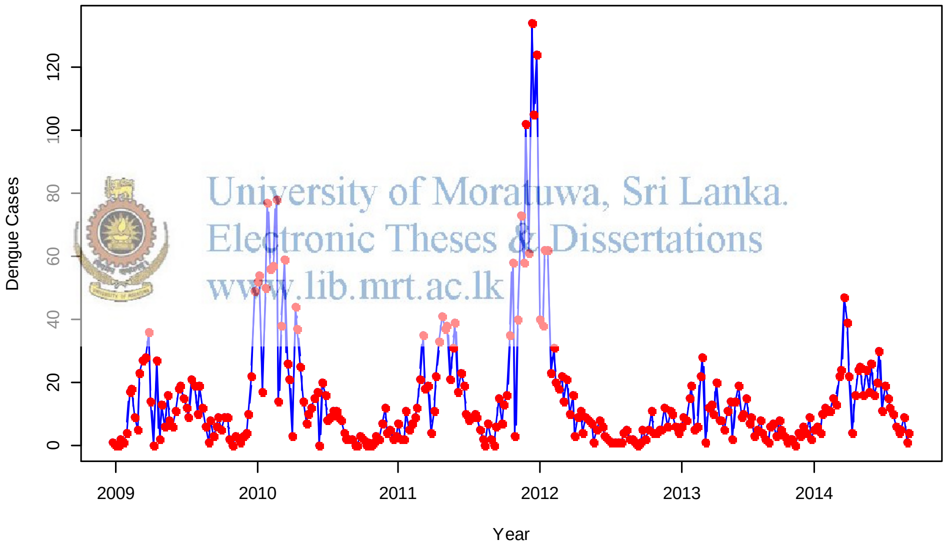


Figure 4.30: Weekly distribution of confirmed dengue cases in Batticalo District

4.2.5.2 Ampara district

Ampara district is located in Eastern Province, Sri Lanka. Dengue incidence in Ampara district possesses annual seasonality with peak during the beginning of the year and end of the year. Relatively higher number of dengue cases reported in both 2009 and 2010. Similar to other districts in eastern province and North province highest peak was recorded in 2010.

Table 4.16: Descriptive statistics of Dengue Cases – Ampara District

Year	**Dengue Cases**					
	Minimum	Median	Mean	SD	Maximum	Total
2009	0	7	8.10	7.36	37	421
2010	0	5	9.61	11.76	61	484
2011	0	2	3.83	4.48	24	199
2012	0	2	3.39	4.03	17	176
2013	0	5	7.82	9.17	47	383
2014*	0	4	4.56	3.17	12	164
Overall	0	4	6.24	7.78	61	1827

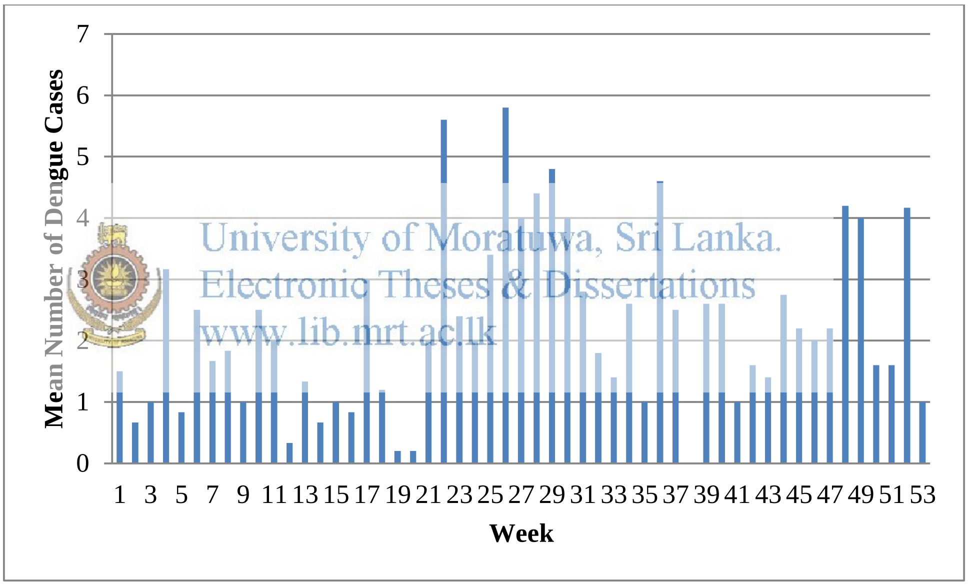


Figure 4.31: Distribution of weekly mean number of dengue cases – Ampara District

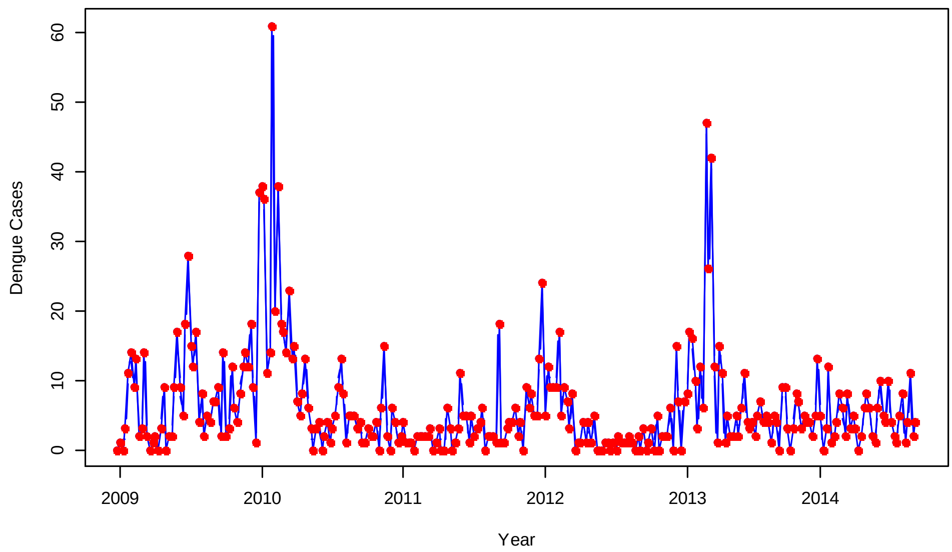


Figure 4.32: Weekly distribution of confirmed dengue cases in Ampara District

4.2.5.3 Trincomalee district

Trincomalee district possess a tropical wet and dry climate. The time series of weekly dengue cases in Trincomalee generated a peak in 2010 and the next peak was reported in the year of 2014. Visual inspection shows from 2011 to 2013 the number of cases are too low for any clear pattern to be visible.

Table 4.17: Descriptive statistics of Dengue Cases – Trincomalee District

Year	**Dengue Cases**					
	Minimum	Median	Mean	SD	Maximum	Total
2009	0	2	3.8	4.78	19	200
2010	0	5.5	11.48	16.34	81	597
2011	0	2.5	2.73	2.49	9	142
2012	0	1	2.31	2.74	11	120
2013	0	1	2.76	2.84	13	135
2014*	0	8	10.50	9.32	40	378
Overall	0	3	5.37	8.89	81	1572

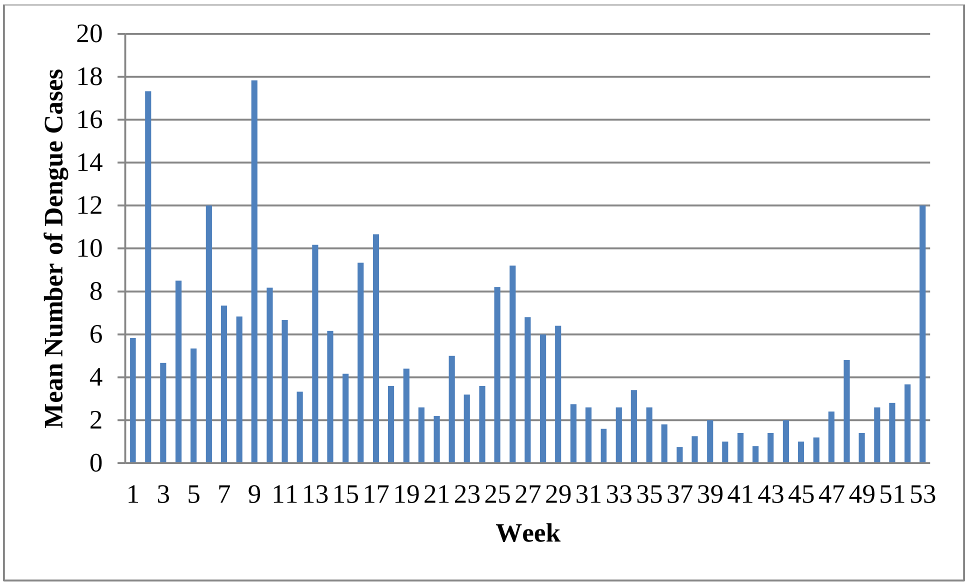


Figure 4.33: Distribution of weekly mean number of dengue cases – Trincomalee District

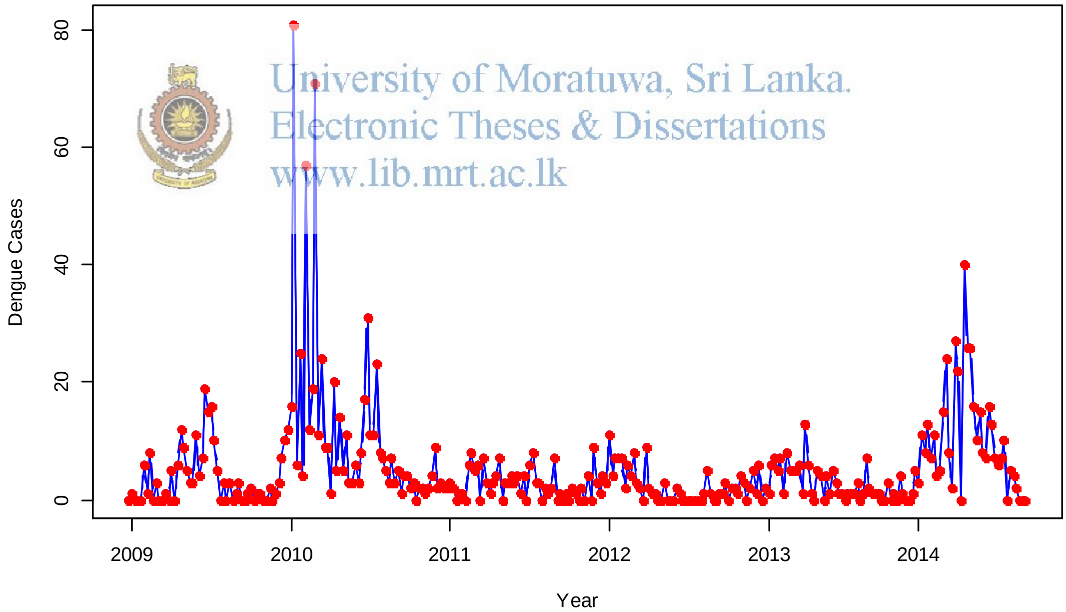


Figure 4.34: Weekly distribution of confirmed dengue cases in Trincomalee District

4.2.6 North Western province

4.2.6.1 Kurunagala districts

Climate in Kurunagala district is topical throughout the year. During the monsoons from May to August and October to January, heavy rains can be expected. According to figure 4.36 dengue cases revealed a strong seasonal pattern. There are two peaks per year. The peak occurred during week 25 – 31 is more significant than the peak occurred in December – January.

Table 4.18: Descriptive statistics of Dengue Cases – Kurunagala District

Year	Dengue Cases					
	Minimum	Median	Mean	SD	Maximum	Total
2009	4	25	45.69	46.82	228	2376
2010	1	19.5	23.23	19.89	91	1208
2011	1	17	16.67	8.33	38	867
2012	1	36	39.58	35.39	219	2058
2013	7	27	33.29	24.63	130	1631
2014*	1	24.5	32.50	24.14	86	1170
Overall	1	23	31.77	30.85	228	9310

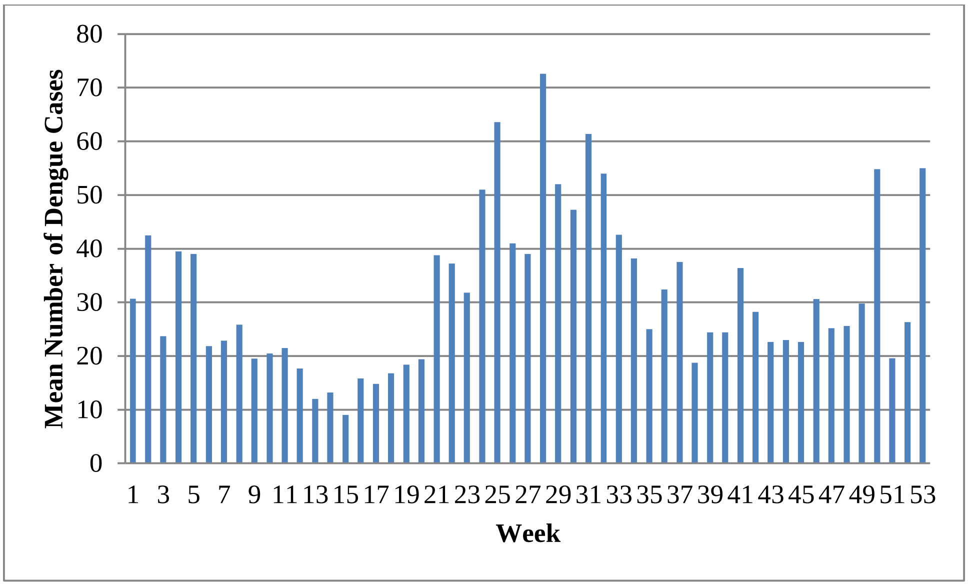


Figure 4.35: Distribution of weekly mean number of dengue cases – Kurunagala District

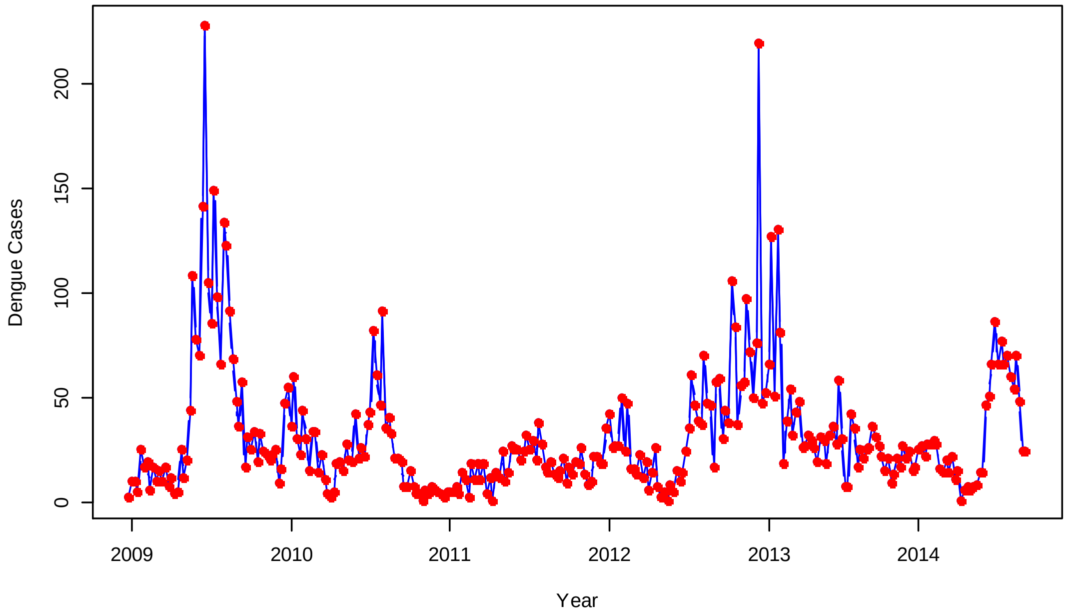


Figure 4.36: Weekly distribution of confirmed dengue cases in Kurunagala District

4.2.6.2 Puttalam district

Puttalam district is in North Western province of Sri Lanka. Puttalam district experienced an unexpected outbreak in 2010 that was out of the sequence with the typical epidemic cycle. Another unexpected outbreak was observed in 2013, the second outbreak is substantially higher than the first one in 2010. In contrast there was a drastic downward trend in 2012 was partially due to the effectiveness of strengthened vector control programmes implemented in year 2012.

Table 4.19: Descriptive statistics of Dengue Cases – Puttalam District

Year	**Dengue Cases**					
	Minimum	Median	Mean	SD	Maximum	Total
2009	0	6.5	12.94	16.9	85	673
2010	1	8	12.94	14.58	84	673
2011	0	6	7.25	6.07	31	377
2012	0	10	19.77	25.49	123	1028
2013	0	10	12.94	9.91	45	634
2014*	0	8.5	9.69	8.24	38	349
Overall	0	8	12.74	15.54	123	3734

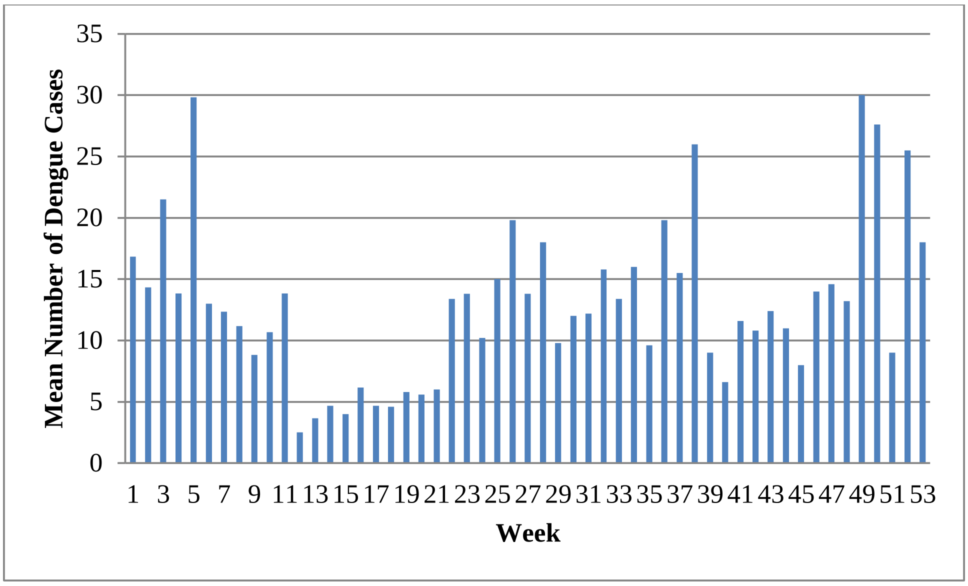


Figure 4.37: Distribution of weekly mean number of dengue cases – Puttalam District

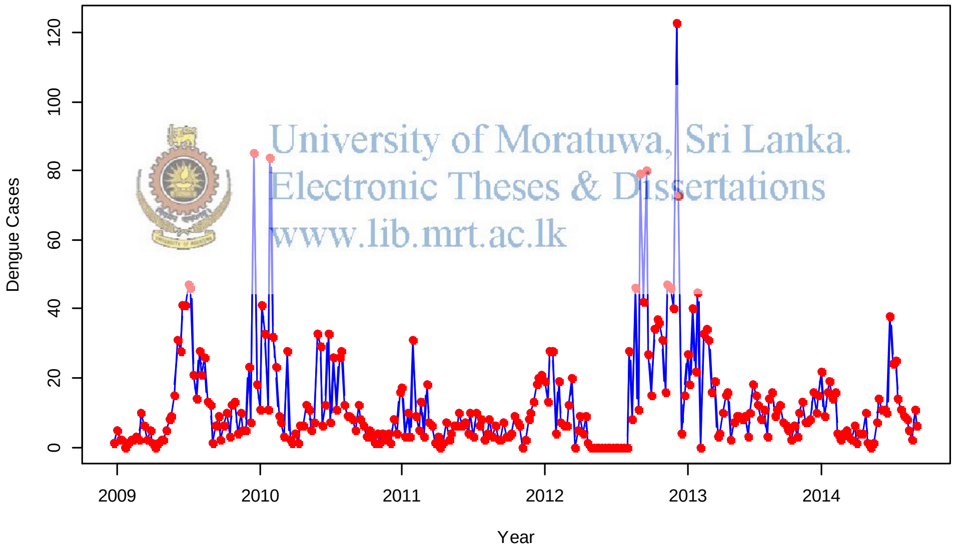


Figure 4.38: Weekly distribution of confirmed dengue cases in Puttalam District

4.2.7 North Central province

4.2.7.1 Anuradhapura district

Anaradhapura district is in the dry zone of Sri Lanka. Dengue cases were recorded once or several times a year without a clear seasonal pattern. Incidence rates of DF have increased significantly during 2009 – 2010. Number of dengue cases recorded in the year 2010 is thrice as much as the number of cases in year 2012. After 2010 there was a downward trend in the incidence of dengue cases. Variation of dengue cases in 2011 is relatively low compared to other years.

Table 4.20: Descriptive statistics of Dengue Cases – Anuradhapura District

Year	Dengue Cases					
	Minimum	Median	Mean	SD	Maximum	Total
2009	0	5.5	10.75	10.37	40	559
2010	0	9	15.94	19.94	112	829
2011	0	4	4.40	2.99	15	229
2012	0	4	5.50	6.25	31	286
2013	0	6	7.71	5.80	24	378
2014*	0	5.5	6.39	4.62	20	230
Overall	0	5	8.57	10.99	112	2511

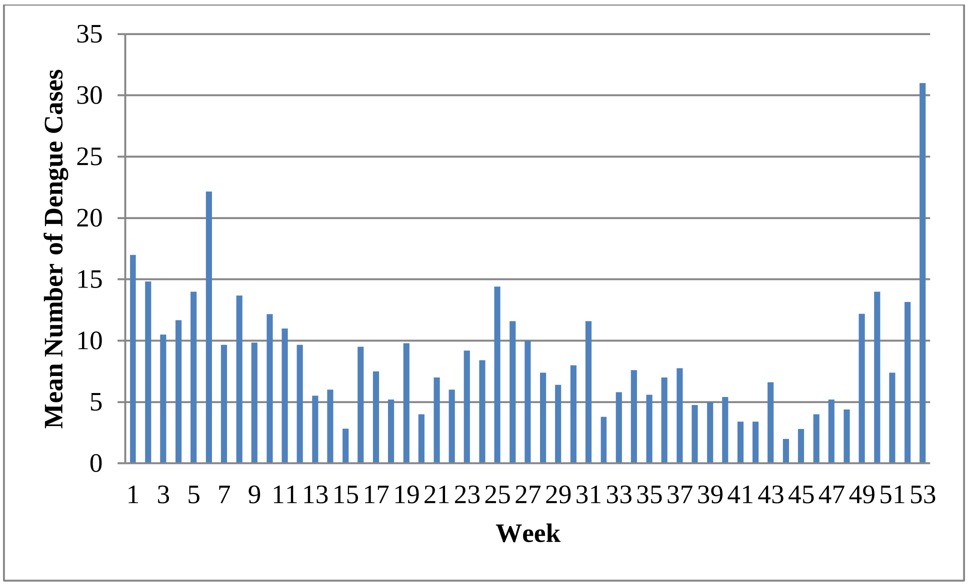


Figure 4.39: Distribution of weekly mean number of dengue cases – Anuradhapura District

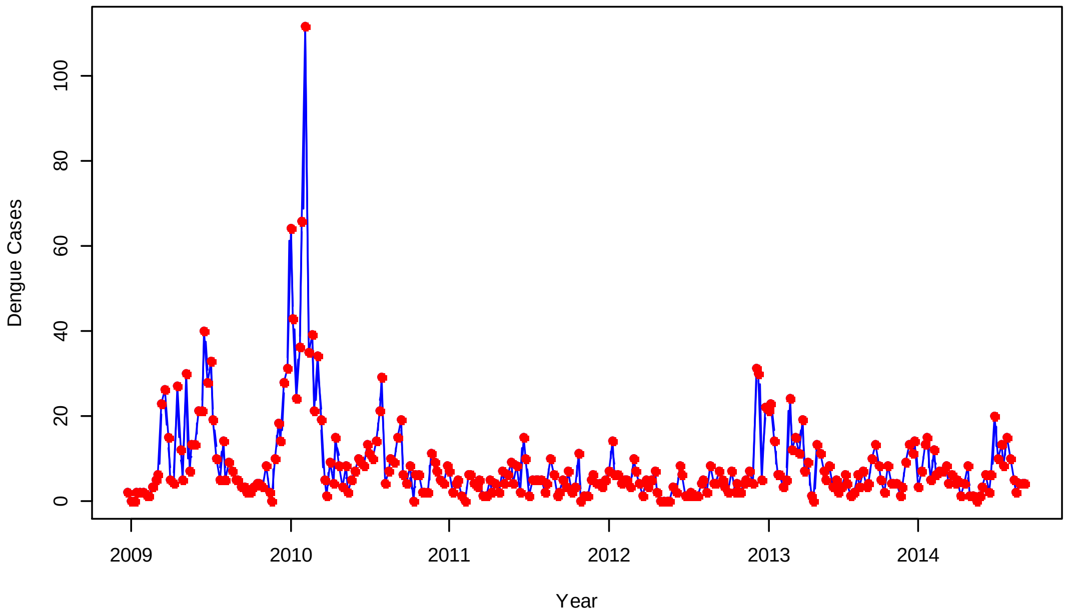


Figure 4.40: Weekly distribution of confirmed dengue cases in Anuradhapura District

4.2.7.2 Polonnaruwa district

Polonnaruwa district has a tropical climate most of the year. The incidence of dengue strongly fluctuated from year to year and between months within a year. According to figure 4.41 and figure 4.42 higher numbers of cases generally occurred from June to September. The drastic downward trend in 2014 was partially due to the effectiveness of strengthened vector control programs implemented at the end of 2013.

Table 4.21: Descriptive statistics of Dengue Cases – Polonnaruwa District

Year	**Dengue Cases**					
	Minimum	Median	Mean	SD	Maximum	Total
2009	0	2	3.173	3.568	21	165
2010	0	4	6.538	6.254	23	340
2011	0	3	3.712	3.114	13	193
2012	0	2	2.827	3.154	14	147
2013	0	6	6.735	5.028	21	330
2014*	0	0	3.111	4.868	17	112
Overall	0	3	4.392	4.713	23	1287

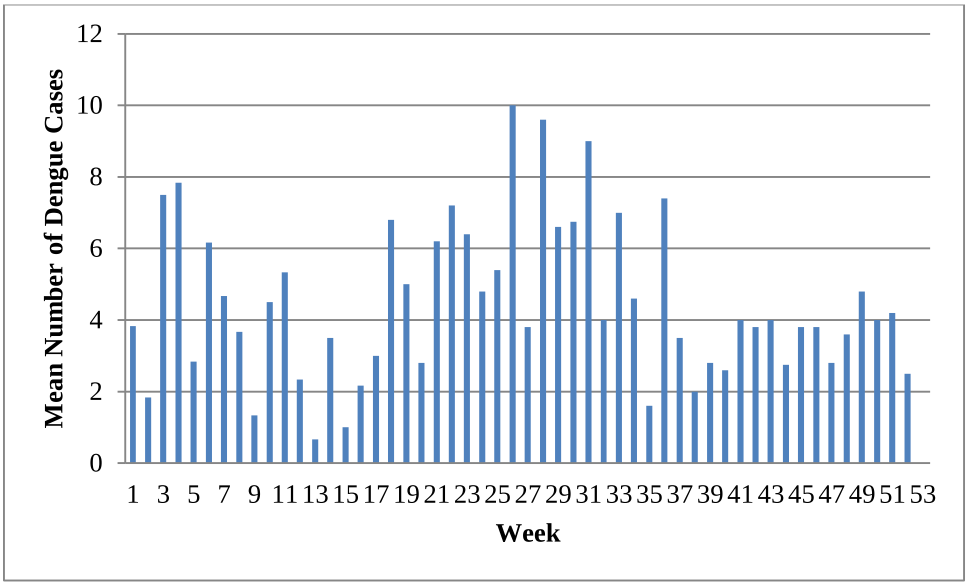


Figure 4.41: Distribution of weekly mean number of dengue cases – Polonnaruwa District

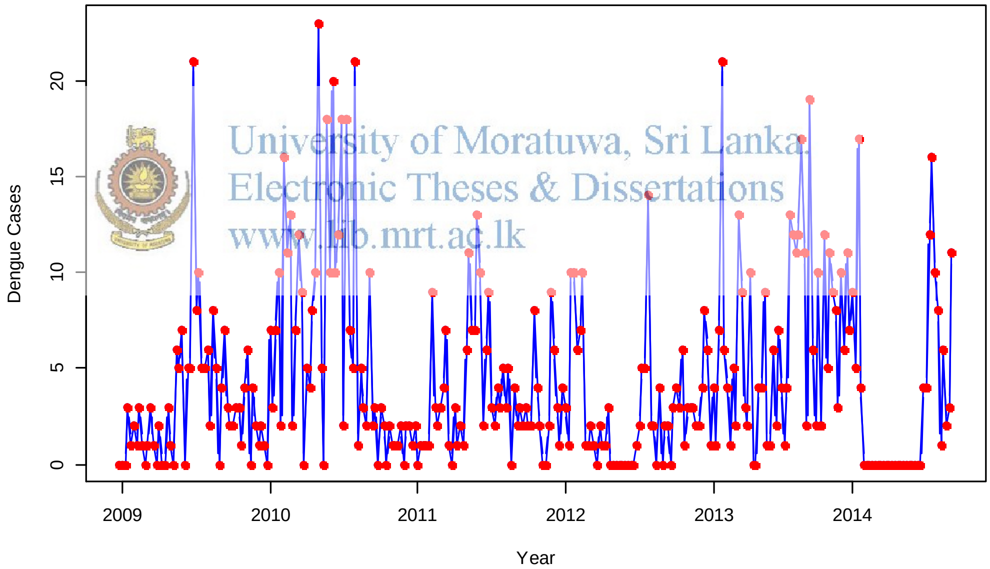


Figure 4.42: Weekly distribution of confirmed dengue cases in Polonnaruwa District

4.2.8 Uva province

4.2.8.1 Badulla district

Badulla district is situated hilly parts of the island. The time series of monthly dengue cases in Badulla district shows a drastic upward trend in 2010 and 2011. Even though Badulla possess cold climate, fair number of dengue cases has been recorded throughout the study period. According to figure 4.43 and 4.44 higher number of dengue cases generally occurred during the mid of the year. This peak was less distinct after 2012.

Table 4.22: Descriptive statistics of Dengue Cases – Badulla District

Year	Dengue Cases					
	Minimum	Median	Mean	SD	Maximum	Total
2009	0	4	5.654	6.15	36	294
2010	0	9	16.19	19.68	112	842
2011	0	7	10.17	11.85	73	529
2012	0	3	4.50	4.57	16	234
2013	0	6	6.86	4.21	22	336
2014*	0	9	9.69	6.97	31	349
Overall	0	6	8.819	11.27	112	2584

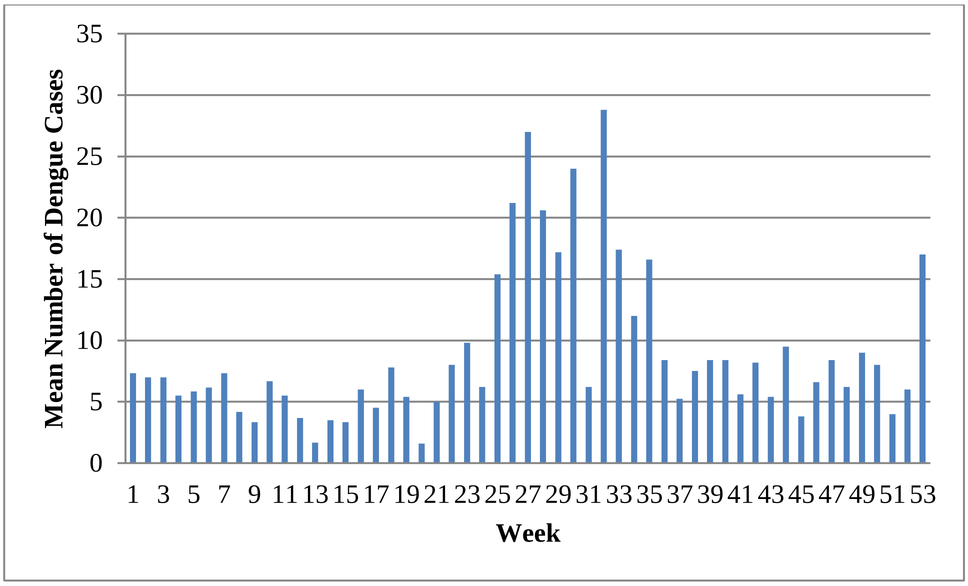


Figure 4.43: Distribution of weekly mean number of dengue cases – Badulla District

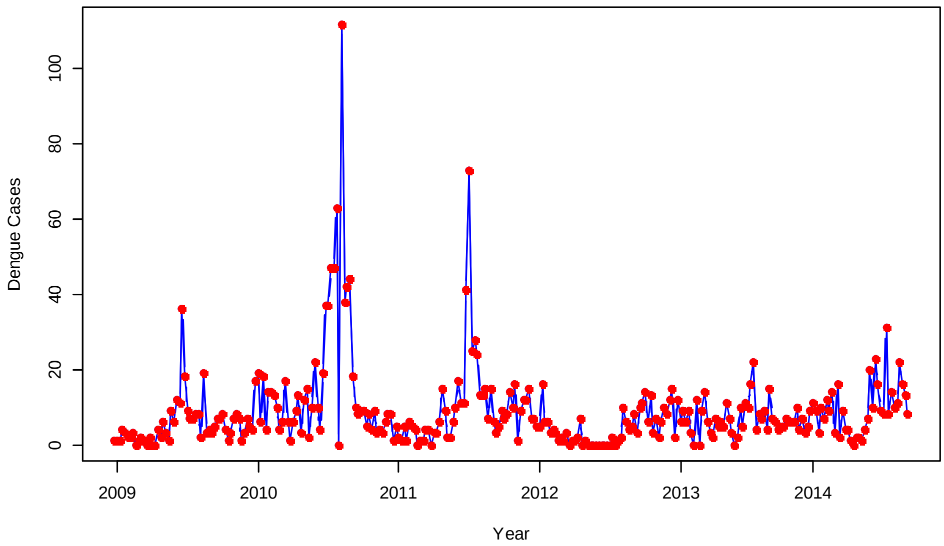


Figure 4.44: Weekly distribution of confirmed dengue cases in Badulla District

4.2.8.2 Monaragala district

Monaragala District is situated in Uva Province. According to figure 4.45 there has been a drastic upward trend in the year of 2010. As shown in figure 4.45 and figure 4.46 higher number of dengue cases generally occurred from June to September. This peak was less distinct after 2010.

Table 4.23: Descriptive statistics of Dengue Cases – Monaragala District

Year	Dengue Cases					
	Minimum	Median	Mean	SD	Maximum	Total
2009	0	2	3.29	3.61	14	171
2010	1	9	15.08	17.52	95	784
2011	0	5	4.87	3.50	18	253
2012	0	3	2.86	2.19	9	147
2013	0	3	3.35	2.38	10	164
2014*	0	4	4.56	3.20	12	164
Overall	0	4	5.744	8.966	95	1683

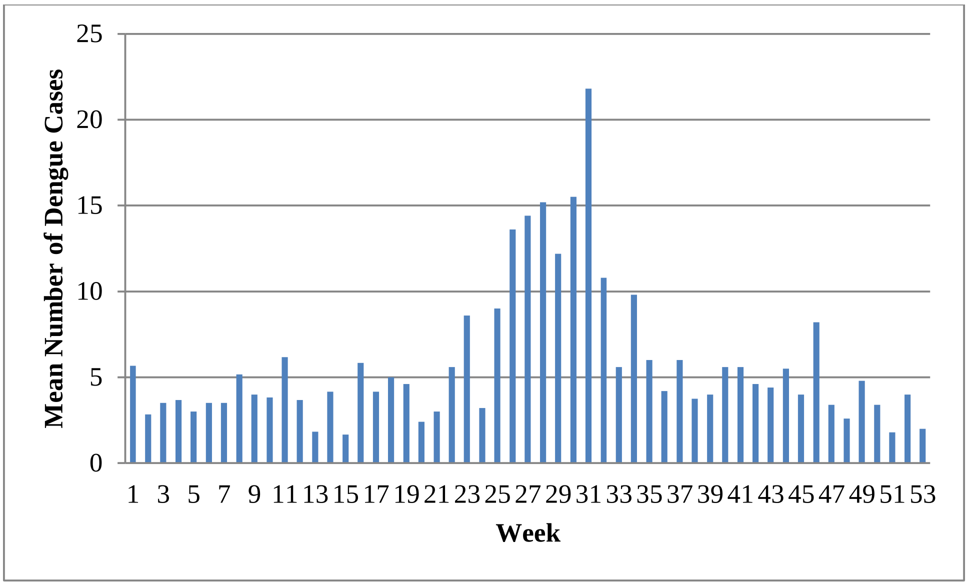


Figure 4.45: Distribution of weekly mean number of dengue cases – Monaragala District

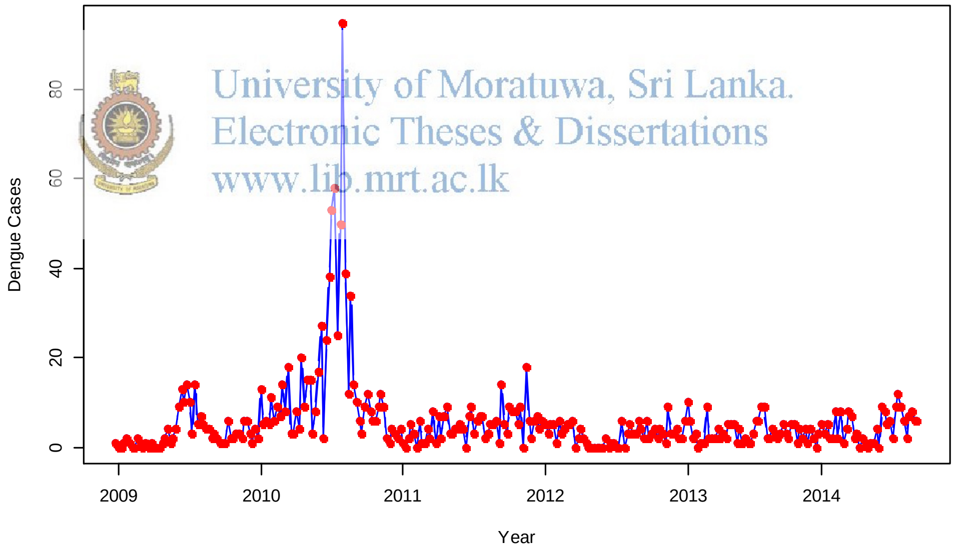


Figure 4.46: Weekly distribution of confirmed dengue cases in Monaragala District

4.2.9 Sabaragamuwa province

4.2.9 Ratnapura district

Ratnapura district features a tropical rainforest climate. In contrast to other districts a large peak of dengue cases occurred in 2014. Sudden upward outbreaks can be seen in 2009, 2010 and 2012. These peaks are of roughly equal magnitudes. As shown in figure 4.47 higher number of cases generally occurred from May to September. Even though the year 2014 consists 36 weeks, throughout the study period highest number of dengue cases recorded in 2014.

Table 4.24: Descriptive statistics of Dengue Cases – Ratnapura District

Year	**Dengue Cases**					
	Minimum	Median	Mean	SD	Maximum	Total
2009	0	9.5	27.33	32.79	112	1421
2010	1	24	34.08	29.47	121	1772
2011	1	15.5	14.56	8.25	33	757
2012	5	27	32.56	23.86	128	1693
2013	4	20	21.51	13.49	57	1054
2014*	0	15	43.78	58.45	234	1576
Overall	0	18	28.24	31.15	234	8273

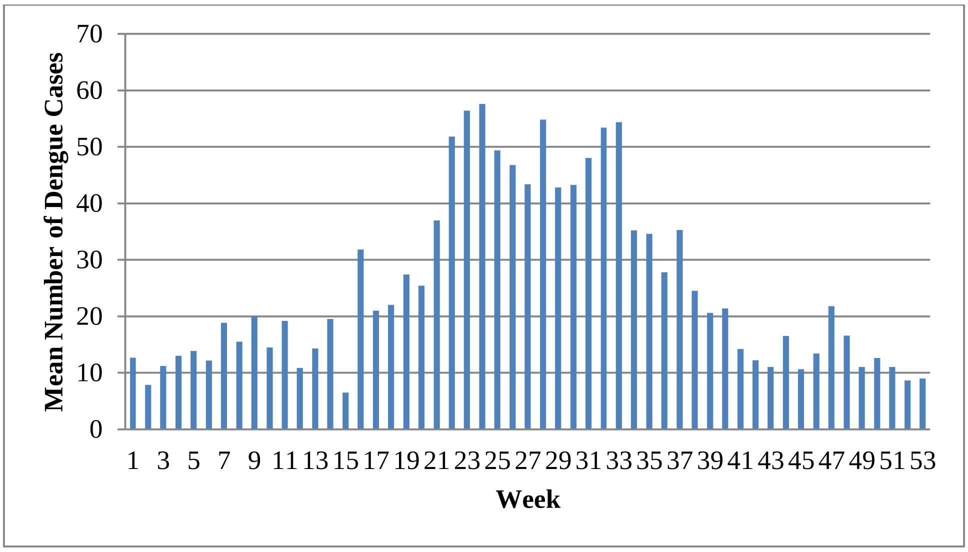


Figure 4.47: Distribution of weekly mean number of dengue cases – Ratnapura District

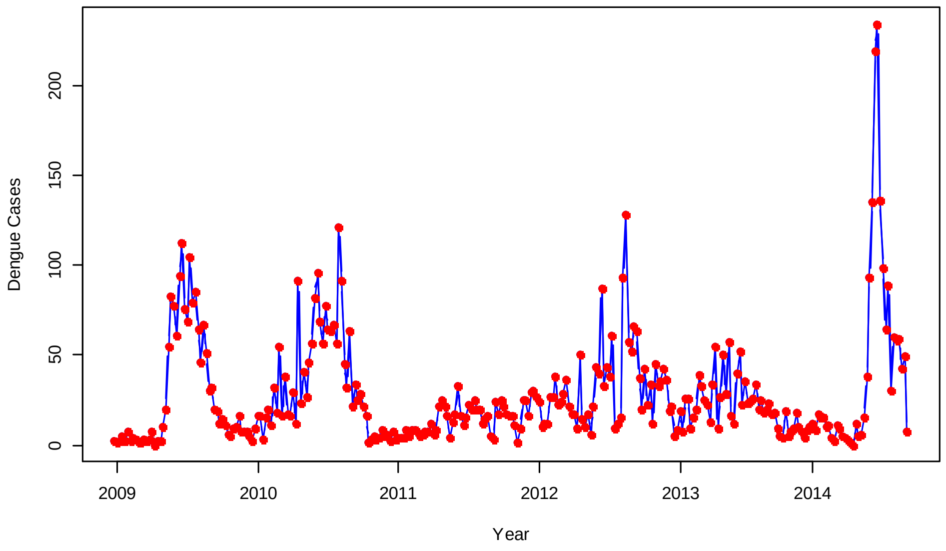


Figure 4.48: Weekly distribution of confirmed dengue cases in Ratnapura District

4.2.9.2 Kegalle district

There is no clear seasonal pattern in the occurrence of dengue incidence in Kegalle district. Higher number of cases generally occurred from June to October. Similar to other districts drastic upward trend can be seen in the year of 2009.

Table 4.25: Descriptive statistics of Dengue Cases – Kegalle District

Year	**Dengue Cases**					
	Minimum	Median	Mean	SD	Maximum	Total
2009	1	24	43.83	47.56	250	2279
2010	0	10.5	13.35	11.00	39	694
2011	0	14	17.06	13.47	63	887
2012	0	28	22.90	17.92	80	1451
2013	1	19	19.78	8.78	49	969
2014*	3	19.5	27.47	21.11	86	989
Overall	0	19	24.81	25.99	250	7269

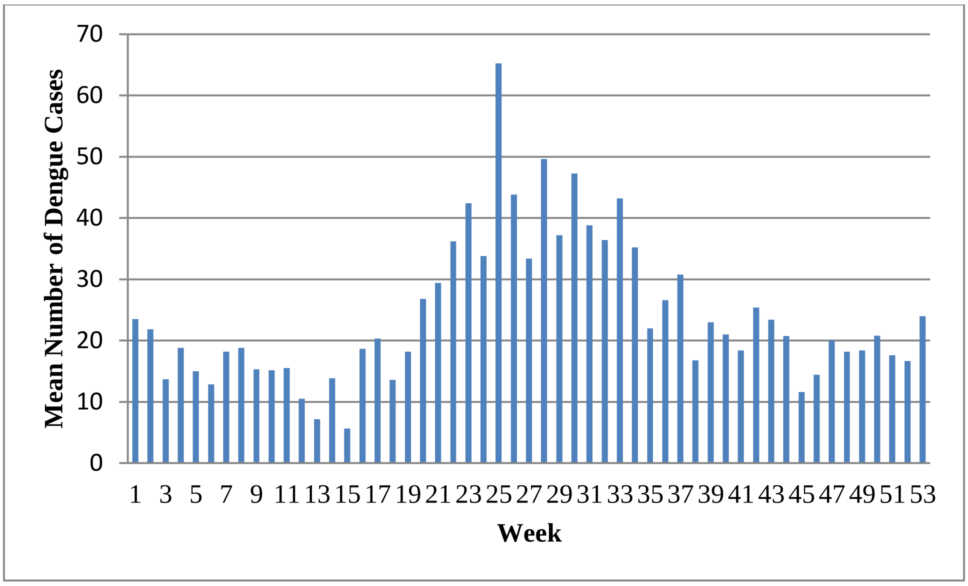


Figure 4.49: Distribution of weekly mean number of dengue cases – Kegalle District

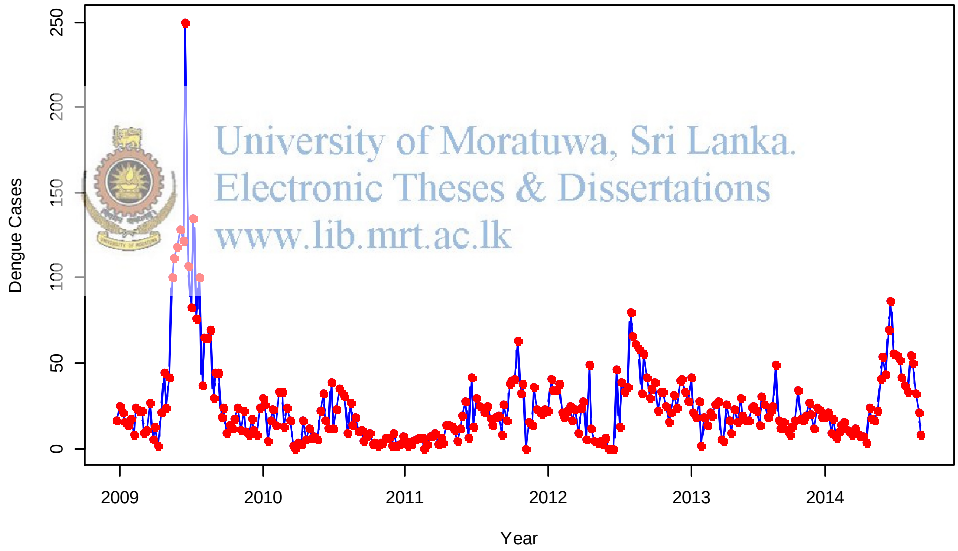


Figure 4.50: Weekly distribution of confirmed dengue cases in Kegalle District

4.3 Descriptive Statistics of Climatic Variables

To understand how climate in Colombo district might affect dengue incidence it is important to first be aware of patterns in climatic factors; mean temperature, maximum temperature, minimum temperature, precipitation, wind speed, visibility, humidity and wind speed.

Temperature

Temperature, precipitation, and humidity are critical to mosquito survival, reproduction, and development and can influence mosquito presence and abundance. Temperature affects the dengue system through numerous biological mechanisms. Vast majority of studies examining the effects of temperature on dengue virus transmission most often used mean temperature as the temperature representative. In nature, however, mosquitoes and their pathogens do not simply experience mean conditions, but instead subjected to temperatures that fluctuate throughout the day. Hence we consider three states of temperature; mean temperature, minimum temperature and maximum temperature. During 2009 – September, 2014, the weekly mean temperature ranged from 24^0C to 30^0C with an overall mean of 27.7^0C. Mean air temperature remains relatively constant. The highest mean value was recorded in 2009. According to Nakhapakorn and Tripathi, (2005) temperature higher than 20^0C is the favorable for Aedes aegypti mosquitoes.

Table 4.26: Descriptive Statistics of weekly mean temperature

Year	Weekly mean temperature				
	Minimum	Median	Mean	SD	Maximum
2009	26.175	27.657	27.659	0.781	29.657
2010	25.229	27.793	27.656	0.965	29.477
2011	24.186	27.750	27.599	1.014	29.357
2012	25.757	26.657	27.640	0.883	29.557
2013	26.029	27.550	27.641	0.818	29.657
2014*	26.243	28.379	28.180	0.824	29.500
Overall	24.186	27.723	27.705	0.899	29.657

Descriptive statistics of weekly maximum temperature by year is presented in table 4.27. For the study period (52^{nd} week, 2008 – 36^{th} week, 2014), the maximum temperature ranged from $27^{0}C$ to $33^{0}C$, where the highest occurred in 2013. Mean temperature of 2014 is slightly higher than other years. Mean value of minimum temperature for the period 2011 – 2013 was below the overall mean value of $25^{0}C$; while it was above the overall mean for years 2009, 2010 and 2014.

Table 4.27: Descriptive Statistics of weekly maximum temperature

Year	Maximum temperature				
	Minimum	Median	Mean	SD	Maximum
2009	29.700	30.712	30.789	0.754	32.700
2010	28.186	30.457	30.768	1.143	32.786
2011	27.314	30.720	30.653	0.887	32.986
2012	29.014	30.993	30.996	0.662	32.229
2013	29.343	30.793	30.936	0.930	33.714
2014*	30.257	31.514	31.510	0.774	33.229
Overall	27.314	30.871	30.911	0.905	33.714

Table 4.28: Descriptive Statistics of weekly minimum temperature

Year	Minimum temperature				
	Minimum	Median	Mean	SD	Maximum
2009	22.180	24.986	25.203	1.442	27.700
2010	22.629	25.221	25.103	1.099	27.071
2011	21.400	24.707	24.954	1.363	27.843
2012	20.829	24.486	24.664	1.421	27.414
2013	20.071	25.114	24.945	1.182	27.114
2014*	22.200	25.400	25.357	1.470	28.043
Overall	20.829	24.979	25.021	1.336	28.043

Precipitation

Precipitation is one of the most important environmental factors affecting biological process of mosquitoes, including their interaction with virus. During the study period, the weekly mean precipitation ranged from 0mm to 71mm. In contrast to temperature variation the variation of precipitation is higher than the temperature components. The reason for that might be Sri Lanka gets rainfall mainly from two rainy seasons: southwest monsoon (May to August) and northeast monsoon (November to February). As shown in table 4.29, Colombo experienced highest mean weekly precipitation in year 2013 followed by 2010.

Table 4.29: Descriptive Statistics of weekly precipitation

Year	**Precipitation**				
	Minimum	Median	Mean	SD	Maximum
2009	0.000	3.380	5.620	8.420	55.240
2010	0.000	2.430	9.070	14.710	65.860
2011	0.000	2.050	5.015	6.540	33.273
2012	0.000	4.209	6.300	6.968	29.646
2013	0.000	4.190	6.790	11.000	71.340
2014*	0.000	2.279	3.597	4.298	19.849
Overall	0.000	2.994	6.193	9.539	71.340

Humidity

Sri Lanka is primarily a tropical country with high humidity and warm temperature throughout the year. More specifically Colombo district is a coastal district, it would be expected that relative humidity will be high for most days of the year, thus an important factor on mosquito density and dengue transmission. Throughout the study period mean humidity was approximately 80%.

Table 4.30: Descriptive Statistics of humidity

Year	Humidity				
	Minimum	Median	Mean	SD	Maximum
2009	65.200	79.857	79.049	4.629	87.000
2010	69.286	81.500	80.790	5.042	90.286
2011	71.571	79.929	79.786	3.641	89.857
2012	69.286	79.857	79.615	4.208	88.286
2013	62.000	80.143	79.720	4.444	86.857
2014*	68.429	79.607	78.414	4.205	86.857
Overall	62.000	80.000	79.624	4.410	90.286

Mean Visibility

Mean visibility remains constant throughout the study period at a mean of 20km. Except 2009 visibility ranged from approximatelt 15km – 20km. But in 2009 minimum visibility droped to approximately 11km. Further variation of mean visibility in 2009 is approximately twice as much as higher than the other years.

Table 4.31: Descriptive Statistics of visibility

Year	Visibility				
	Minimum	Median	Mean	SD	Maximum
2009	10.943	19.486	19.081	1.617	20.000
2010	17.014	19.464	19.264	0.724	20.000
2011	15.229	19.743	19.552	0.725	20.043
2012	16.914	19.864	19.666	0.528	20.114
2013	18.357	19.893	19.751	0.330	20.286
2014*	17.757	19.871	19.603	0.594	20.200
Overall	10.943	19.736	19.478	0.897	20.286

Wind Speed

Descriptive statistics of mean wind speed and maximum sustained wind speed is shown in table 4.32 and table 4.33 respectively. Colombo district experienced highest weekly mean wind speed in 2009 while the lowest mean wind speed also recorded in the same year. Both the descriptive statistics of mean wind speed and maximum sustained wind speed revealed that year 2009 experienced lower wind speed.

Table 4.32: Descriptive Statistics of mean wind speed

Year	Mean Wind Speed				
	Minimum	Median	Mean	SD	Maximum
2009	0.850	4.781	5.248	2.401	14.386
2010	1.786	5.017	4.868	1.627	8.157
2011	2.271	5.493	5.338	1.738	8.829
2012	1.957	4.664	4.742	1.351	7.800
2013	2.671	5.357	5.521	1.827	10.029
2014*	3.500	6.157	5.748	1.535	8.443
Overall	0.850	5.157	5.215	1.806	14.386

Table 4.33: Descriptive Statistics of maximum sustained wind speed

Year	Mean Sustained Wind Speed				
	Minimum	Median	Mean	SD	Maximum
2009	4.600	9.064	9.546	3.291	23.271
2010	5.214	10.093	10.166	2.542	20.943
2011	6.586	10.514	10.744	2.522	19.314
2012	6.014	10.057	10.610	2.766	22.029
2013	6.914	10.636	11.584	4.375	29.686
2014*	7.971	10.961	10.827	1.700	17.014
Overall	4.600	10.143	10.559	3.066	29.686

Pearson's correlation analyses between all weather parameters were assessed. According to the table 4.34 there is a strong linear relationship between minimum temperature and mean temperature. Further there is a strong linear relationship between wind speed and maximum sustained wind speed. Most of the relations are statistically significant at 0.05 level of significant. The relationship between maximum sustained wind speed and minimum temperature is significant at 0.1 level of significant.

Table 4.34: Pearson's correlation coefficients matrix of meteorological variables in Colombo District, Sri Lanka, January 2009 – September 2014

	T	Tmax	Tmin	H	PP	VV	V	VM
Tmax	0.531 0.000							
Tmin	**0.814** 0.000	0.040 0.496						
H	-0.127 0.017	-0.584 0.000	0.221 0.000					
PP	-0.198 0.002	-0.199 0.001	-0.141 0.034	0.483 0.000				
VV	0.335 0.000	0.169 0.005	0.250 0.000	-0.214 0.000	-0.307 0.000			
V	0.220 0.004	-0.068 0.196	0.355 0.000	-0.240 0.000	-0.253 0.000	-0.059 0.156		
VM	0.096 0.168	-0.024 0.654	0.122 0.066	-0.139 0.017	-0.091 0.145	-0.113 0.046	**0.750** 0.000	

Cell Contents: Pearson correlation
P-Value

4.4. Association Between Climate Variables and Dengue Incidence, Colombo District

It is evident from the figures 4.51 – 4.57 that there is a lag relationship between climatic variables and dengue incidence. The variation of mean temperature and minimum temperature is approximately same. There is a slight increase in those temperature scales from April to June. Maximum temperature is significantly higher during the period of March - August compared to remaining months of the year. Maximum temperature is low during from 25th week to 31st week, at the same time higher number of dengue cases recorded. During the first half of the year maximum temperature is significantly higher than the 2nd half of the year. When the maximum temperature is higher number of dengue cases is significantly lower. A rise in temperature may evaporate small ponds and other places for mosquito breeding, thus reducing the growth of mosquitoes. According to figure 4.54 there is an inverse relationship between number of dengue cases and precipitation. Precipitation is significantly higher during the period of week 10 -25 and weeks of 41 – 50. In contrast, number of dengue outbreaks within that period is significantly lower compared to other weeks. Strong rainfall causing floods may results in the disappearance of small ponds and thereby the feasible places for mosquito breeding. But at the following the heavy rain dengue cases significantly increases, because from 10 – 25 weeks heavy rainfall was recorded, following that 25 – 35 higher number of dengue cases recorded. According to figure 4.55 visibility remains approximately constant throughout the study period. According to figures 5.56 and figure 4.57 graphical examinations showed that the overall distribution of dengue cases was similar to the distribution of mean wind speed and maximum sustained wind speed. According to figure 4.58 relative humidity remains constant throughout the study period. Humidity contributes to the transmission of dengue fever by influencing the activities and survival of the mosquito vector. Low humidity causes mosquitoes to feed more frequently to compensate for dehydration, while high relative humidity increases the metabolic process in adult mosquitoes

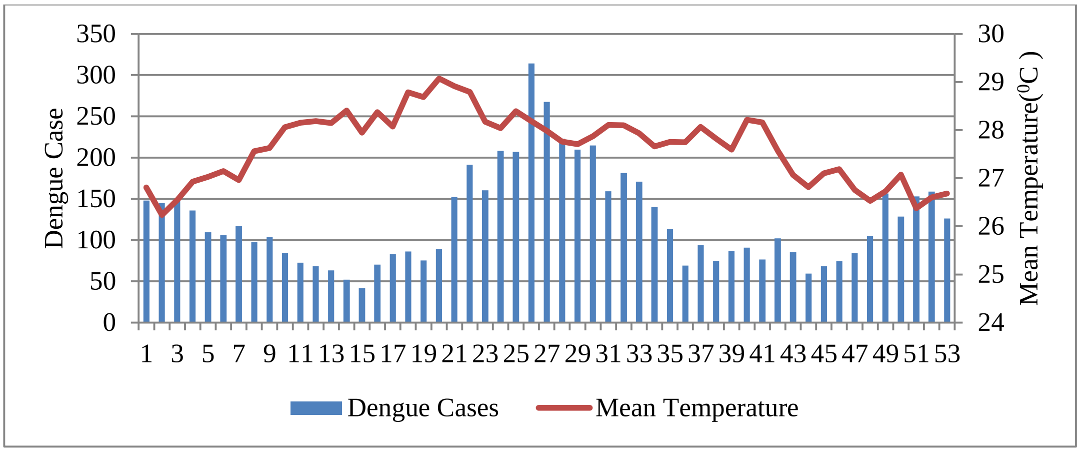


Figure 4.51: Relationship between weekly mean reported dengue cases and weekly mean temperature

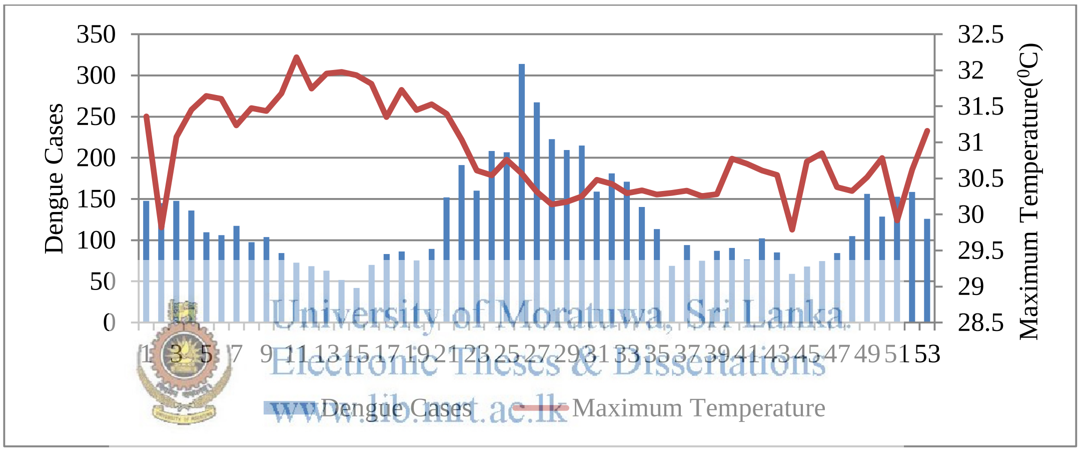


Figure 4.52: Relationship between weekly mean reported dengue cases and weekly mean maximum temperature

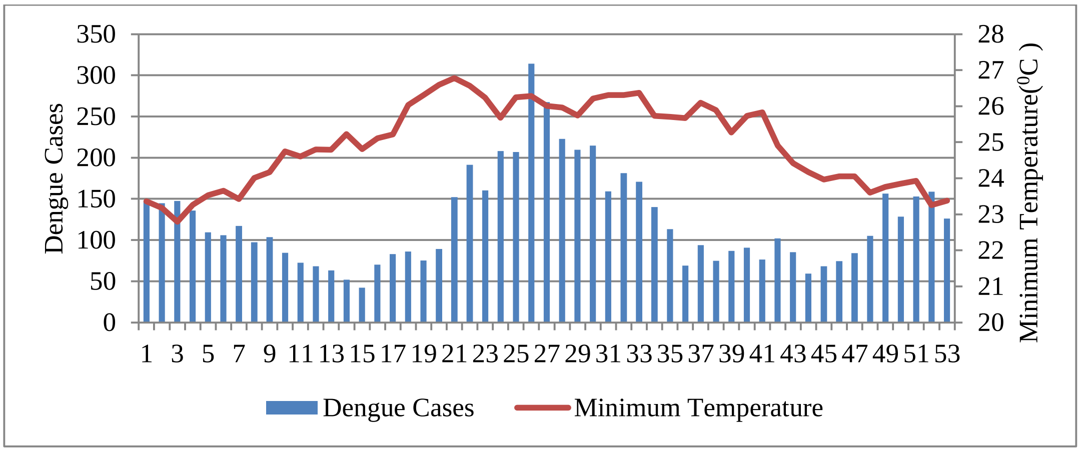


Figure 4.53: Relationship between weekly mean reported dengue cases and weekly mean minimum temperature

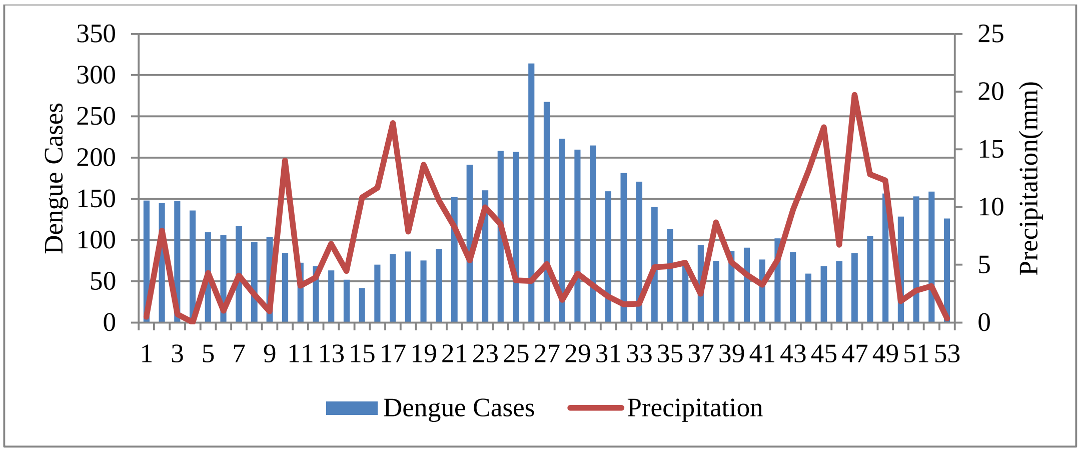


Figure 4.54: Relationship between weekly mean reported dengue cases and weekly mean precipitation

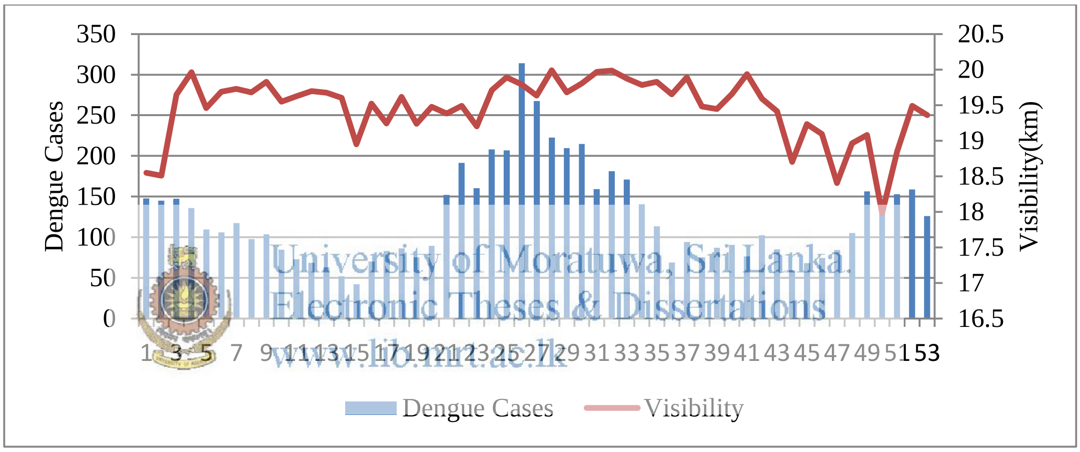


Figure 4.55: Relationship between weekly mean reported dengue cases and mean visibility

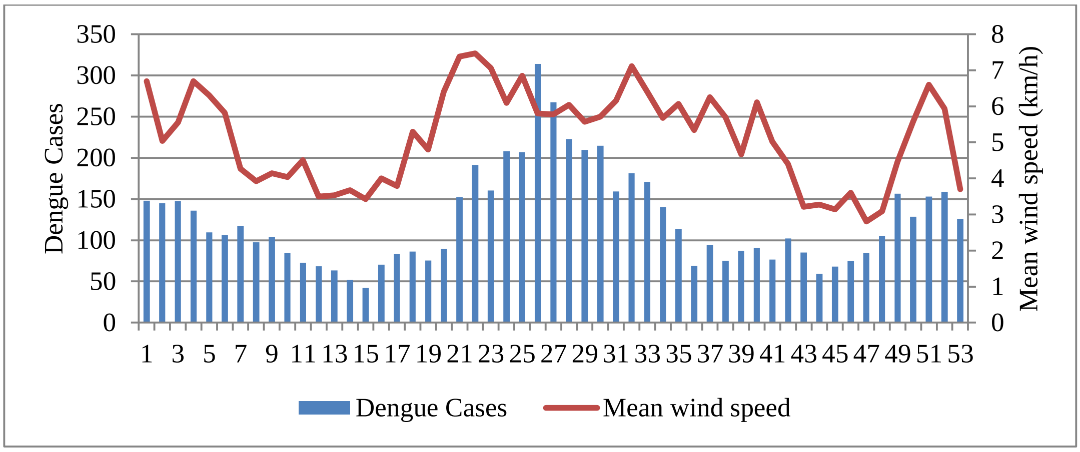


Figure 4.56: Relationship between weekly mean reported dengue cases and mean wind speed

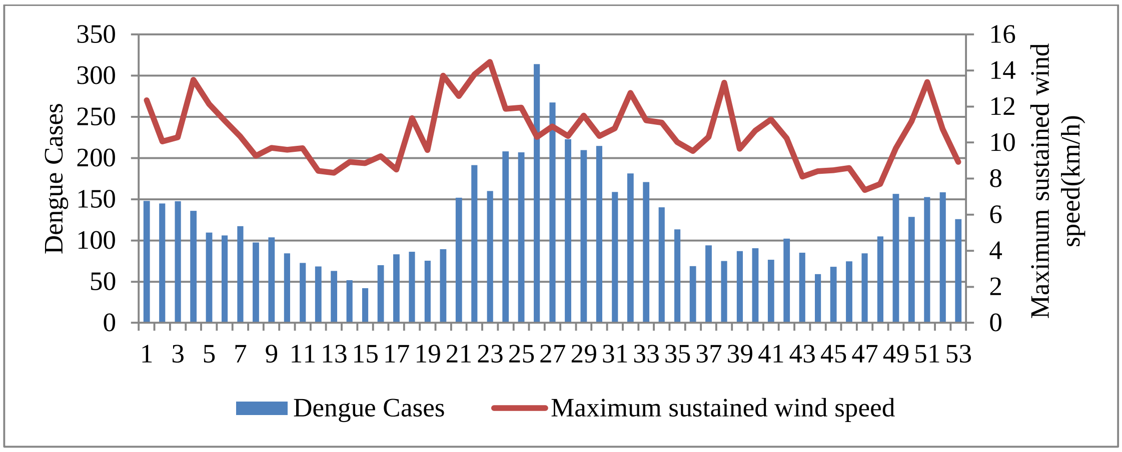


Figure 4.57: Relationship between weekly mean reported dengue cases and maximum sustained wind speed

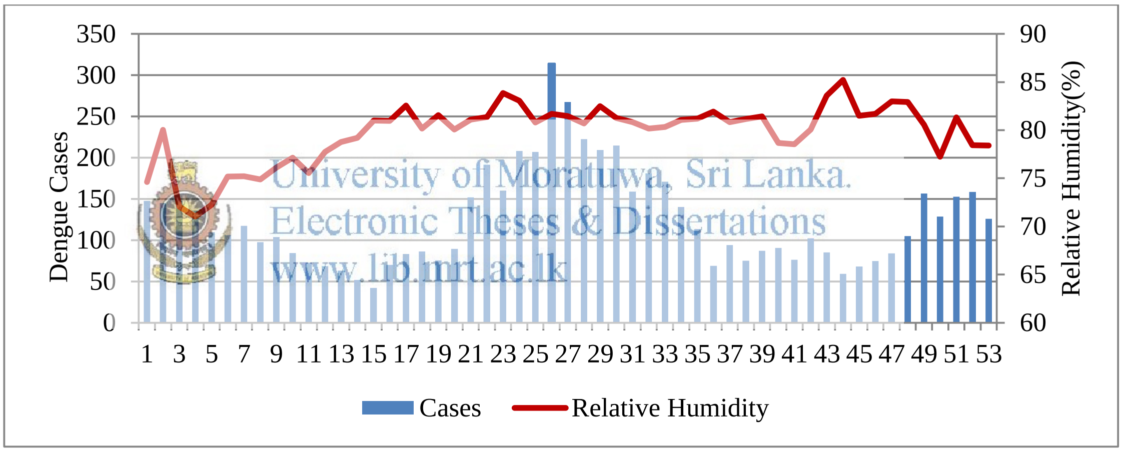


Figure 4.58: Relationship between weekly mean reported dengue cases and relative humidity

CHAPTER 05

WAVELET ANALYSES

5.1 Overview

The aim of this chapter is to present the results of wavelet analysis of dengue incidence and its association with climatic variables. This chapter consists of 5 sections. Section 5.2 illustrates the results of wavelet analysis of aggregated dengue incidence in 25 districts in Sri Lanka form 2009 to 2014. Note that the time series for year 2014 exists only up to September. To investigate the spatial differences in dengue periodicity, we performed wavelet analysis for individual time series of each province. Wavelet analysis of time series data of dengue incidence from 25 districts of Sri Lanka are displayed in section 5.3. Further dengue dynamics showed different evolutions across the 25 time series which can be divided into two groups based on wavelet cluster analysis. The results of wavelet cluster analysis are shown in section 5.4. In section 5.5, we examine the relationships between climatic factors and dengue incidence and especially explore the phase relationships between the climatic variables and dengue incidence by using wavelet coherency analysis.

5.2 Wavelet Analysis of the Aggregated Dengue Cases in 25 districts in Sri Lanka

Wavelet analysis was performed to explore the periodicity in dengue incidence time series. Wavelet analysis provides the possibility of investigating and quantifying the temporal evolution of time series with different rhythmic components. In addition, wavelet analysis allows detection of changes in periodicity in time. The Morlet wavelet was used and all analyses were performed with R 3.1.2 software. Prior to wavelet analyses, the data for all series were square root transformed and normalized in order to dampen extreme variability.

Figure 5.1 shows the time series of aggregated dengue incidence in 25 districts in Sri Lanka. Dengue cases occur year round but there is a strong seasonality with most cases occurring from September to March and reaching a peak from November to

January. The largest inter-annual variability in dengue cases occurs from October to December. The country experienced an unexpected dengue outbreak in 2009 and 2010. Drastic downward trends at the end of 2010 and mid of 2012 were partially due to the effectiveness of strengthened vector control programs implemented by the government. Large peaks of dengue incidence occurred in 2009 and 2014. Wavelet power spectrum of aggregated dengue incidence is shown in figure 5.2 and its corresponding averaged power spectrum is shown in figure 5.3. The plot of wavelet power spectra show that dengue outbreaks varied at different periods and the periodicity of the signal varies through time. Colour code for increasing spectrum intensity varies from blue to red; black solid lines show statistically significant areas. Significant was set at $p < 0.05$. ; Parabolic lines demarcate the cone of influence (the region of the spectrum in which edge effects are significant). Figure 5.2 shows high power oscillation bands between 26 and 52 week. This oscillation bands are less distinct during the year of 2013. Moreover, Wavelet analysis reveals a significant 26-week periodicity during 2009 – 2011, 2012 and in 2014. However, the oscillation bands are partly outside of the COI due to the limited length of the time series. The average wavelet power in figure 5.3 had a much stronger peak in power at period of 26.237673 weeks because variability at that particular persisted over the entire study period. Secondary periodicity was observed in the 30 – 52 week band. The tip of the secondary peak is located at a periodicity of 41.649710 weeks. The 8-16 week periodic band cycle presents weak non significant power throughout the study period, which is consistent with the corresponding averaged power spectrum which shows no peak for the periodicity of 8-16 weeks. Several very high frequency periodicities with peaks at 2-8 week periods are also seen in figure 5.6. These periodicities appear in an intermittent pattern.

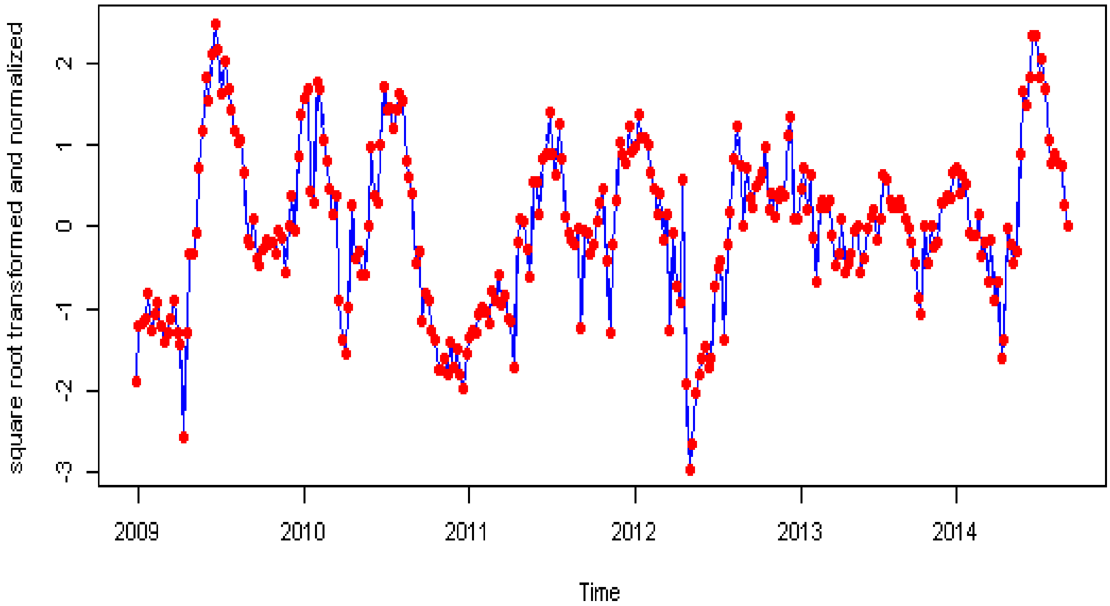


Figure 5.1: Time series plot of square root transformed and normalized aggregated dengue cases in Sri Lanka, 2009 – September, 2014.

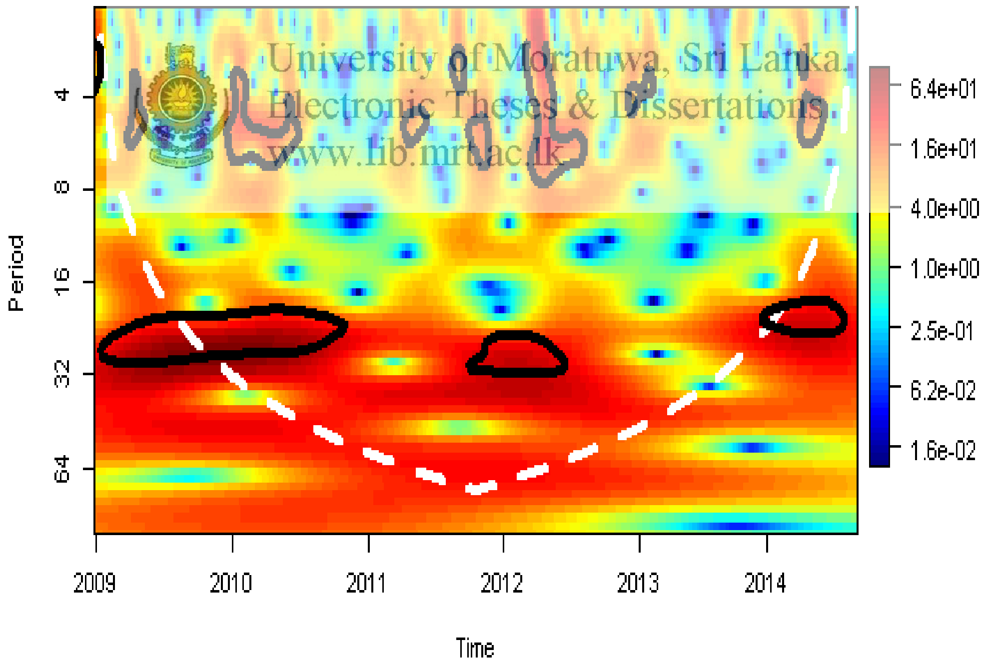


Figure 5.2: Wavelet power spectrum of the aggregated weekly dengue cases time series for Sri Lanka, from 2009 – September, 2014.

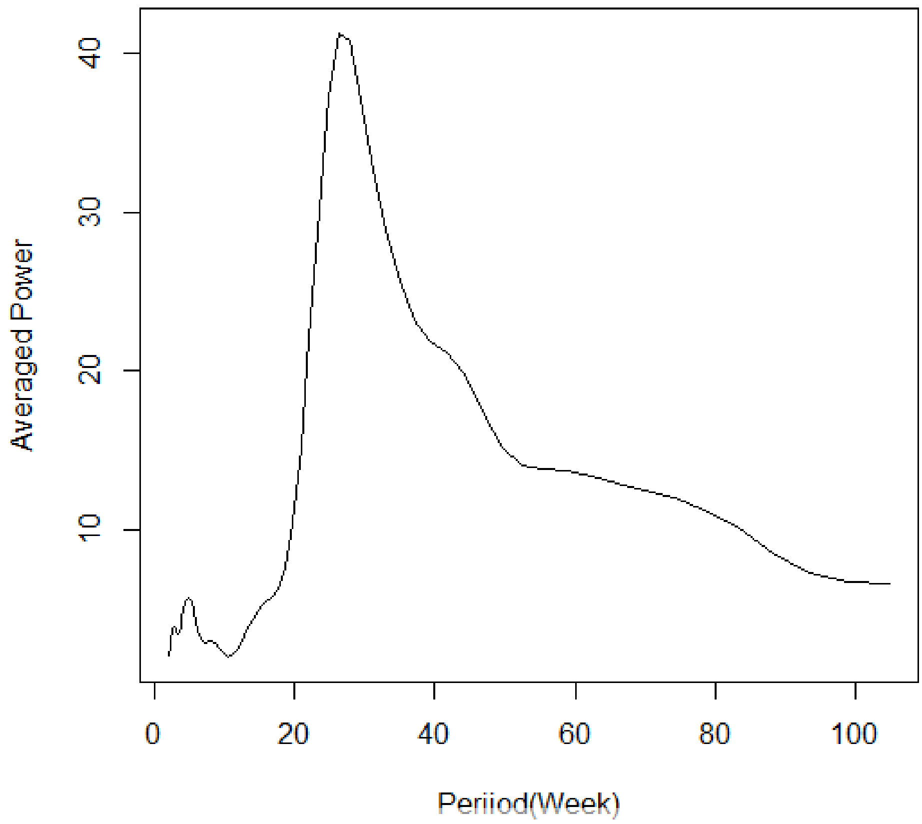


Figure 5.3: Average wavelet power spectrum

5.3 Periodicity of Dengue Incidence by Districts

Figure 5.4 and figure 5.5 show the wavelet power spectra of each district and their corresponding mean wavelet power spectra respectively. For each district, measurements were obtained from 294 weeks starting from 52nd week (December) of 2008 to 36th week (September) of 2014. Because the number of cases varies among populations, that is, the epidemiology patterns may be similar although the magnitude of the expression may vary, all time series were square root transformed and normalized before the analysis. This time – frequency analysis of the signal provides information on the different frequencies as time progresses.

In general for all districts, the wavelet power spectra show periodicities, with substantial heterogeneity in the relative strength. More specifically, periodicities were detected in the 2 – 8 week and 26 – 60 week bands. There is no consistent significant band in any of these 25 districts. Overall, high power bands are mostly distributed in

26-52 week period. In addition, several very high significant frequency cycles are seen in the 2 – 6 week band. These periodicities appear in an intermittent fashion. The 8-16 week periodic band cycle presents very weak non-significant power throughout the study periods.

Throughout the entire time series for districts, with relatively high population density, Colombo, Gampaha, Kalutara, Kandy, Nuwara Eliya, Galle, Hambantota, Matara and Batticalo, relatively high and significant power was observed at the 26 – 52 week period with some intermittently significant fluctuations occurring at the lower periods (< 8 weeks). Other districts with high population density such as Kurunagala, Puttalam, Anuradhapura, Monaragala, Ratnapura and kegalle also exhibit a similar behavior but 26-52 week significant oscillation bands are partly outside of the COI. In Killinochchie and Mulative, the dark blue portion of the figure corresponds to the dengue epidemics during the year 2009. Both districts recorded zero number of dengue cases throughout the whole year. The large significant red portion in Vavuniya district corresponds to sudden increase in the number of dengue incidence in the year of 2010.

Largest number of dengue cases has been reported from Colombo and Gampaha districts during the study period. Wavelet power spectrum of Gampaha and Colombo exhibits a similar behavior. Both spectra show continuous oscillating modes at both 26 week and 40-52 week during the whole time period indicating both annual and sub annual periodicity. This annual periodicity is reflected in the DF incidence time series, by a slow increase of incidence from the beginning of the year to the weeks 50–52 (December), followed by a faster increase of incidence until weeks 26–27 (June). Nevertheless, these modes of oscillation vary in strength. The dominant mode is 26 week periodicity. This is further confirmed by the average wavelet power spectra. Moreover, in Colombo district 26 week periodicity is significant in 2010, 2011 – 2012 and in 2014. Gampaha district shows a significant 26 week periodicity in 2009 -2010 and in 2012. In both districts annual periodicity did not reach statistical significant compared to null hypothesis: the variability of the observed time-series is equivalent to the expected variability of a random process with similar first-order autocorrelation. Furthermore, considerable numbers of patients have been reported from Kalutara district, which shows significant power around 32 - week and 64 – week in 2011 – 2013. High power periodicities of 32 week and 64 week were observed in Hambantota, Matara and Kandy districts. But these periodicities were not statistically significant.

The wavelet power spectrum of Rathnapura district generated a peak in power around 52 week. Wavelet time series analysis in Nuwara Eliya district identified multiple significant bands within 26 – 52 week during the period 2009 – 2012. No significant periodicity was detected after 2013. For Galle district an approximate 52 week cycle was detected from 2009 to 2012, and then a decreasing period from approximately 52 week to 26 week was clearly seen from the 2nd half of 2011 to 2013. After this no clear significant periodicity was detected but large portion appeared as high power.

Higher concentration of the power was observed, districts in Northern Province, Eastern Province, North Western Province, North Central province and Uva province at various periodicities over different periods of time. But the oscillation bands are less distinct in Killinochchi, Vavuniya, Mulative and Trincomalee.

The average wavelet power spectrum for Kandy, Matale, Jaffna, Vavuniya, Badulla, Monaragala and Kegalle are much greater than at all periods indicating much stronger variation.

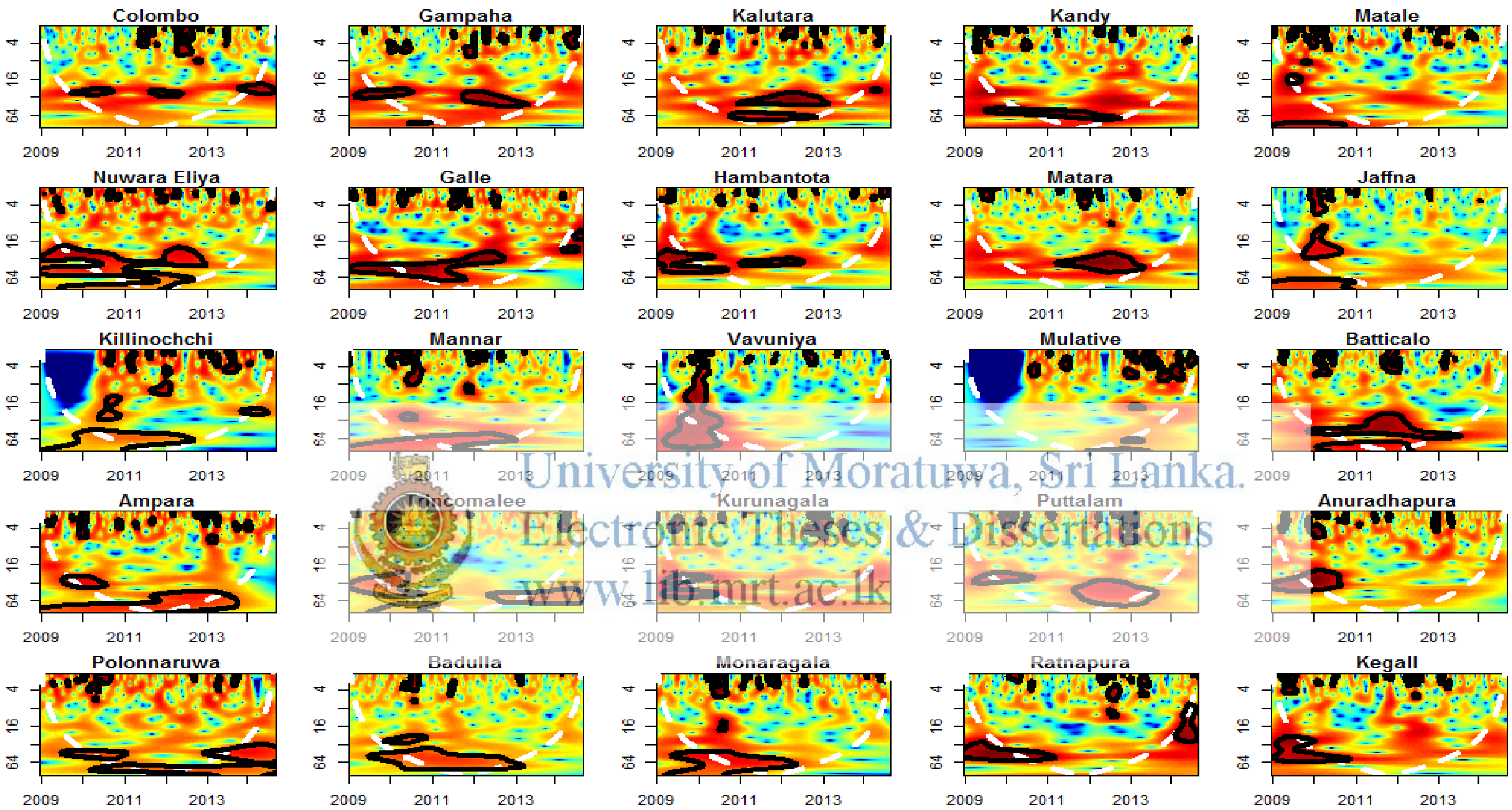


Figure 5.4: Wavelet power spectra of dengue incidence in Sri Lanka. For each signal, this mathematical decomposition yielded a wavelet power spectrum, which was plotted using heat maps with time on the x-axis, period (which is inversely related to frequency or scales) on the y-axis, and variance on the z-axis

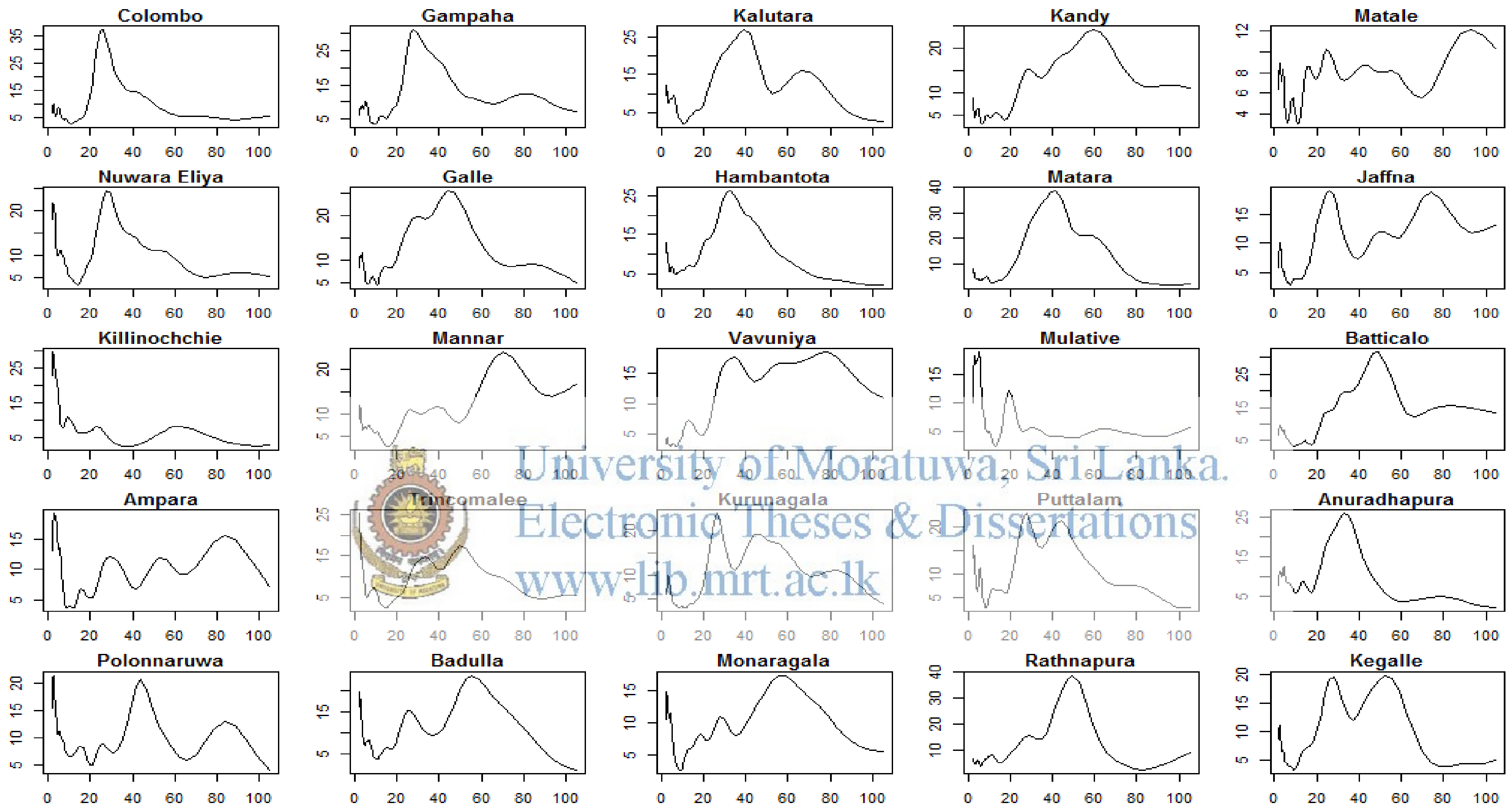


Figure 5.5: Average wavelet power spectrums by districts (time on the x-axis, average power on the y-axis)

5.4 Wavelet Cluster Analysis

Dengue dynamics showed different evolutions across the 25 districts which can be devided into two groups based on wavelet cluster analysis. The first group consists of 18 districts. Colombo, Gampaha, Kandy, Matale, Nuwara Eliya, Galle, Hambantota, Matara, Jaffna, Killinochchie, Mannar, Vavuniya, Trincomalee, kurunagala, Puttalam, Monaragala, Ratnapura and Kegalle are the members of cluster 01 while, Mulative, Ampara, Batticalo, Anuradhapura, Polonnaruwa and Badulla belong to 2^{nd} cluster. The timing of statistically significant periodicities differs among districts even within a cluster. Except Kalutara district all other districts in cluster 2 were located on the east side of the country.

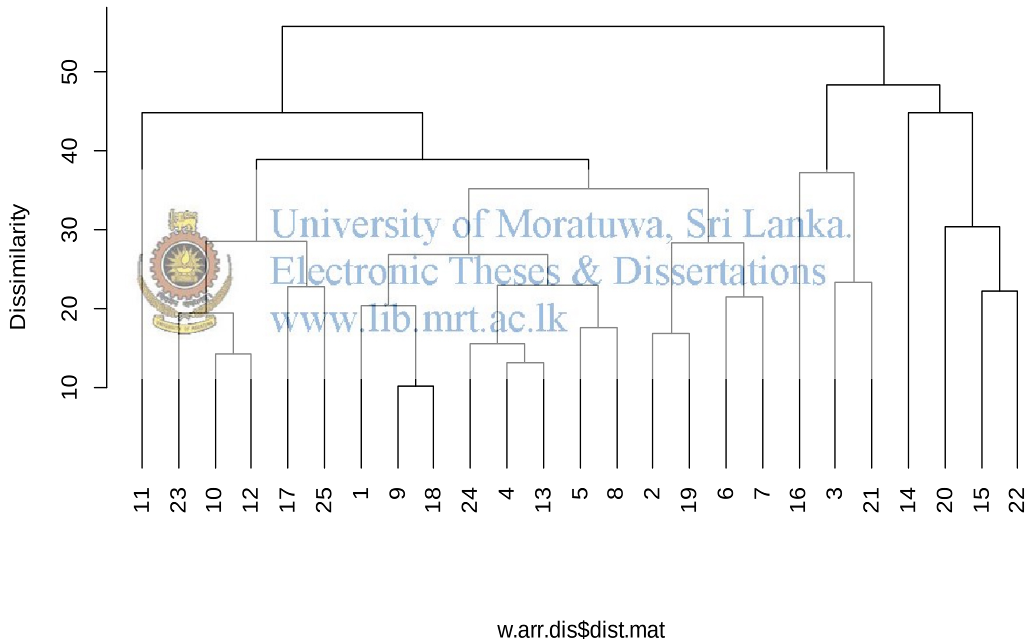


Figure 5.6: Dendogram of wavelet cluster analysis of weekly dengue incidence for each district of Sri Lanka, from 58^{th} week of 2008 to 36^{th} week of 2014

[11-Killinochchi, 23 – Monaragala, 10-Jaffna, 12-Mannar, 17-Trincomalee, 25-Kegalle, 1-Colombo, 9-Matara, 18-Kurunegala, 24-Ratnapura, 4-kandy, 13-Vavuniya, 5-Matale, 8-Hambantota, 2-Gampaha, 19-Puttalam, 6-Nuwara Eliya, 7-Galle, 16-Ampara, 3-Kalutara, 21-Polonnaruwa, 14-Mullative, 20-Anuradhapura, 15-Batticaloa, 22-Badulla]

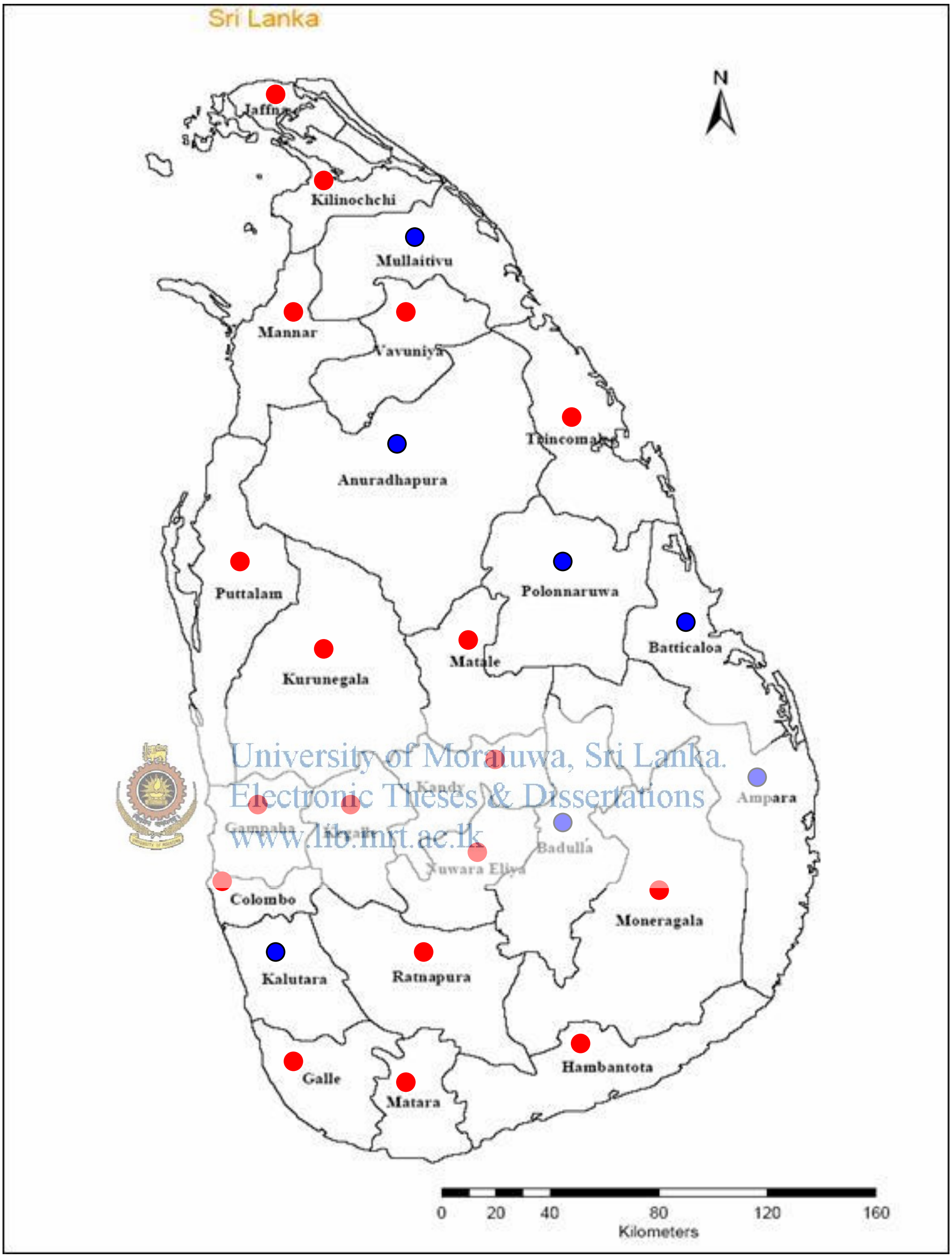


Figure 5.7: Results of wavelet cluster analysis (red-cluster 01, blue – cluster 02)

5.5 Association Between Dengue Counts and Climate Variability

Section 5.5 presents estimated wavelet coherence and phase differences for all examined pairs of climatic factors with dengue incidence. Prior to wavelet coherence analysis, the data for all series were square root transformed in order to dampen extremes in variability. Section 5.5.1 presents the wavelet structure of climate variables. Results of wavelet coherency between dengue incidence and climate variables are listed in section 5.5.2.

5.5.1 Wavelet transformation of climatic variables

The wavelet power spectra of climatic variables; mean, minimum, maximum temperature, humidity, precipitation, visibility, wind speed and maximum sustained wind speed in Colombo and their corresponding average power spectra are shown in figure 5.8 and figure 5.9 respectively.

Throughout the entire time series, all climate variables exhibited intermittent significant and high wavelet power at lower periods (< 8 weeks). In general for all climate variables high power bands can be seen at 26 week periodicity and/ or 52 week periodicity, confirming annual and sub-annual periodicities, as observed on the dengue incidence time series.

Wavelet analysis reveals significant 52-week periodicity in all temperature measures; mean temperature, maximum temperature and minimum temperature (figure 5.8 (a,b,c)) that are constant through time. This is further illustrated by average wavelet power spectra, which has pronounced peak at a 52 week periodicity. The tip of the peak is located at a periodicity of 52.475346. High power was also present in the 26 - 28 week period range, but did not reach significance compared to autocorrelated null hypothesis: the variability of the observed time series is equivalent to the expected variability of a random process with similar first-order autocorrelation. Relative humidity shows both annual (52 week) and sub-annual (26 week) significant periodicities as shown in figure 5.8 (d). For humidity, wavelet power at the 26 week period was consistently high, but significant during the year of 2010.The precipitation time series displays discrete character. Precipitation episodes interrupted by periods of dryness. Wavelet power spectrum of precipitation show a significant continuous band at 25 – 32 week period for the time period mid of 2009 – mid of 2011. After this no clear periodicity was detected. Time series plot of mean visibility is not dominated by any periodic pattern. Except some few irregular variations can be seen in 2009, 2010 and 2011. According to the wavelet power spectrum of mean visibility (figure 5.8 (f)) there is a strong periodic band around 32 week and 64 week persisting continuously over the interval from 2009 to mid of 2011. For mean wind speed , wavelet power was consistently high at a period of ~ 26 week with occational significant fluctuatios (figure 5.8 (g)). A non-significant, less pronounced 52 – week periodicity was also observed in mean wind speed. In contrast to the other climate variables, statistically significant continuous oscillation bands are not distinguishable in maximum sustained wind speed but significant spots can be seen within 2 – 26 week period.

The average wavelet power spectra (figure 5.9) of all climate variables except precipitation show peak in power at period of ~ 52 weeks. Mean temperature, maximum temperature, minimum temperature and humidity had a much stronger peak in power at periods of ~52 weeks because variability at that particular period persisted over the entire time series. This peak exceeds the 95% confidence level, confirming that the annual cycle, indeed, highly significant. The mean wavelet power for humidity is much greater than at all periods, indicating much stronger variation.

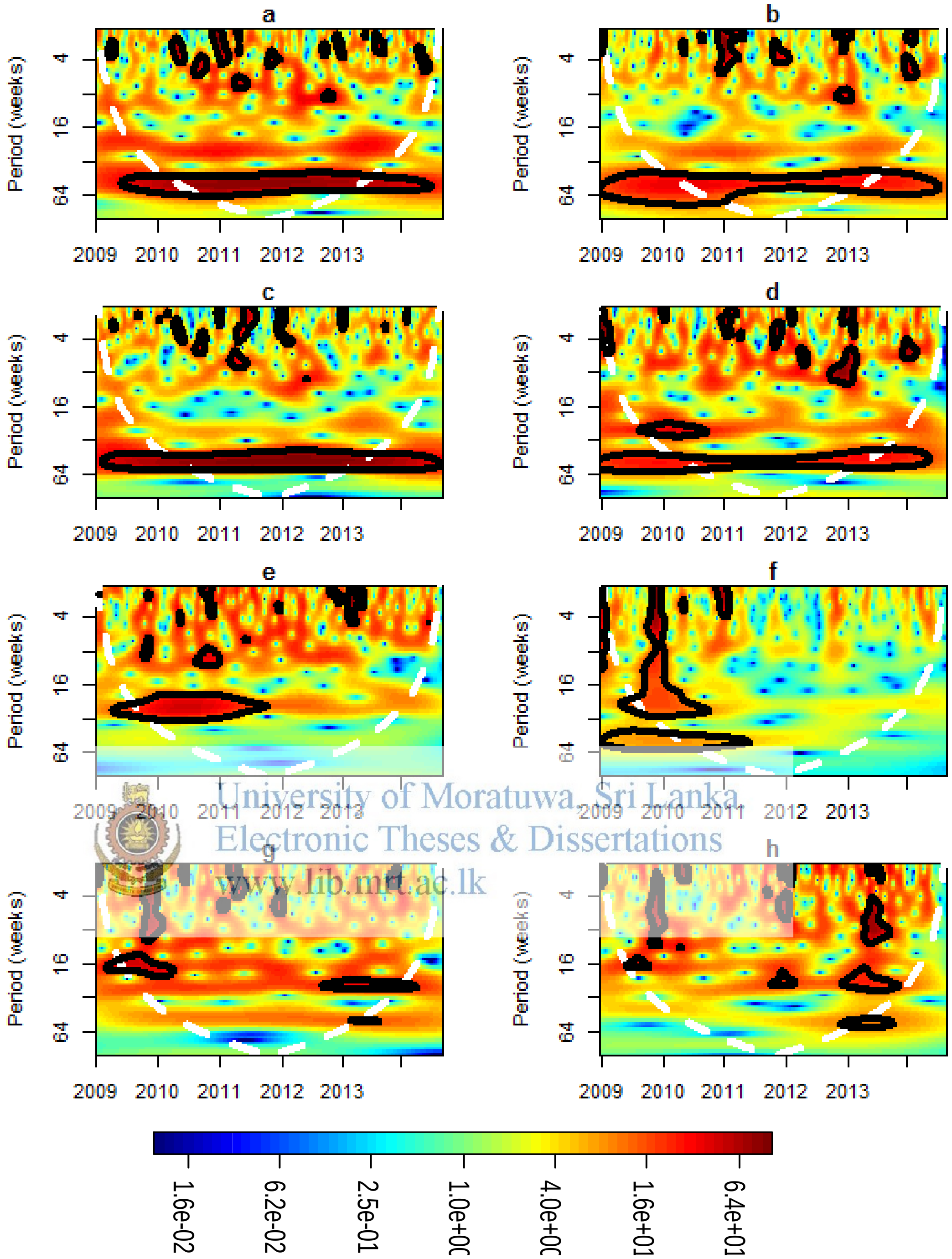


Figure 5.8: Wavelet power spectra of climatic variables in Colombo districts, (a) mean temperature, (b) maximum temperature, (c) minimum temperature, (d) humidity, (e) precipitation, (f) mean visibility, (g) mean wind speed, (f) maximum sustained wind speed. (The black contour lines show the 5% significance level. The dashed white line denotes the COI where edge effects become important.)

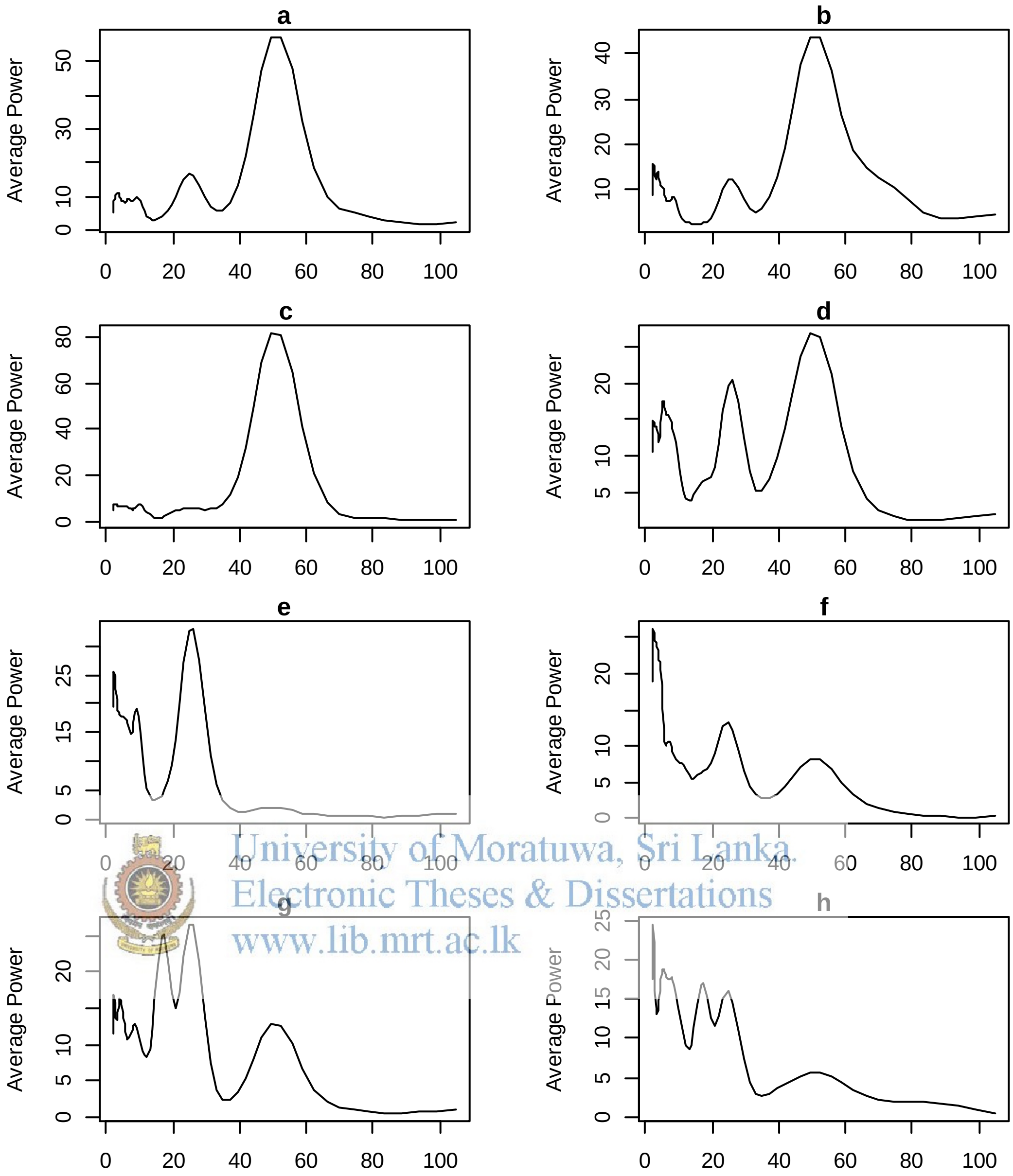


Figure 5.9: Average wavelet power spectrums (time on the x-axis): (a) mean temperature, (b) maximum temperature, (c) minimum temperature, (d) humidity, (e) precipitation, (f) mean visibility, (g) mean wind speed, (f) maximum sustained wind speed .

5.5.2 Coherences between meteorological variables and DF/ DHF cases in Colombo

The main purpose of wavelet coherence analysis is to identify the co-movement of dengue incidence with climatic variables in the time frequency space. Further we can determine whether the presence of a particular frequency at a given time in the disease corresponds to the presence of that same frequency at the same time in a climate covariate and with the cross wavelet phase analysis we determine the time lag separating these two series as well. The time series plots and cross wavelet power spectra between dengue incidence and climate variables are shown in figure 5.11 - figure 5.26.

Cross wavelet coherency analysis revealed that dengue incidence showed significant coherence with all climatic factors but with different periodicities and phase relationships. In general, wavelet coherence reveals two main regions of high and significant coherence. The first one is for the 26 – 30 week (sub annual) periodic band; the second is for 52 – 60 week (annual) band. Most of the statistically significant wavelet coherence are neither in phase (arrows pointing right) nor anti-phase (arrows pointing to the left). Most of the arrows are vertical at all significant coherence, indicating a lag difference between the climatic variables and dengue incidence. Except humidity, coherency between the dengue incidence and all the other climate variables lies in the 26-32 weeks of period band keep a consistent phase where climatic factors leading dengue cases by 90 degrees.

The strongest and continuous coherencies are found with precipitation and wind speed over the 26 – 32 weeks of period band during the entire study period. Precipitation coherency with dengue incidence show a consistent phase where precipitation leads by 90 degrees (i.e one quarter of a period). Exception is made for the period around the first half of 2012, where dengue cases leads by 90 degrees. However, dengue cases mostly lead mean wind speed by 90 degrees, except in 2010 and 2014 years where they experienced a shift of phase.

The cross wavelet power spectrums of mean temperature, maximum temperature, humidity and visibility reveals two significant ($p < 0.05$) periodic bands (26 – 30 week and 50 – 52 week) from 2009 to 2012. The analysis of phase differences reveals mean temperature, maximum temperature and visibility lead dengue cases by 90^0 at period of around 26 – 30 week while arrows pointing up at annual period (50 – 52 week) band indicate dengue cases lead climatic factors. In contrast, phase relation of DF/ DHF cases and humidity was opposite to the above, i.e dengue cases lead humidity by 90^0 at period of around 52 weeks while humidity lead dengue cases by 90^0 at sub-annual periodicity. Minimum temperature shows its most persistent significant coherency with dengue at 50 – 52 week band from 2009 to 2012. During the period of 2011 – 2013 visibility shows the weakest coherency with dengue incidence. Maximum sustained wind speed indicates significant coherence over the 26-30 week band of periodicity from 2011 to 2014. Oscillation between maximum sustained wind speed and dengue incidence were not phase locked (as the direction of the arrows varied); the lead was first in dengue cases and started shifting towards a lead for maximum sustained wind speed in 2012.

These results highlighted that these selected lag of climate variables have a strong influence on dengue incidence in Colombo district. The results of cross-wavelet coherence and phase are consistent with those of the cross-correlation functions shown in figure 5.10.

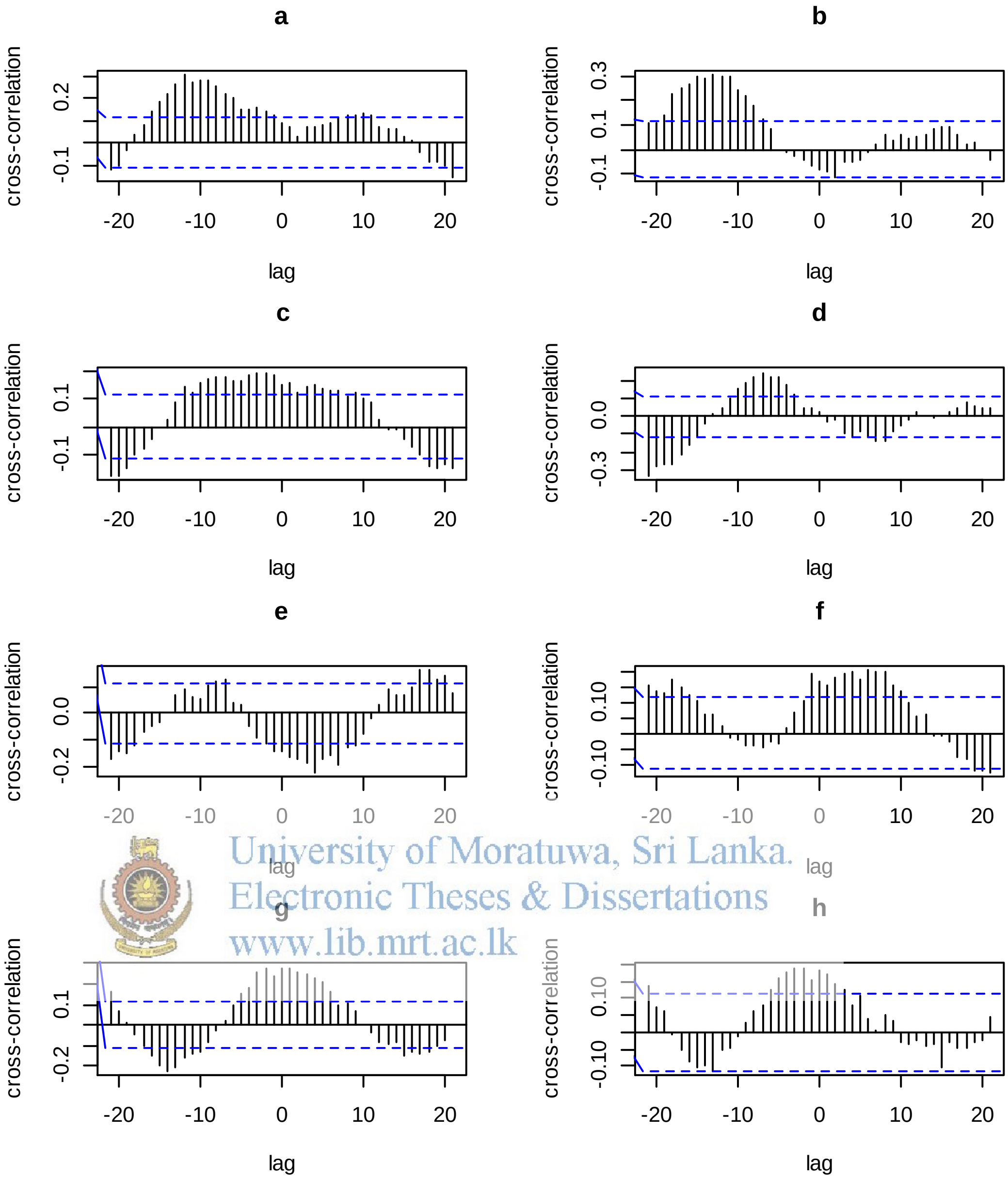


Figure 5.10: Cross-correlation between climatic variables and dengue cases

(a) mean temperature, (b) maximum temperature, (c) minimum temperature, (d) humidity, (e) precipitation, (f) mean visibility, (g) mean wind speed, (f) maximum sustained wind speed . Horizontal blue dotted lines materialize the significance thresholds at $p = 0.05$.

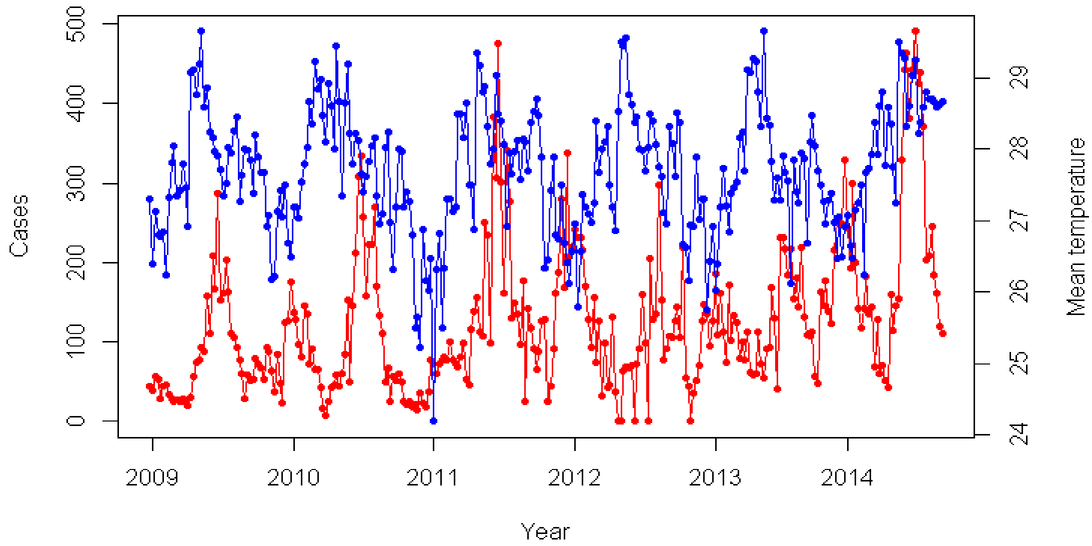


Figure 5.11: Time series plot of square root transformed and normalized aggregated dengue cases (red) and mean temperature (blue)

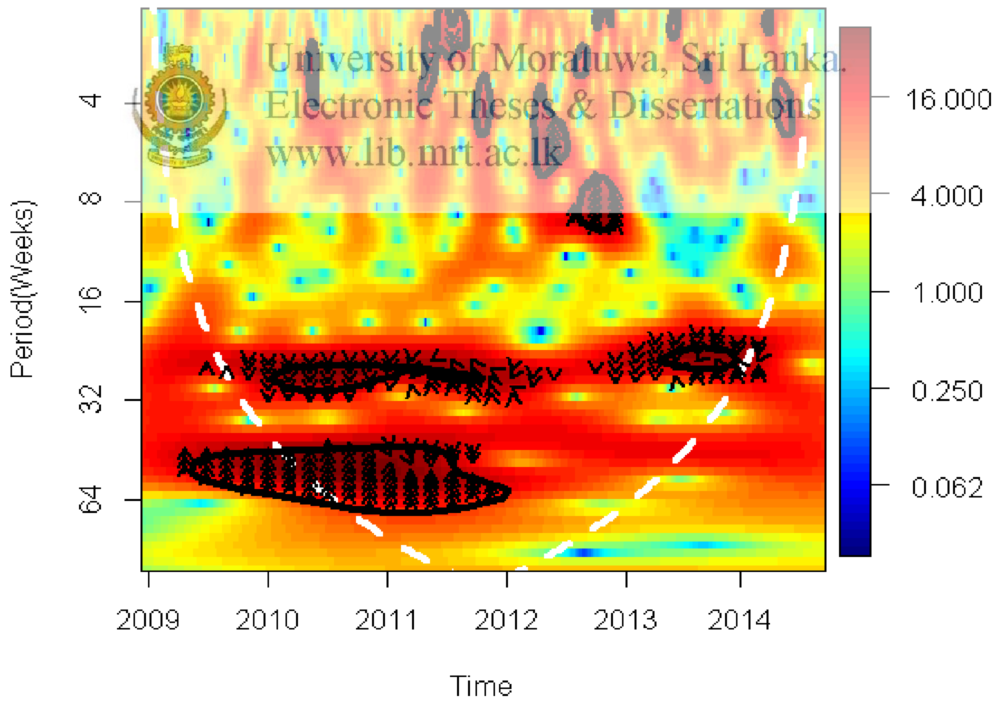


Figure 5.12: Wavelet coherency and phase analyses between dengue notifications and mean temperature.

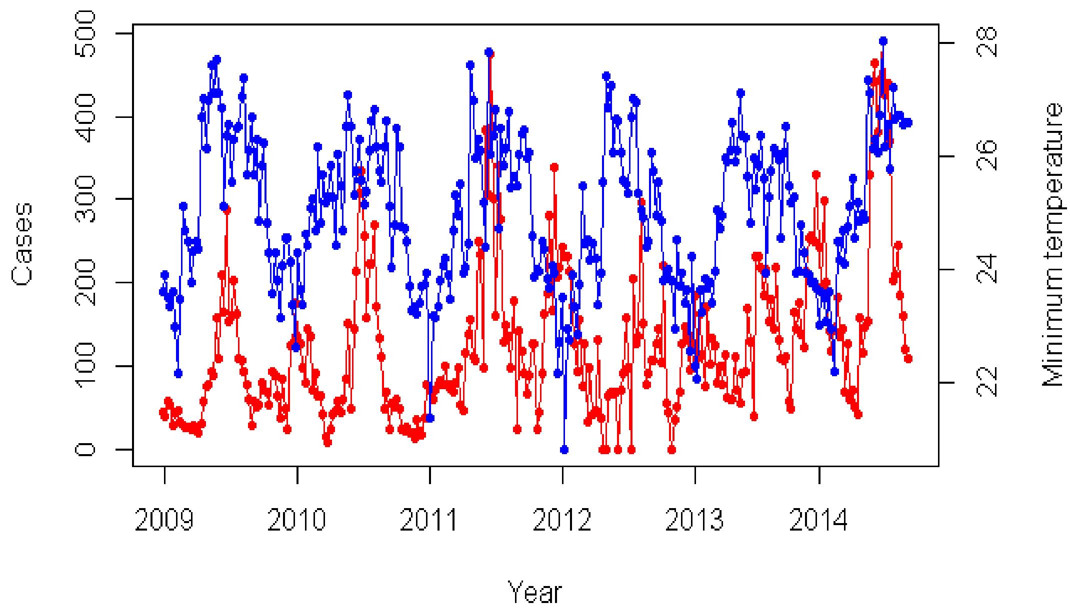


Figure 5.13: Time series plot of square root transformed and normalized aggregated dengue cases (red) and minimum temperature (blue)

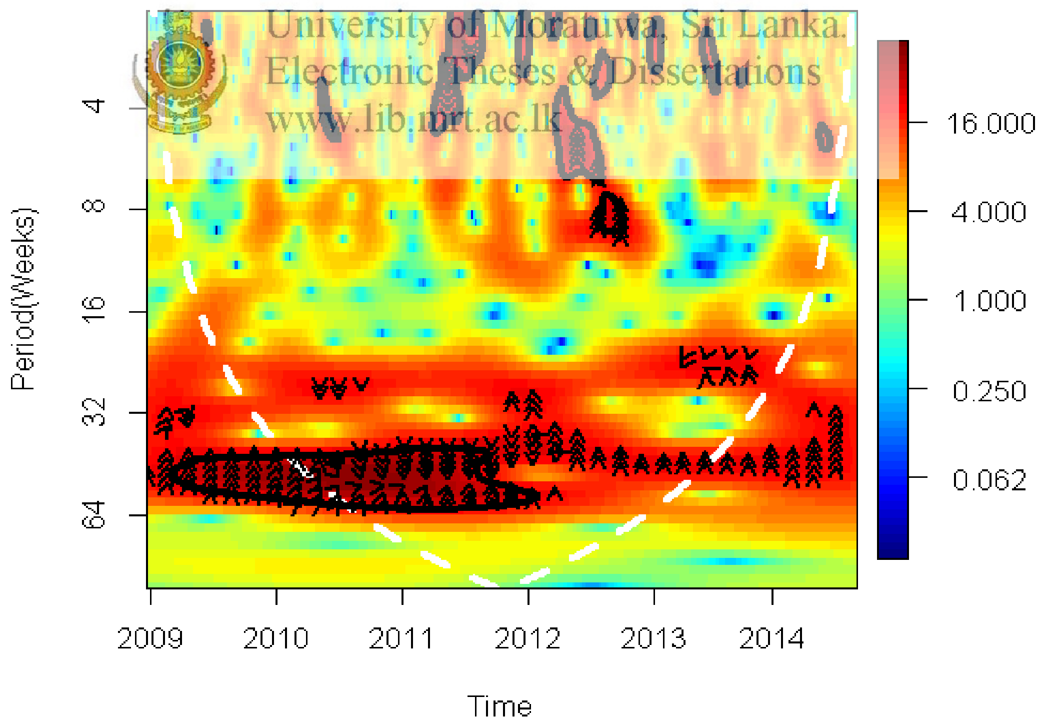


Figure 5.14: Wavelet coherency and phase analyses between dengue notifications and minimum temperature

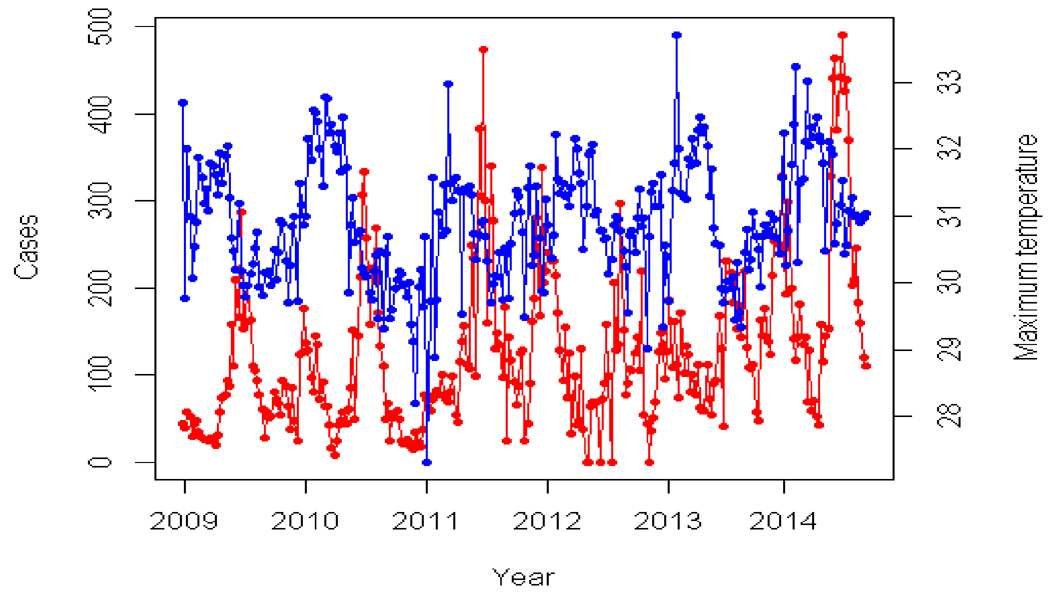


Figure 5.15: Time series plot of square root transformed and normalized aggregated dengue cases (red) and maximum temperature (blue)

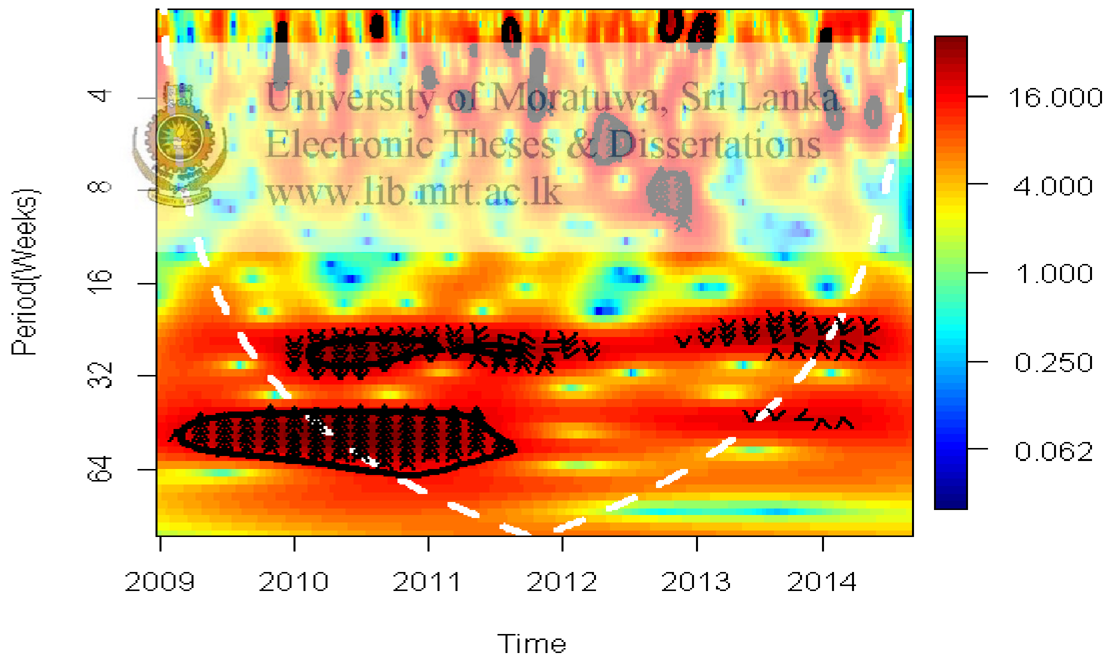


Figure 5.16: Wavelet coherency and phase analyses between dengue notifications and Maximum sustained wind speed.

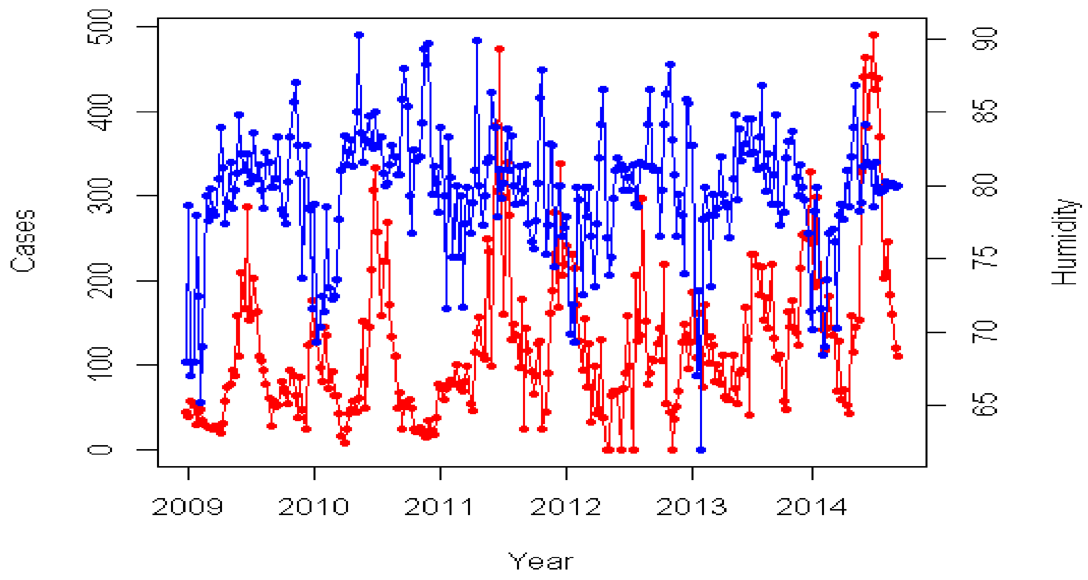


Figure 5.17: Time series plot of square root transformed and normalized aggregated dengue cases (red) and humidity (blue)

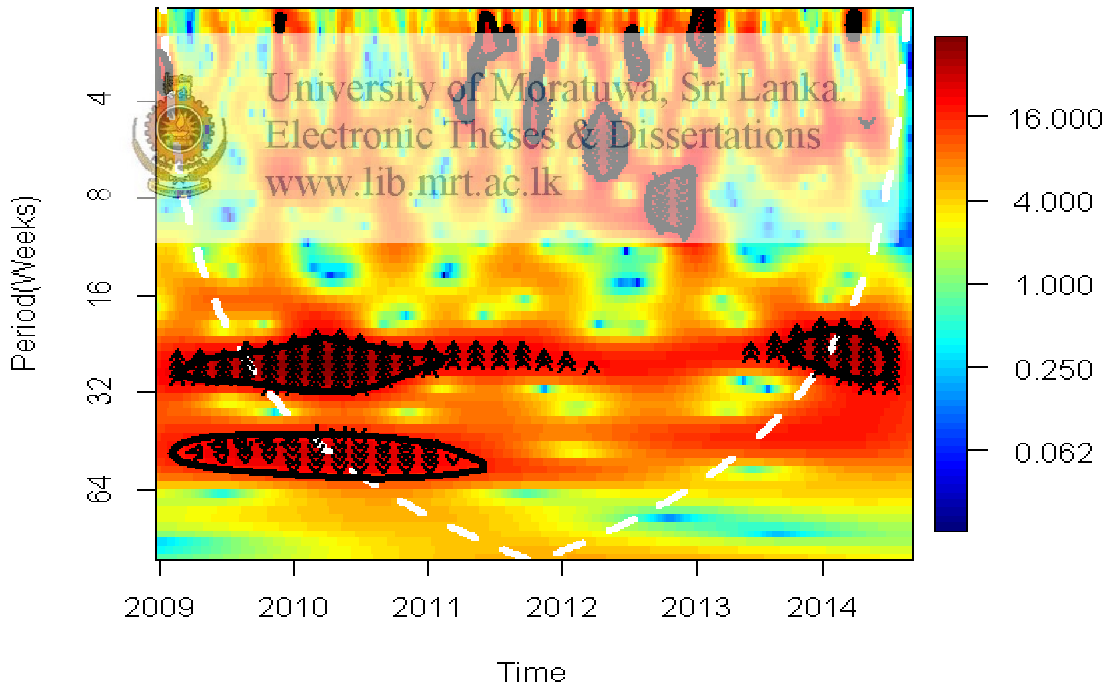


Figure 5.18: Wavelet coherency and phase analyses between dengue notifications and humidity.

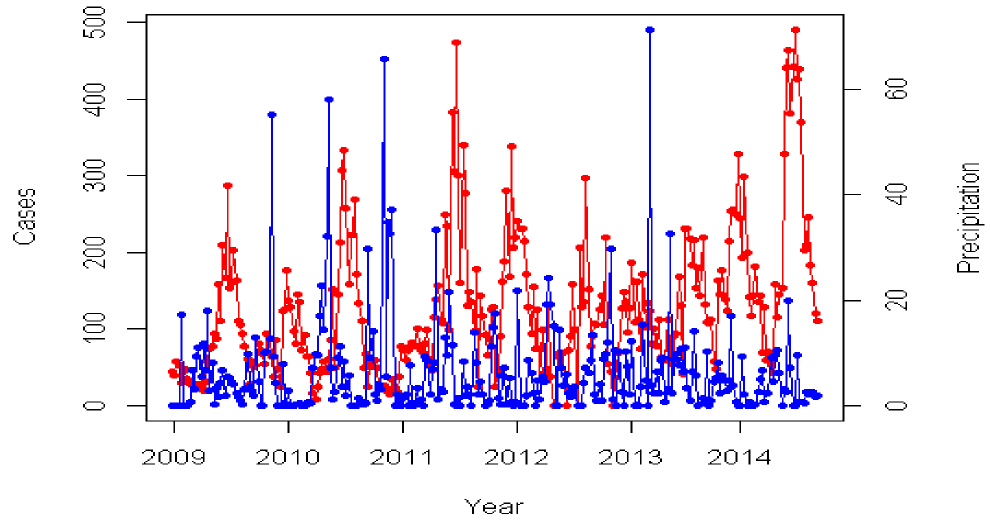


Figure 5.19: Time series plot of square root transformed and normalized aggregated dengue cases (red) and precipitation (blue)

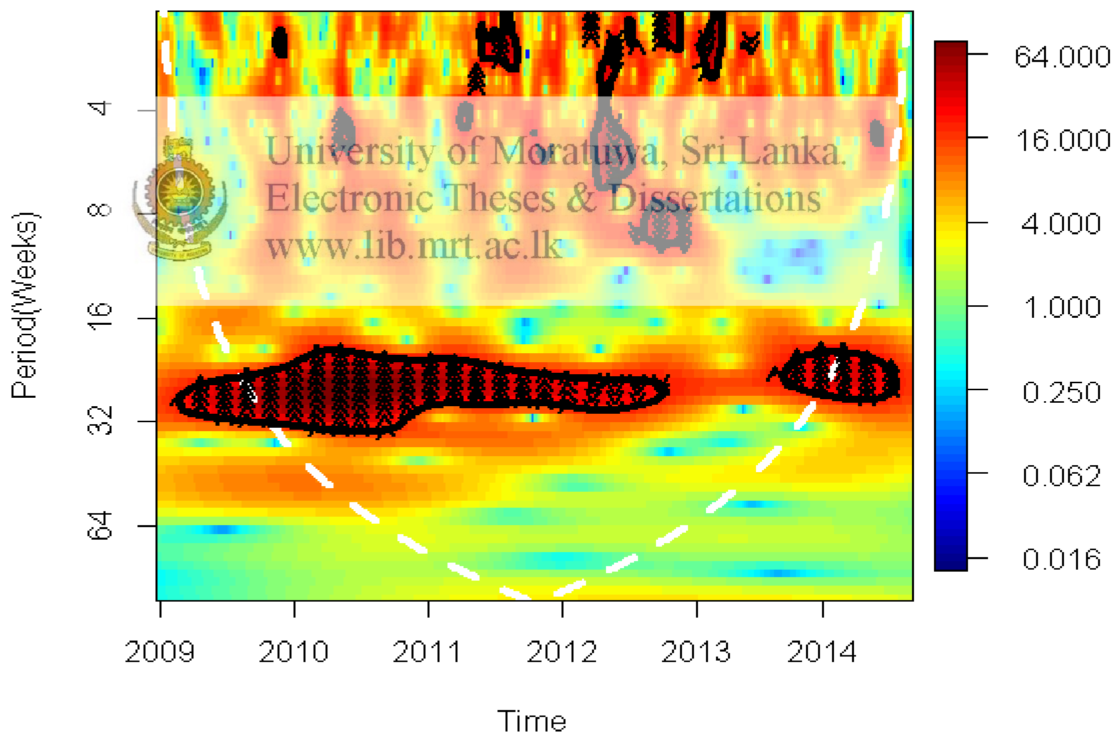


Figure 5.20: Wavelet coherency and phase analyses between dengue notifications and precipitation.

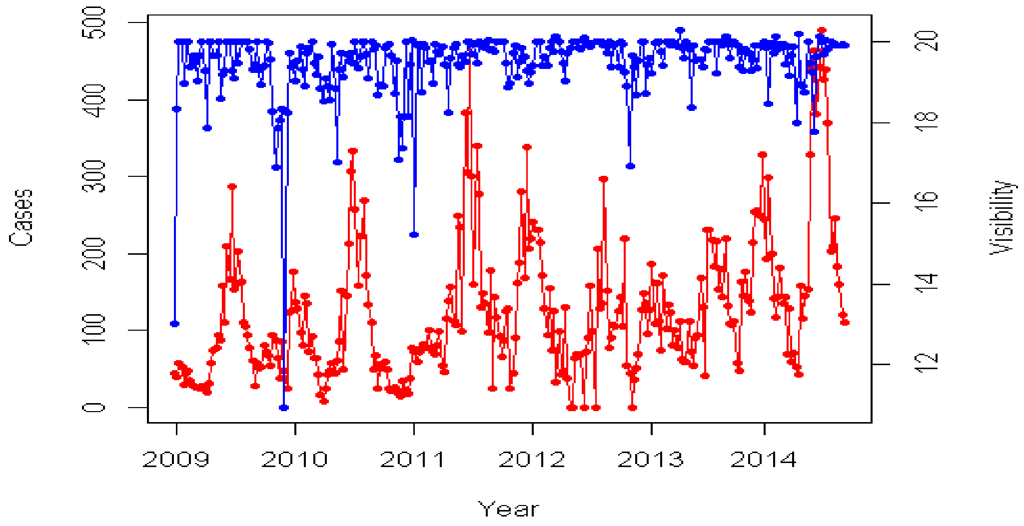


Figure 5.21: Time series plot of square root transformed and normalized aggregated dengue cases (red) and visibility (blue)

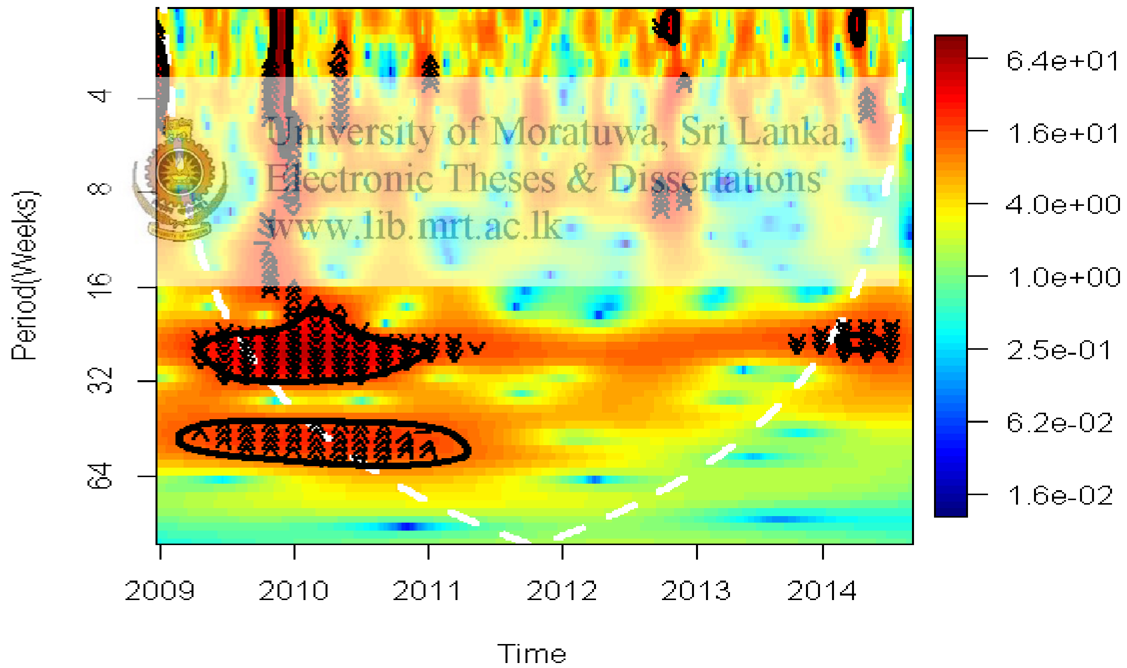


Figure 5.22: Wavelet coherency and phase analyses between dengue notifications and visibility.

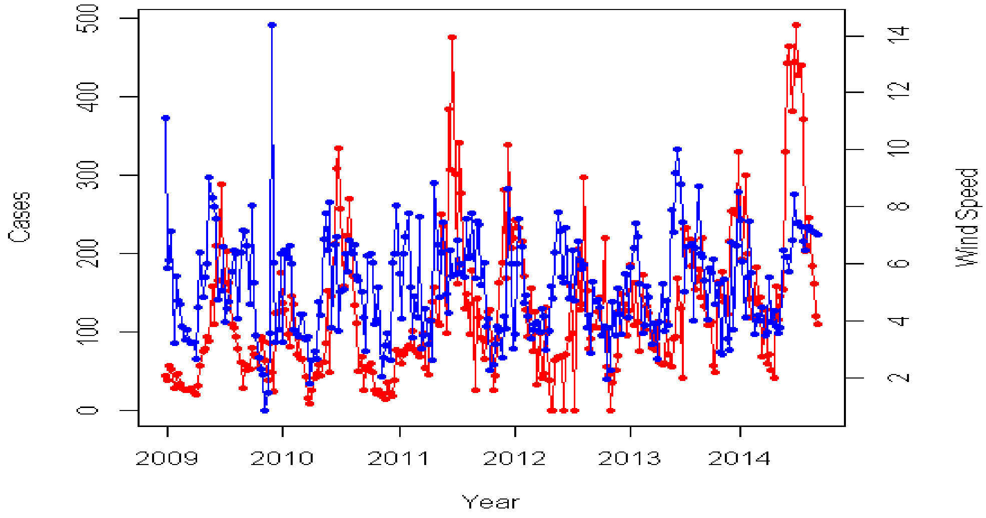


Figure 5.23: Time series plot of square root transformed and normalized aggregated dengue cases (red) and wind speed (blue)

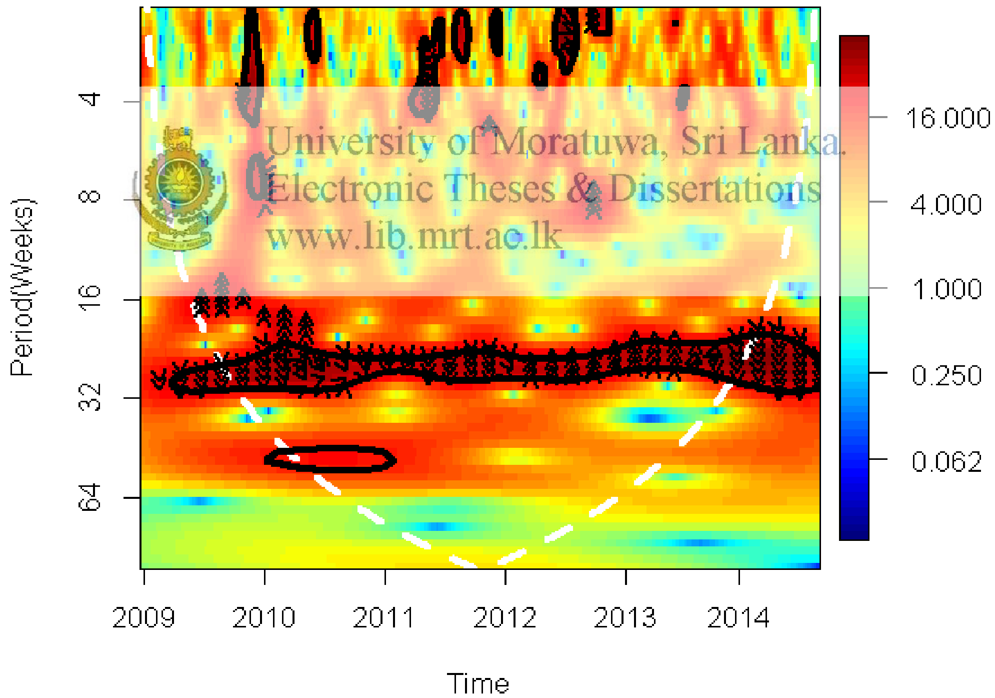


Figure 5.24: Wavelet coherency and phase analyses between dengue notifications and wind speed.

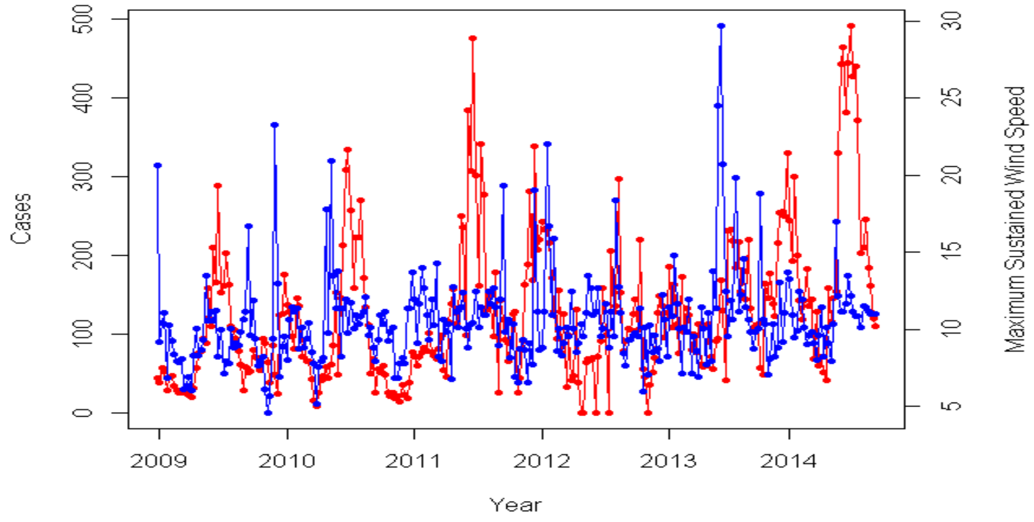


Figure 5.25: Time series plot of square root transformed and normalized aggregated dengue cases (red) and maximum sustained wind speed (blue)

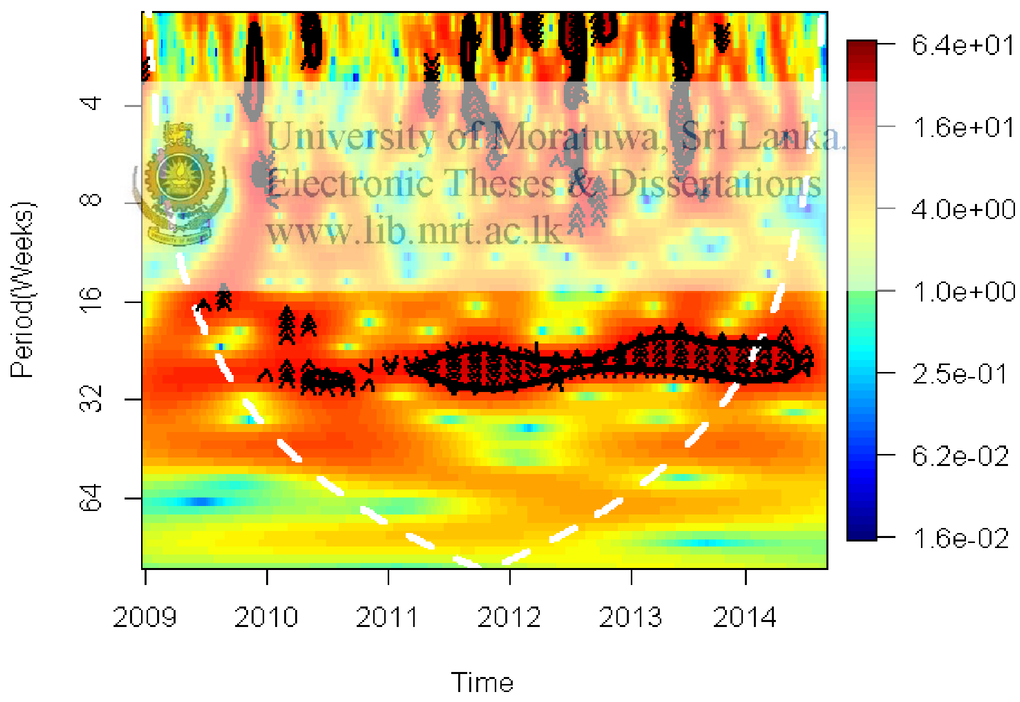


Figure 5.26: Wavelet coherency and phase analyses between dengue notifications and maximum sustained wind speed.

CHAPTER 06

CHANGE POINT ANALYSIS

6.1 Overview

A change point analysis was performed on data used in the study to investigate the presence of any abrupt change in variance for the study period. The results of change point detection are presented in the following subsections.

6.2 Results

Mean temperature, maximum temperature, minimum temperature, humidity and wind speeds are by nature have a diurnal variability and thus have a periodic mean. This was confirmed by the figures in Appendix A. In contrast, the variability of the data appears smaller in some sections and larger in others. This motivates a search for the association between changes in variability in climatic factors and dengue incidence. R version 3.1.2 software was used for the analysis. "cpt.var" function in changepoint package was used to identify the change points in variability. The changes in variance approaches within the cpt.var function require the data to have a fixed value mean over time, and thus this periodic must be removed prior to analysis. Whilst there are a range of options for removing this mean, we choose to take first differences as it does not require any modeling assumptions. Following this, we assume that the differences follow a Normal distribution with changing variance. Here we using PELT segmentation algorithm to detect change points.

Table 6.1 presents the results of change point analysis for the time series of dengue cases and climatic factors. It shows how change points are distributed over time. Cells contain time point (week number) where the change point was detected. For example, first change point in variance for dengue cases were detected at 8^{th} week of 2009. Within a year same colour points represent nearby change points. Figures 6.1 – 6.8 provides more details on the specifications of abrupt changes in climate variables.

Table 6.1: Summary of the results of change point analysis

	Time of the shift detected (week number)								
Year	**Cases**	**TEM**	**TMAX**	**Tm**	**P**	**H**	**VV**	**V**	**VM**
2009	*8*		*4*		*3*	*8*	*2*	*5*	*5*
	14		35		5	45	29	14	14
	20				7		32	47	31
	30				25		47		36
	46				32		50		38
					44				46
					46				50
2010	7		22	46	2	20	16		
	20		31	52	11	36	20		
	38		37		17		40		
			45		20		42		
					29		52		
					32				
					36				
					40				
					43				
					49				
2011	12	17	11	2	17	3	2		17
	19		15	9	41	15	17		35
	36		17	33		17	37		38
	42		20	50		50	40		49
	51		42			52			
2012	4	21	5	3	20	2	16	5	7
	19	35	10		31	4	27	14	30
	22		42		33	13	31		36
	34				49	21	42		40
	39					28	44		
	42					30			
						42			
2013	14	36	6	47	5	2	2	26	18
	16		8	51		4	4	28	29
			50				17		39
							20		41
							22		
2014		5	7	30	27	3	1	6	18
		26	30	35	35	7	3	30	20
		30	35			21	13	35	30
		35				27	24		35
						35	30		
							35		
Total	22	9	21	11	40	13	30	12	26

Row: Total (Total number of change points)

It can be seen that incidence of dengue, maximum temperature, humidity, wind speed and precipitation share similar variability in terms of distribution of change points overtime. During the study period, first change point in variance of dengue cases was recorded in 8th week of 2009. During 4th week – 7th week of 2009, maximum temperature, humidity, precipitation, wind speed and maximum sustained wind speed showed a change points in the variation. Next change points of variation in dengue cases located in 14th week of 2009. Within the same week, mean wind speed and maximum sustained wind speed also show a change in variation. But other climate variables did not show any variation prior and closer to this change point. At 30th week of 2009, a variation has increased drastically; this increase might be due to changes in precipitation and wind speed which were located at 29 – 32 week period. Both the mean temperature and minimum temperature do not show any change in their variations in year 2009.

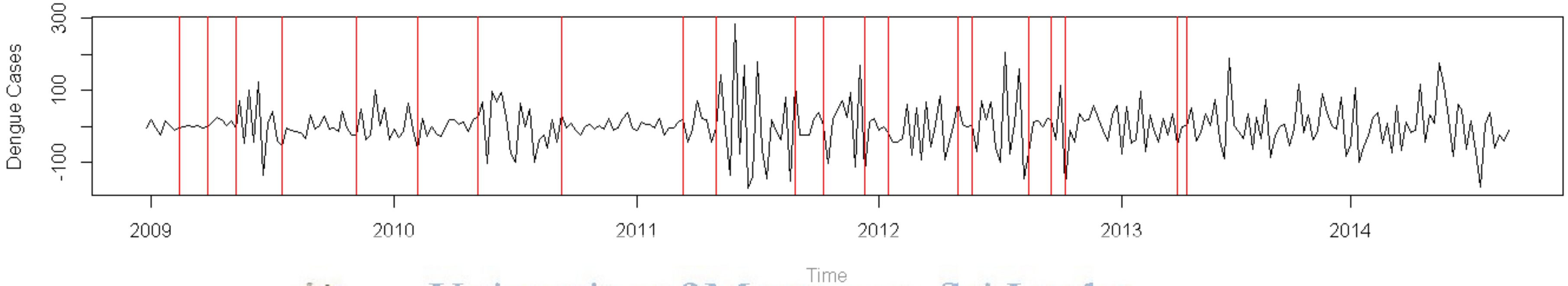
In 2010, three change points were detected in the variation of dengue incidence. In this year both the precipitation and humidity show similar behavior to dengue incidence in terms of location (time point) of change points.

From 2011 – 2012, 11 change points were detected in the variation of dengue incidence. These points were located nearby. During this period, maximum temperature, precipitation and humidity also showed very much similar pattern in terms of change point. More over visibility and maximum sustained wind also showed considerable number of change points during that period.

In 2013, two change points were detected in the variation of dengue cases. Further there is no considerable number of change points in both precipitation and humidity. During this year maximum temperature shows two change points, while precipitation and humidity show only one change point in 5th week and 4th week, respectively. These change points were located two months prior to the change point in dengue incidence. One change point in visibility was also detected. Other climatic variables did not show any change points.

Dengue cases from 1st week of 2014 to 36th week of 2014 does not show any change point with respect to their variation. But, during 26th week – 35th week, all climatic variables showed at least two change points with respect to their variation. Since dengue cases data were not considered after 36th week of 2014, we couldn't see whether this variation has some impact on dengue incidence.

According to figure 6.8, it is noted that after a sudden increase in maximum sustained wind speed there is a sudden drop in dengue incidence. Although it is not established whether this association is causal, high wind speed could conceivably interfere with normal mosquito movements and biting behaviors.



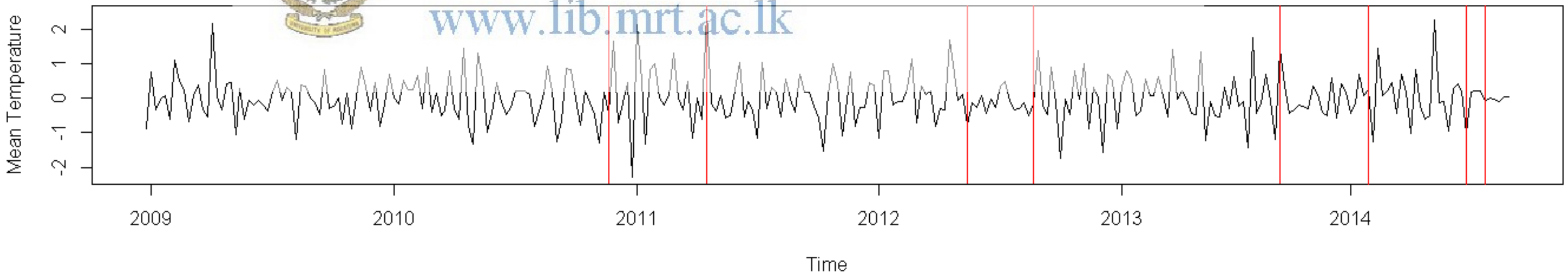


Figure 6.1: (a) First difference of dengue cases with vertical lines depicting change points identified by PELT segmentation , (b) First difference of mean temperature with vertical lines depicting change points identified by PELT segmentation

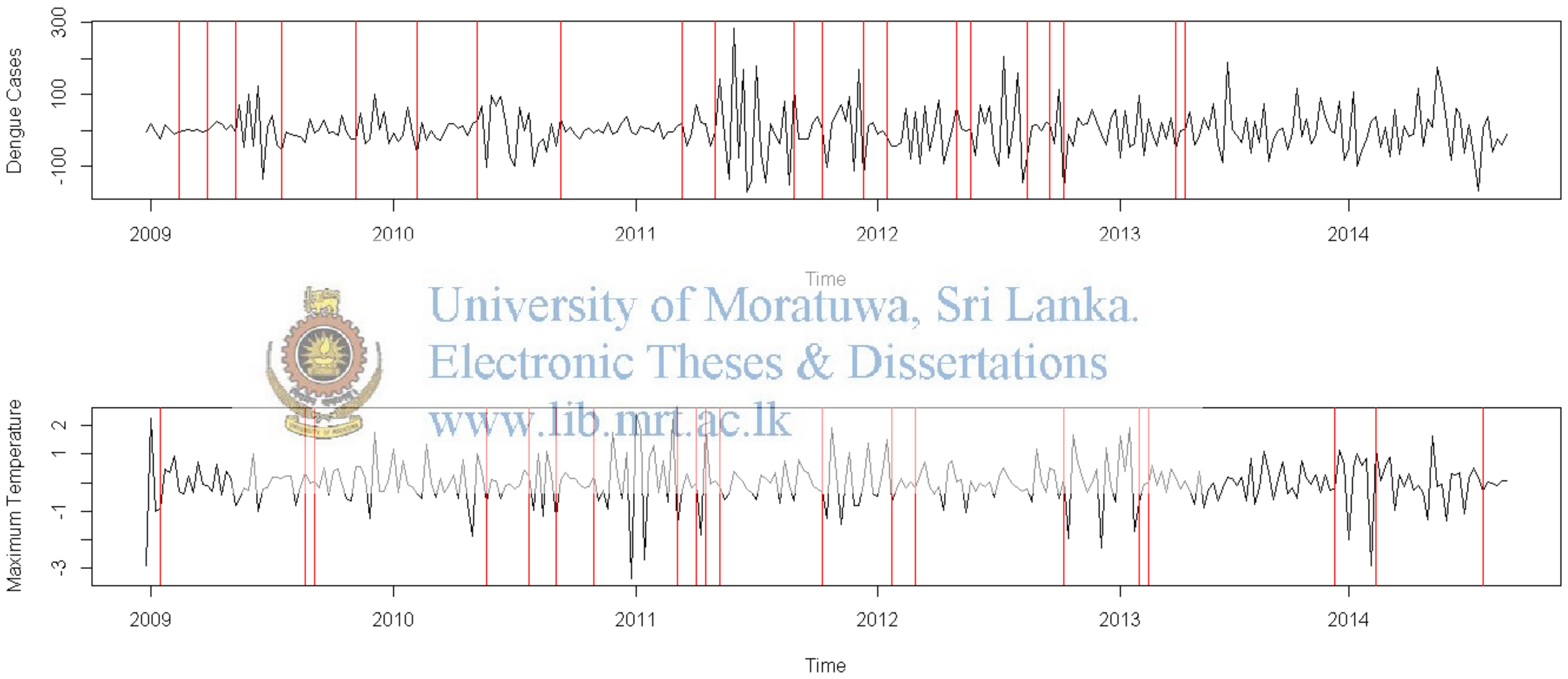


Figure 6.2: (a) First difference of dengue cases with vertical lines depicting change points identified by PELT segmentation , (b) First difference of maximum temperature with vertical lines depicting change points identified by PELT segmentation

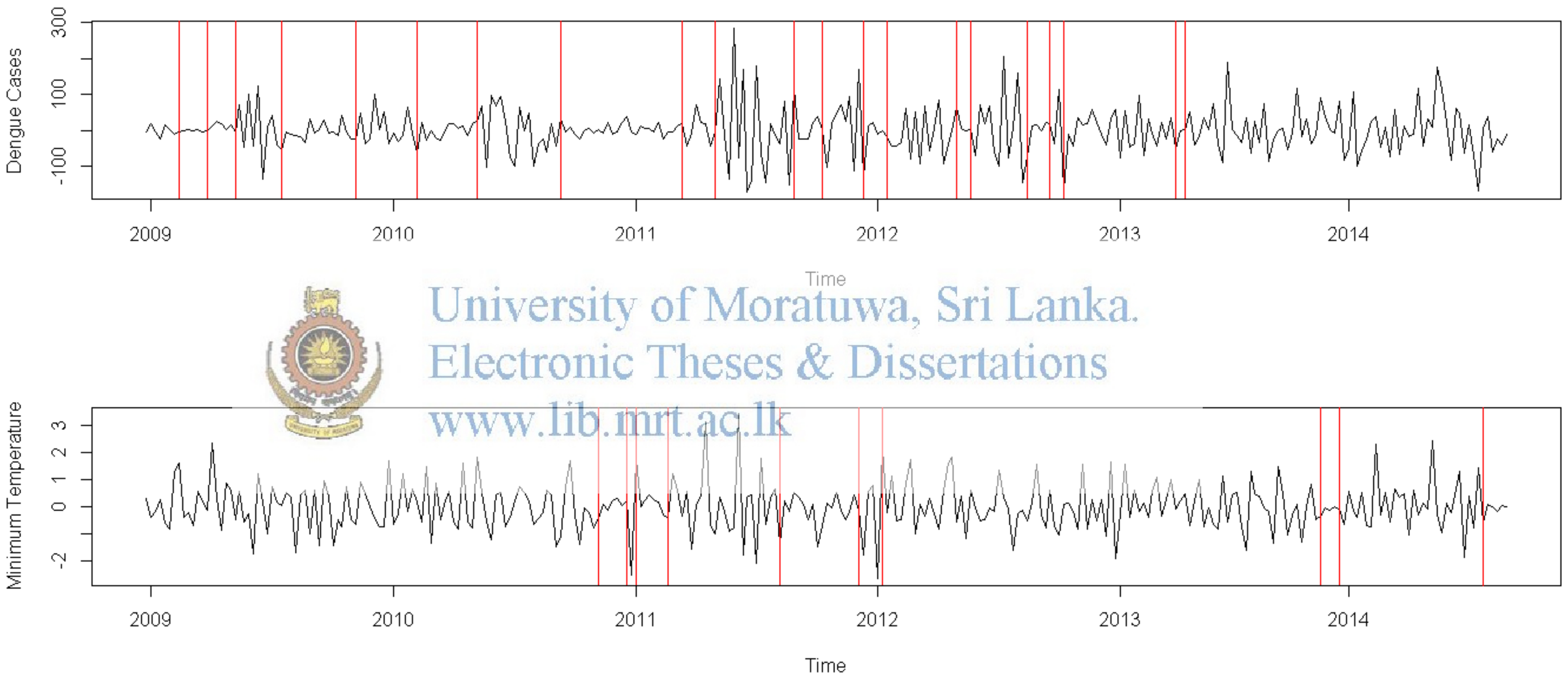


Figure 6.3: (a) First difference of dengue cases with vertical lines depicting change points identified by PELT segmentation , (b) First difference of minimum temperature with vertical lines depicting change points identified by PELT segmentation

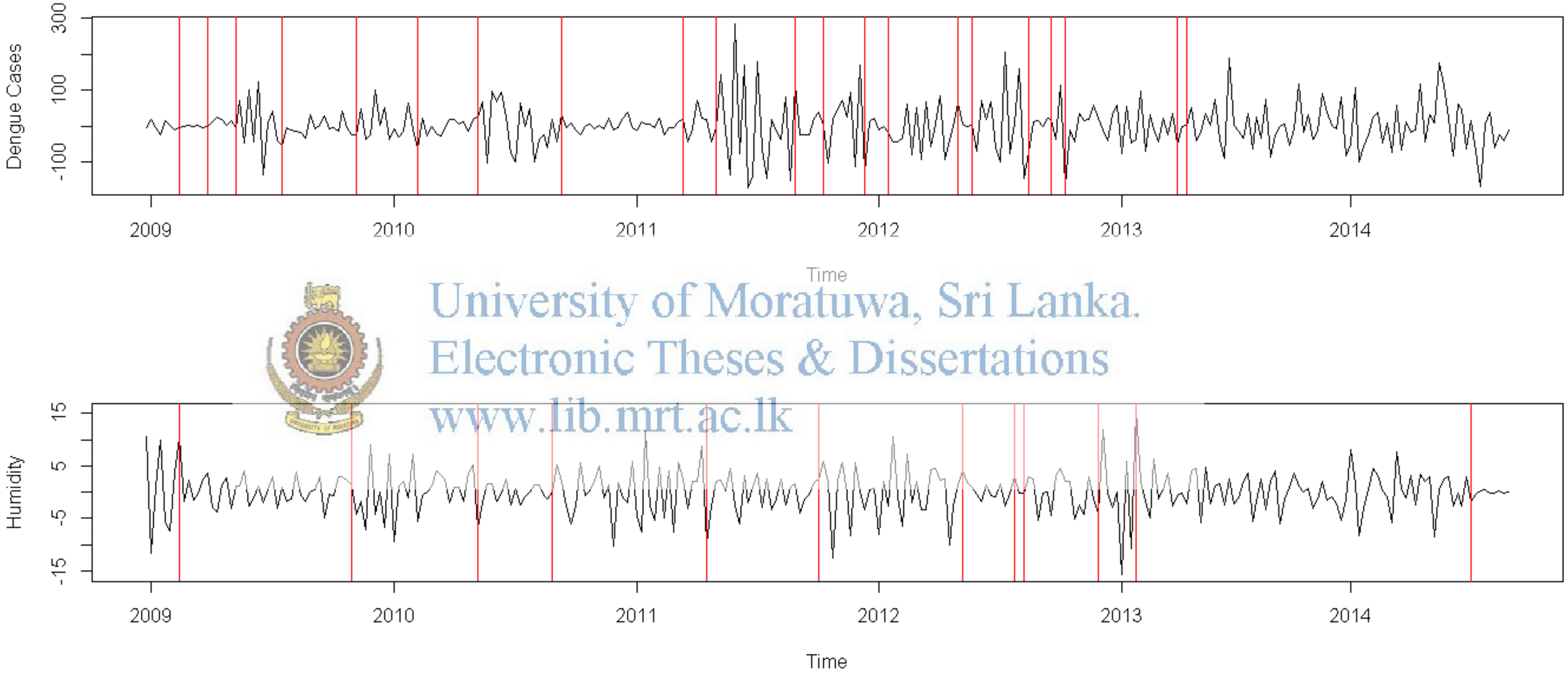


Figure 6.4: (a) First difference of dengue cases with vertical lines depicting change points identified by PELT segmentation , (b) First difference of humidity with vertical lines depicting change points identified by PELT segmentation

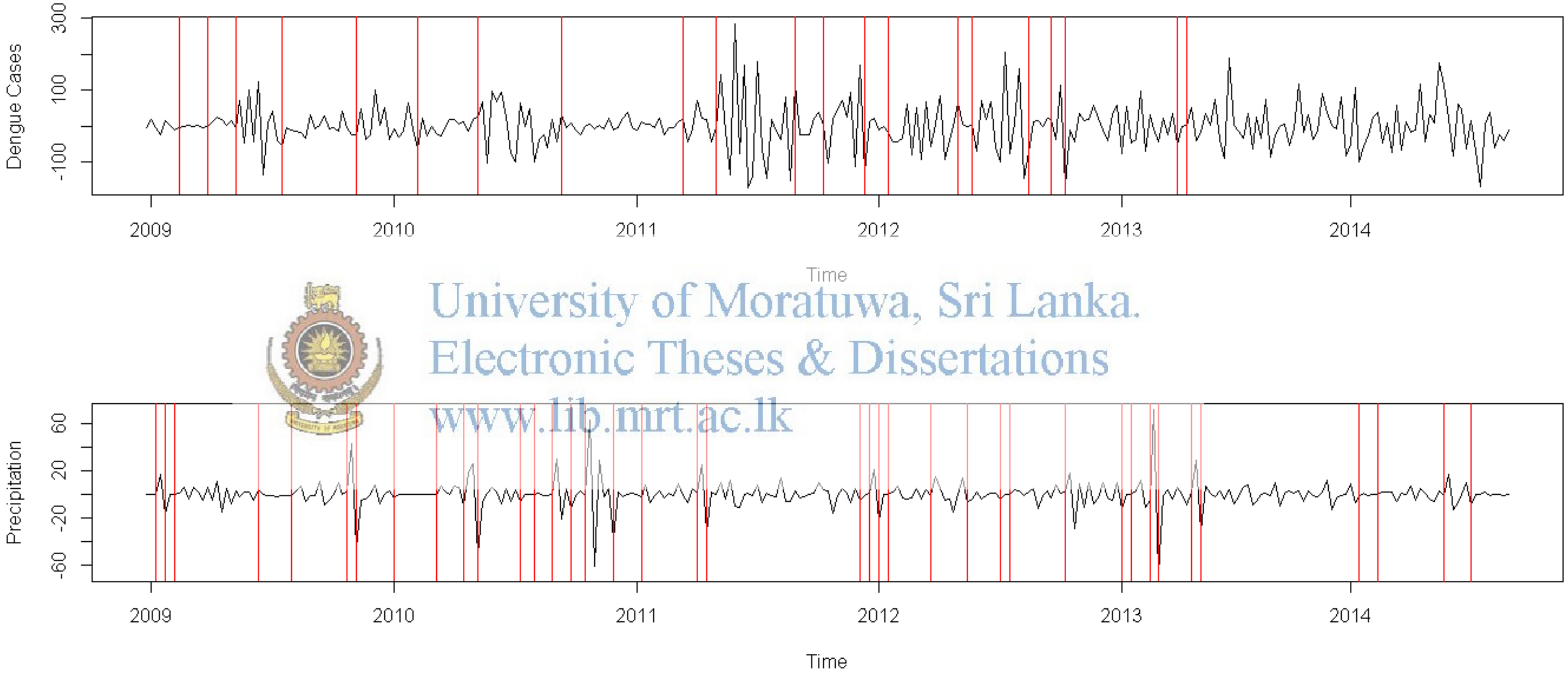


Figure 6.5: (a) First difference of dengue cases with vertical lines depicting change points identified by PELT segmentation , (b) First difference of precipitation with vertical lines depicting change points identified by PELT segmentation

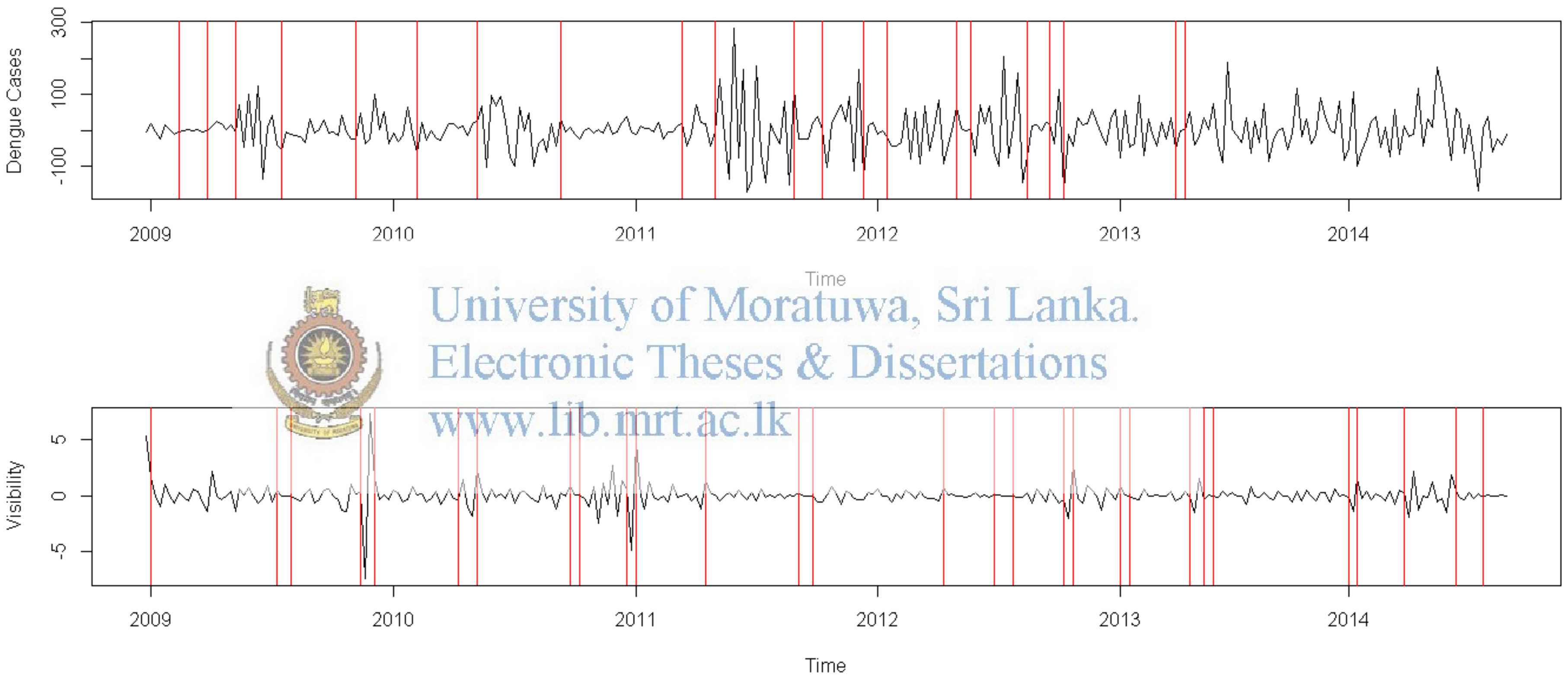


Figure 6.6: (a) First difference of dengue cases with vertical lines depicting change points identified by PELT segmentation , (b) First difference of visibility with vertical lines depicting change points identified by PELT segmentation

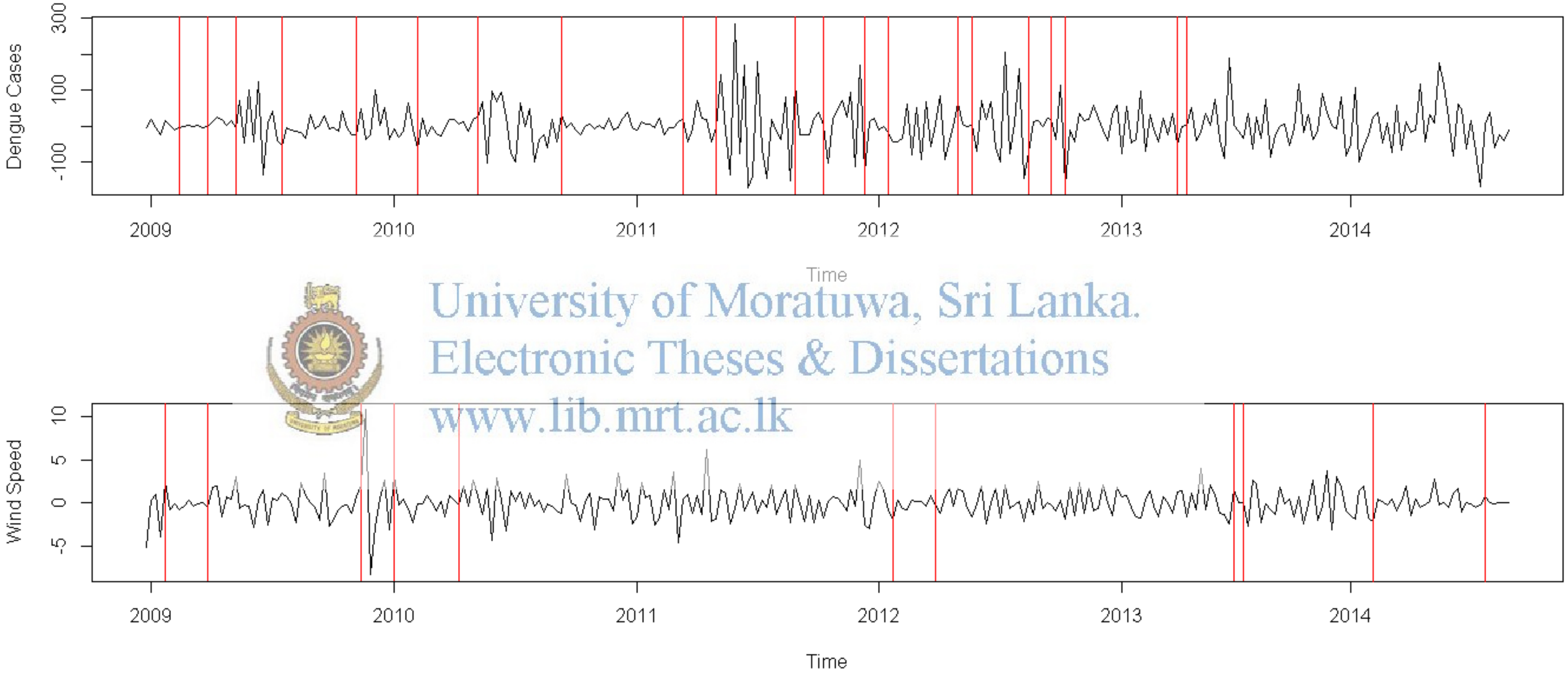


Figure 6.7: (a) First difference of dengue cases with vertical lines depicting change points identified by PELT segmentation , (b) First difference of wind speed with vertical lines depicting change points identified by PELT segmentation

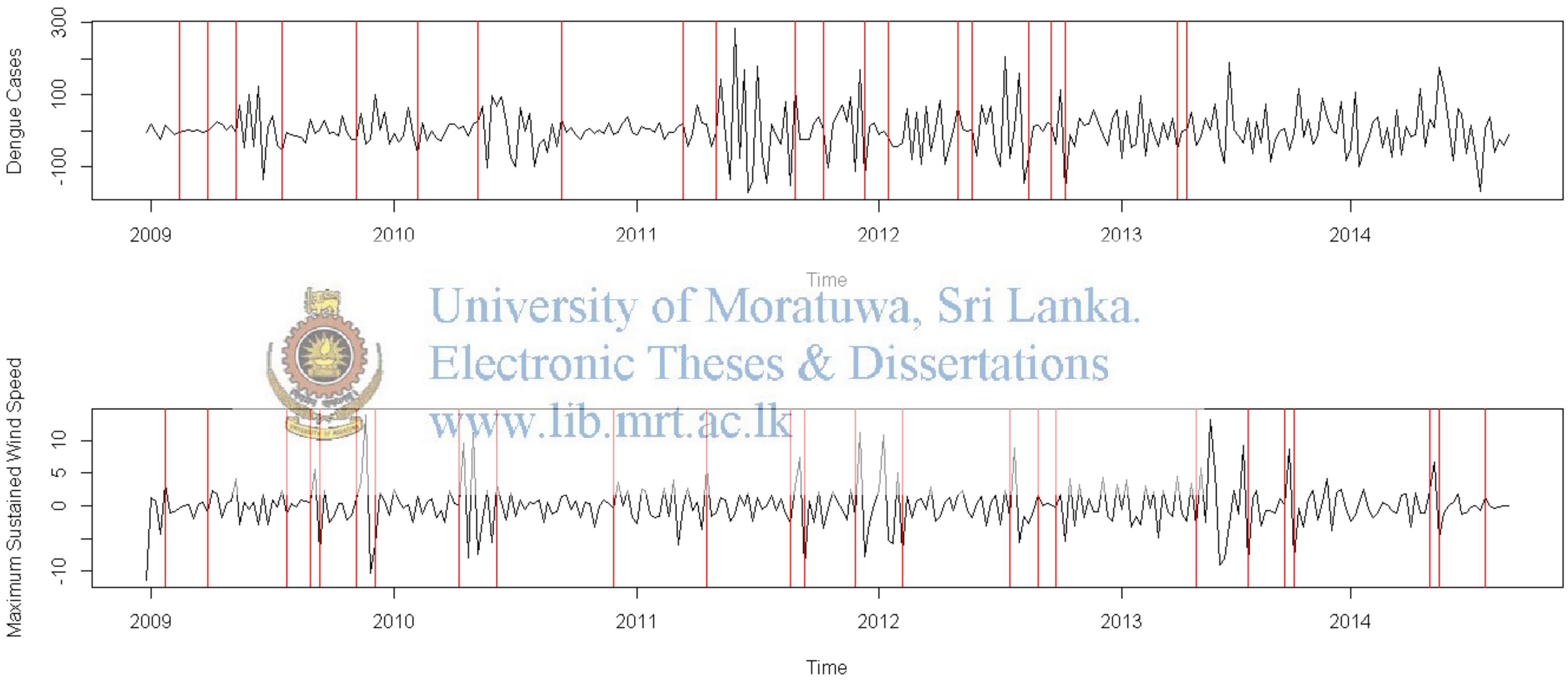


Figure 6.8: (a) First difference of dengue cases with vertical lines depicting change points identified by PELT segmentation, (b) First difference of maximum sustained wind speed with vertical lines depicting change points identified by PELT segmentation

CHAPTER 07

DISTRIBUTED LAG NONLINEAR MODELLING

7.1 Overview

In this chapter, we present the results of Distributed Lag Nonlinear Model (DLNM). Section 7.2 describes the adequacy of the DLNM model while section 7.3 interprets the results of proposed final model.

7.2 Adequacy of the DLNM Model

A Poisson regression combined with distributed lag nonlinear model was used to evaluate and compare the impact of climate variables on dengue incidence from 2009 to 2014 in Colombo district. DLNM was used since it allows for a nonlinear exposure-response relationship and provides flexibility in modeling the time structure of the relationship. Parameter estimations of the model is given in table 7.1 (Appendix C). Model selection is still an issue within the DLNM framework, although simulation studies indicate a good performance of methods based on the Akaike information criterion. Hence the model with minimum QAIC (= 8159.779) and QBIC (= 15483.04) was selected. The residuals were checked to evaluate the adequacy of the model to ensure they were normally distributed and independent over time (Figure 7.1 and figure 7.2).

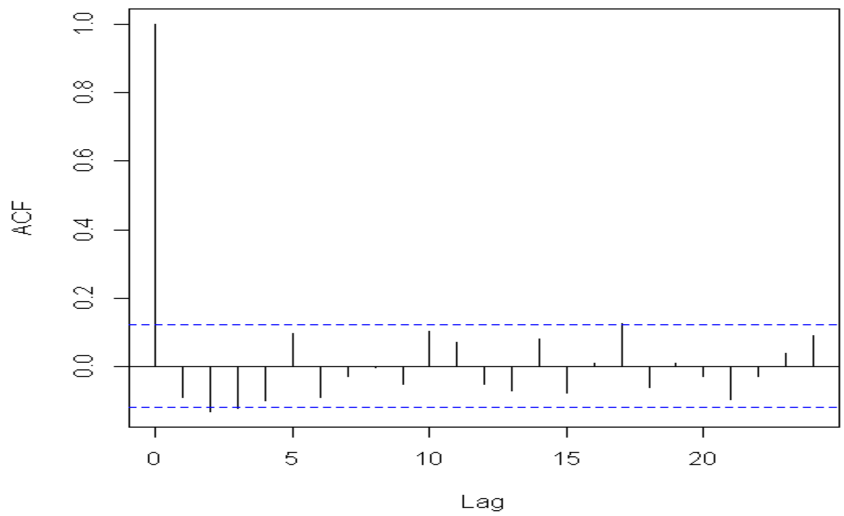


Figure 7.1: ACF plot of residual

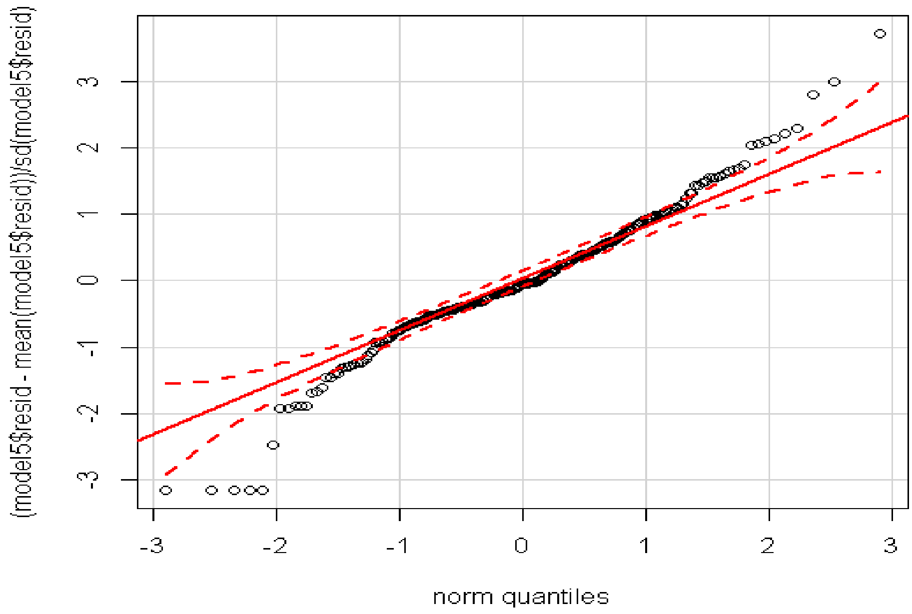


Figure 7.2: Normal probability plot of residuals; Two-sample Kolmogorov-Smirnov test (p = 0.206)

7.3 Interpretation of DLNM Results

Three-dimensional plots of figure 7.3 – figure 7.14 shows the relationship between meteorological variables and the incidence of dengue with various lag weeks. For better interpretative purpose, we plotted specific contour plots of the associations. All the relationship curves were nonlinear, whereas the different variables had different characteristics.

An overall picture of the effect of mean temperature change on dengue incidence was depicted in figure 7.3, showing three-dimensional plot of the relative risk (RR) along temperature change and lags with 27.72265^{0}C as the reference. It is important to note that the relative risk here is the ratio of the probability of dengue incidence occurring at a certain value of a weather variable to the probability of the event occurring at a reference value of the same weather variable. The change of reference may affect the width of confidence interval but it will not affect the RR curve itself. Hence median of each climate variable was chosen as the reference value. Overall, the estimated effect of mean temperature change on dengue was nonlinear. A visual inspection of the figure 7.4 suggests that there was an immediate harmful effect of low mean temperature (<27^{0}C) on dengue incidence at lag 4-9 weeks, and a protective effect (RR<1) of low temperature at lag 10-25 weeks. Figure 7.5, the three-dimensional plot shows that the impact of maximum temperature on dengue incidence, is completely reverse of the behavior of mean temperature.

Figure 7.7 and figure 7.8 show the relationship between precipitation and dengue incidence. In general, it can be seen that a higher precipitation was associated with a higher dengue incidence, but this observed relationship does not hold true when precipitation is 25mm -65mm at lag 5- 25 weeks. According to figure 7.6 the strongest effect of rainfall occurred at lag 0-5 weeks with more than 60mm precipitation, and lag 15-20 weeks with 40-50 mm precipitation. Very high precipitation (>70mm) at lag 15-20 weeks reduce the relative risk of dengue incidence. Further the precipitation around 30-60mm at lag 0-3 weeks has a protective impact on the occurrence of dengue incidence.

Figure 7.9 and figure 7.10 illustrate overall relationship of relative humidity on dengue incidence and its contour plot respectively. Humidity around 60-75 mm has a positive effect on dengue incidence around lag 10-18 weeks. High humidity (>85%) has a protective impact on dengue incidence.

The estimated effect of wind visibility on dengue cases differed for low and high visibility (figure 7.11 and figure 7.12). The risk of dengue transmission increases with visibility. Low visibility (<14 km) has a negative impact on the occurrence of dengue incidence while the high visibility (> 15km) a positive impact on increase of dengue incidence. Figure 7.13 and 7.14 shows the overall depiction of maximum sustained wind speed on dengue incidence. Maximum sustained wind speed (> 25km) at lag 0-10 weeks has a slight positive impact on dengue incidence.

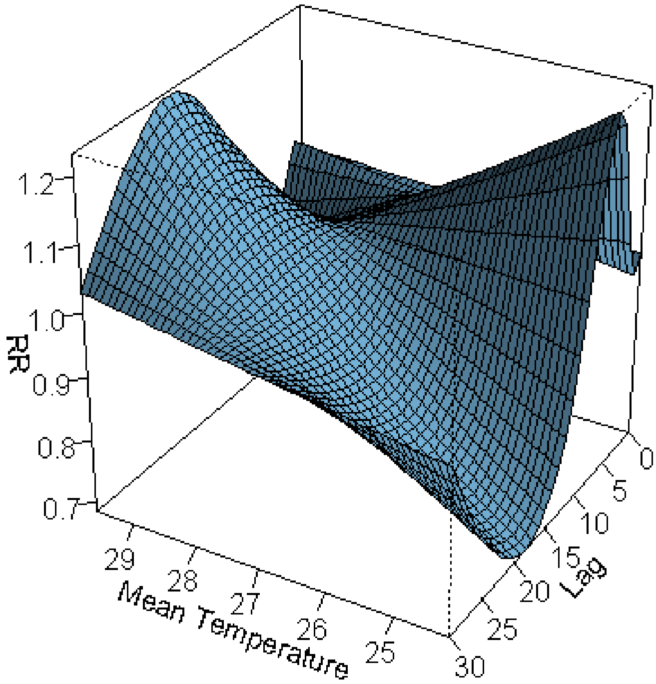


Figure 7.3: 3D plot of RR of dengue cases by mean temperature

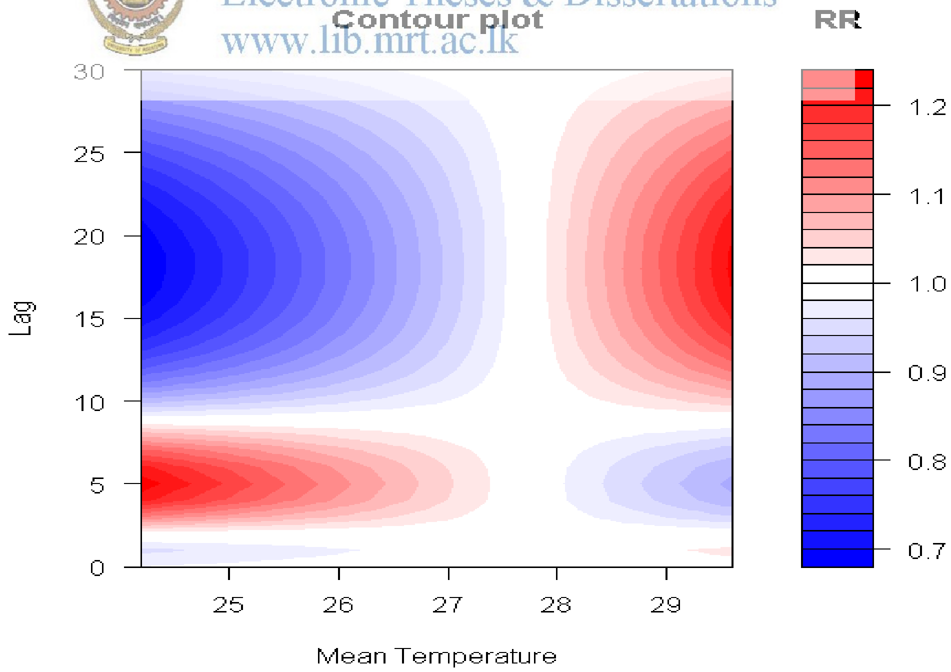


Figure 7.4: Contour plot of RR of dengue cases by mean temperature

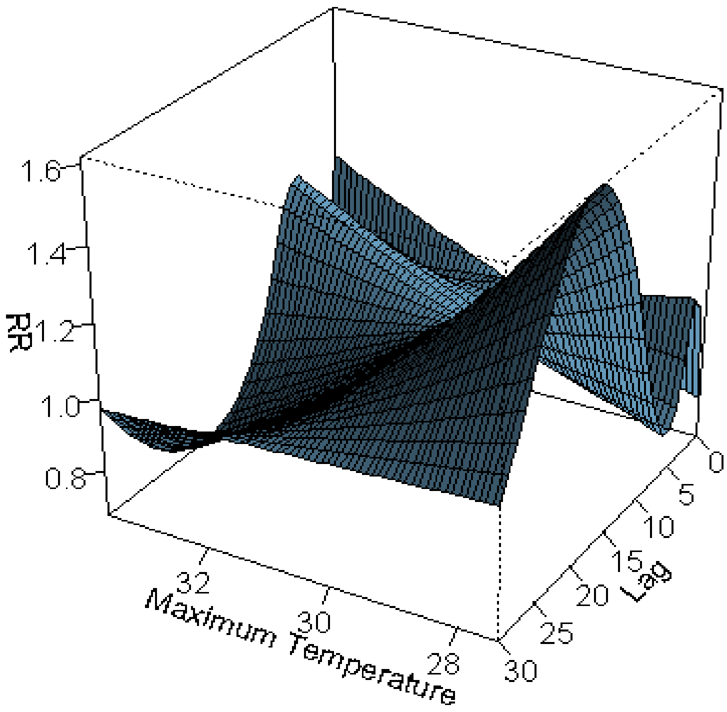


Figure 7.5: 3D plot of RR of dengue cases by maximum temperature

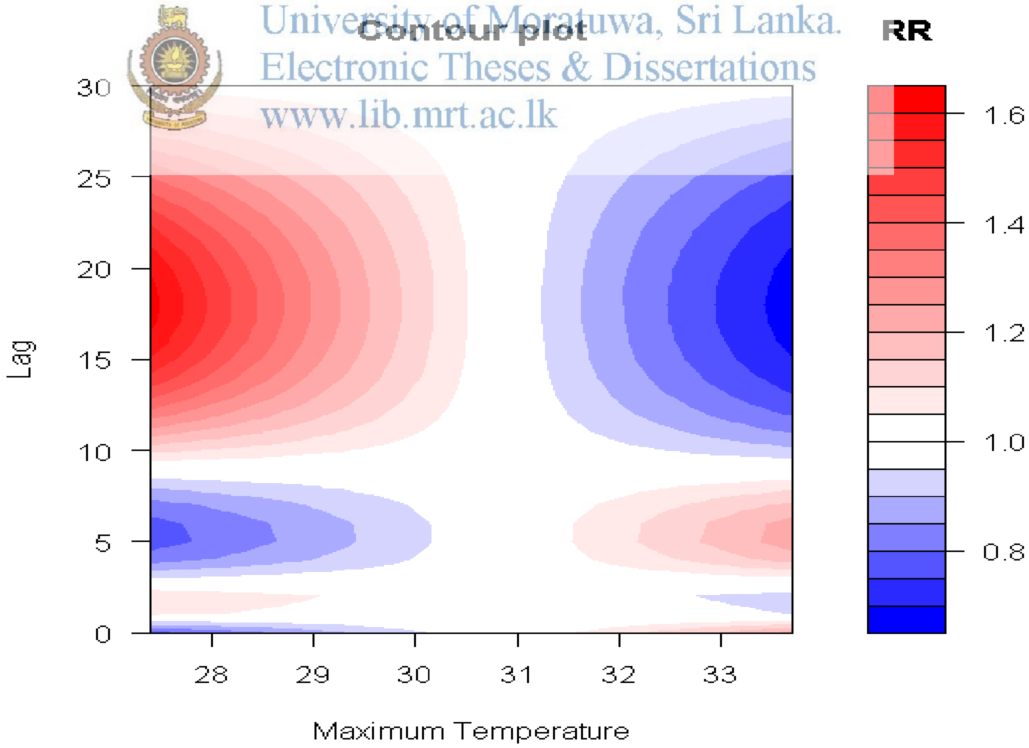


Figure 7.6: Contour plot of RR of dengue cases by maximum temperature

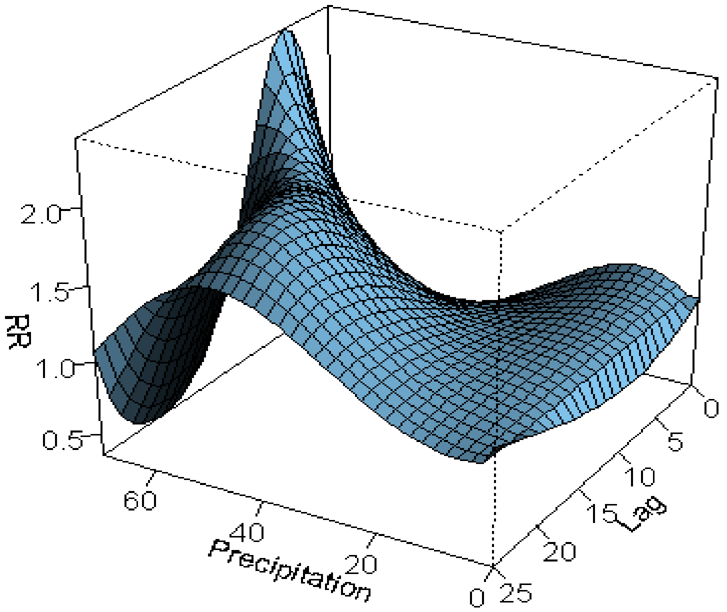


Figure 7.7: 3D plot of RR of dengue cases by precipitation

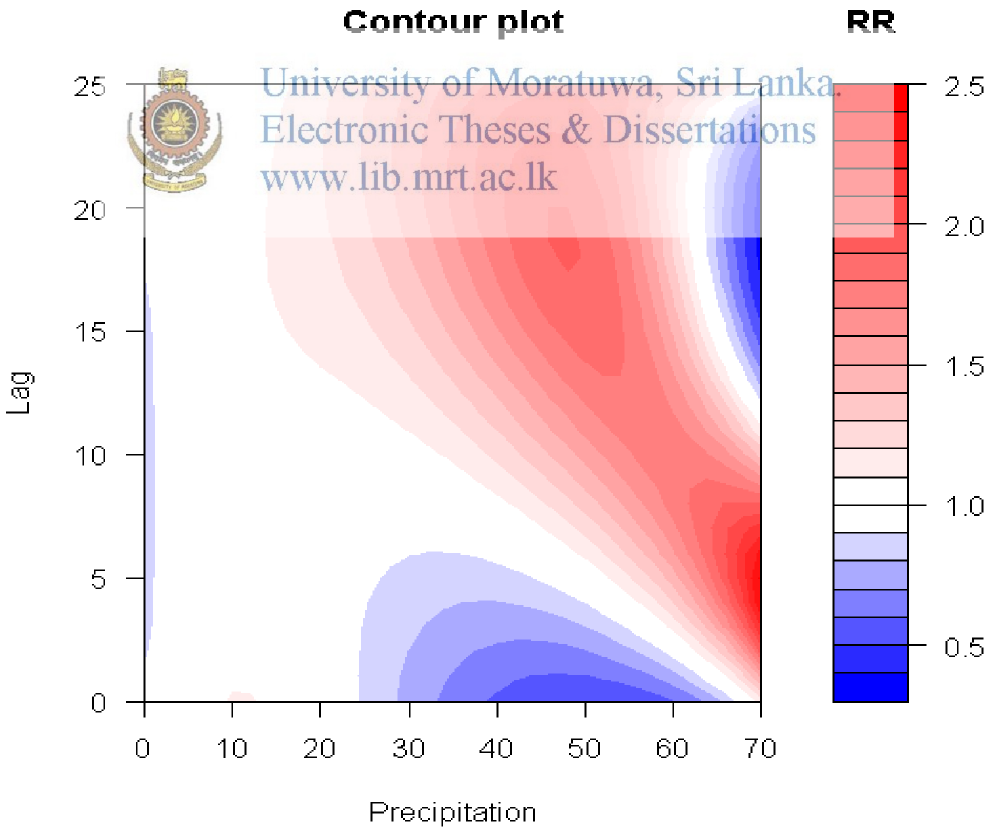


Figure 7.8: Contour plot of dengue cases by precipitation

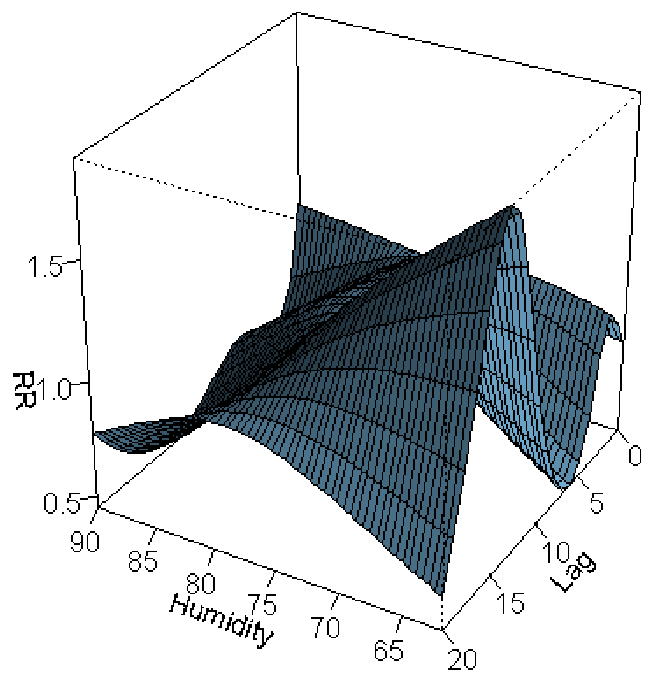


Figure 7.9: 3D plot of RR of dengue cases by humidity

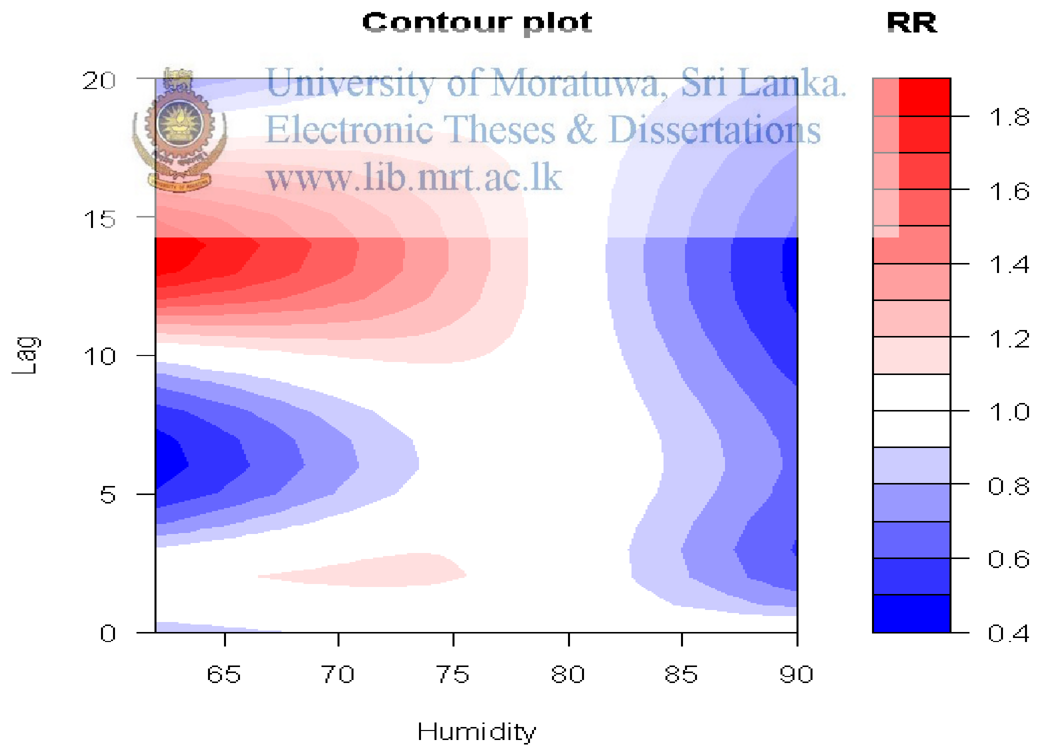


Figure 7.10: Contour plot of RR of dengue cases by humidity

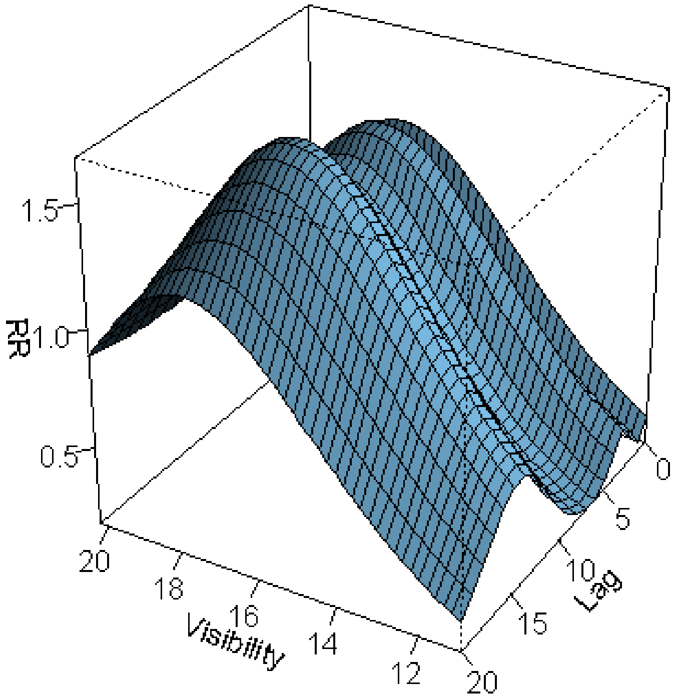


Figure 7.11: 3D plot of RR of dengue cases by visibility

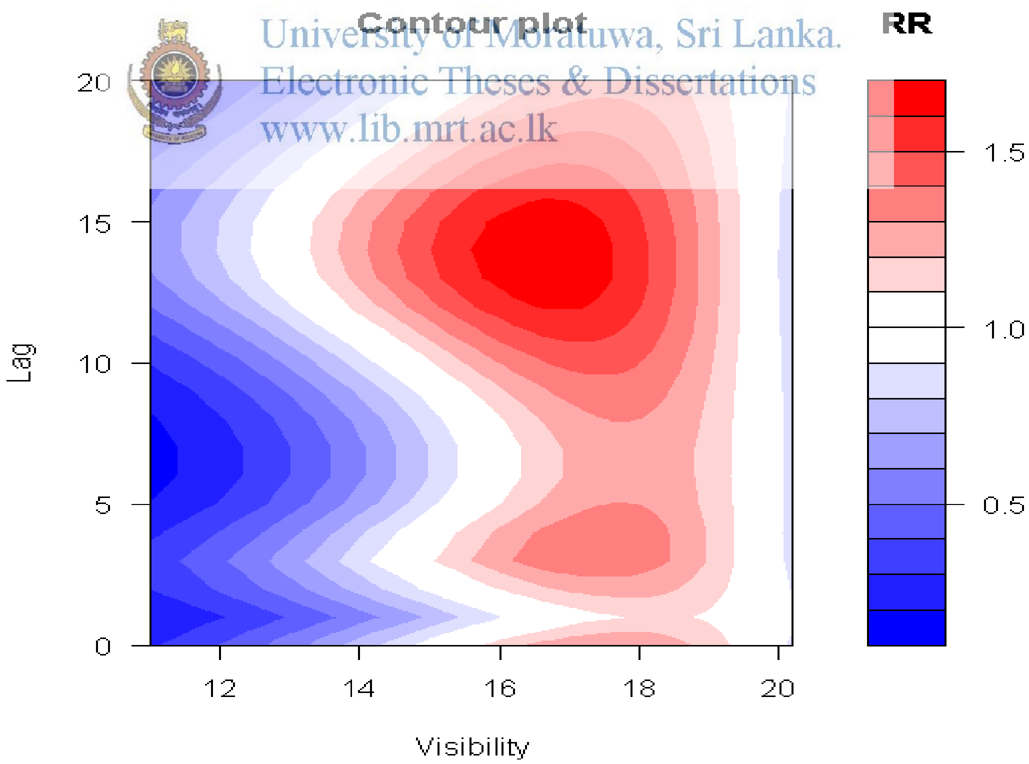


Figure 7.12: Contour plot of RR of dengue cases by visibility

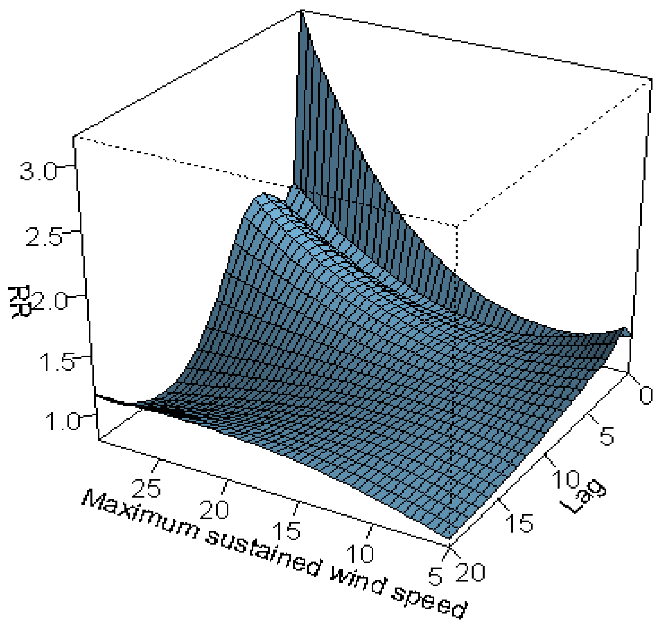


Figure 7.13: 3D plot of RR of dengue cases by wind speed

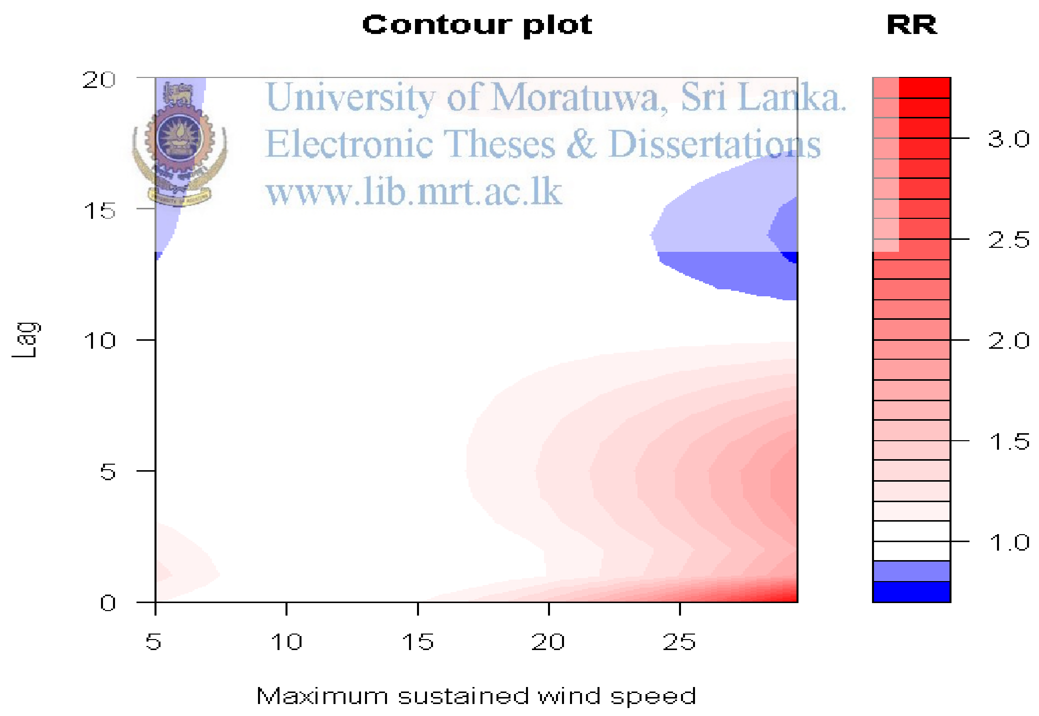


Figure 7.14: Contour plot of RR of dengue cases by wind speed

CHAPTER 8

CONCLUSIONS AND RECOMMENDATIONS

8.1 Overview

This chapter concludes the thesis and describes some of the limitations of the research. In addition to limitations, we critically evaluate and discuss the finding of the thesis and we also describe recommendations for future studies.

8.2 Conclusions and Recommendations

The wavelet power spectrum analysis of dengue dynamics indicates periodicities around 2-8 weeks, 26-32 weeks and 52-64 weeks. 2-8 weeks periodicity appeared in an intermittent pattern. Though we found high power at annual and semi-annual scales in wavelet power spectra of all 25 districts, the significance of those bands are discontinuous. However, dengue dynamics showed different periodicities across 25 districts which can be divided into two clusters based on wavelet cluster analysis. Except Trincomalee district all districts in cluster 01 were located in the left side of the coutry while in cluster 02, except Kalutara district all the other districts were located in the right side of the country. These two clusters may have influenced from southwest monsoon and northeast monsoon. The unusual pattern of dengue incidence in Kalutara district could be due to rubber cultivation. Massive number of coconut shells used for collection of rubber milk in the rubber planatation and discarded coconut shells caused breeding of mosquitoes. Moreover, rubber tree rain gutter system forms an ideal condition for the proliferation of mosquitoes. Furthermore, massive pineapple cultivation in rubber states also fueling for dengue vector profusion in the district. The periodicities of dengue incidence in cluster 01 are accordance with dengue dynamics in Thailand (Alshehri, 2013; Jeefoo, 2012) and South Vietnam (Cuong et al., 2011). Annual periodic patterns are a common phenomenon in dengue transmission and have been reported in many tropical and subtropical countries (Thai et al., 2010). There was a large decrease in the variability of dengue incidence in 2013. Possible explanations for the observed decrease could be a modification of the climate conditions, a reduction in transmission due to declining mosquito populations, declining contact between human and mosquito populations, and/or modifications in diagnosis, classification and reporting dengue cases.

Significant periodicity was present on annual scale for mean temperature, minimum temperature, maximum temperature and humidity. Precipitation showed a significant periodicity at 26 week. Wavelet coherency revealed a significant non-stationary association between all climatic variables and dengue incidence. The association between dengue and climate reported here is strong but transient. Wavelet coherency analyses revealed that dengue transmission co-varied with mean temperature, maximum temperature, humidity and visibility at both annual and biannual cycles. The cross wavelet power spectra for minimum temperature, precipitation, mean wind speed and maximum sustained wind speed show strong and significant signal for the 26 week period band. This suggests that mean temperature, humidity and precipitation have well differentiated roles in dengue transmission. Except wind speed, the significance of the association between dengue incidence and other climatic variables are discontinuous. Wavelet phase analyses revealed most of the statistically significant wavelet coherence is neither in phase nor anti phase. Most of the arrows are vertical at all significant coherence, indicating a lag difference between climate variables and dengue incidence.

In Hanoi dengue transmission demonstrates clear annual cycles that are associated with a lag of around two months with seasonal increases in mean temperature and rainfall (Cuong et al., 2011). We observed a significant association between dengue incidence and wind speed. Other authors (Cuong et al., 2011; Luz et al., 2011) also noted a pattern of high wind speed being associated with periods of low dengue notifications. Although it is not established whether this association is casual high wind speed could conceivable interfere with normal movement and biting behaviors. A previous study reported no apparent relationship between dengue and climate in Bangkok between 1966 and 1998 (An & Rocklov, 2014; Fairos et al., 2010). However, in this work the authors used spectral density analysis, which is not sensitive to nonstationary effects. Conventional statistical methods may fail to reveal a strong relationship between climate and a health outcome when discontinuous associations are present.

Considering the results of change point analysis, there were 22 change points in the variation of dengue dynamics in Colombo district. Most of the change points were detected in 2009, 2011 and 2012. Changes in the variation of dengue incidence in 2009, 2011 and 2012 are very much similar to the changes in the precipitation and humidity.

Results of distributed lag nonlinear model revealed mean temperature around 25^0C – 26^0C prior to 5 weeks and 28^0C – 29^0C temperature prior to lag 10 – 25 weeks , high precipitation (>30mm), humidity 65% - 75% prior to lag of 10-15 weeks and high visibility(> 16km) have an harmful impact on increasing relative risk of dengue incidence. Rainfall season is positively associated with high dengue incidence. This is line with the studies that reported the highest risk of dengue cases related to rainfall in Mexico, Brazil (Cheong et al., 2013). Rainfall influences the abundance of dengue vectors and aquatic populations (eggs, larvae, and pupa). Increased rainfall supports more suitable breeding sites for the immature development of the aquatic population. Further very high rainfall (> 70mm) at lag 15 – 20 weeks and rainfall between 30mm – 60mm have a protective impact on the occurrence of dengue incidence. Rainfall directly influences the density of the mosquitoes, however, strong rainfall causing floods may results in the disappearance of small ponds and thereby the feasible places for mosquito breeding (Gasparrini et al., 2010). Hence, the impact of rainfall on mosquito growth and distribution should be viewed within the geographical location of the study area. For example, if the region under consideration is a plain area with appropriate and fully covered sanitation systems, mosquito breeding may be less, while, if the region is an area where water remains stagnant for days, the area would be more vulnerable to a rapid increase in mosquito population due to rain. According to the results of distributed lag non linear model we observed high visibility being associated with high dengue notifications. Although it is not established whether this association is causal, high visibility could help the mosquito movements and biting behaviors. In our analyses, temperature, humidity and precipitation explained most the variance of the dengue cases.

Wavelet analysis, change point detection approach and distributed lag nonlinear models have revealed several pieces of evidence for a complex, nonstationary, nonlinear relationship between climatic variables and dengue incidence and periodicity of dengue incidence across the island. However, there were some limitations in this study. We only examined the association between climate variables and dengue incidence, but non-climatic factors, such as human activities, socioeconomic status, vector control programs, and drug resistance may also affect the spread of this disease. However, these non-climatic factors are unlikely to vary significantly on a weekly scale and were unavailable for this research. Further studies on the impact of climate change on dengue need to take all the other contributing factors into consideration in order to make meaningful public policy recommendations.

Our findings provide insights into the long-term persistence and spatial spread of dengue throughout Sri Lanka. Further studies on a more extensive time series dataset of a larger area could shed more light onto the spatio-temporal patterns in Sri Lanka. There is considerable interest in the role played by climate variability as a factor driving diseases (An & Rocklov, 2014). Further studies should use this approach to examine relationships between climate and dengue fever on regional and global scales.

Dengue prevention and control activities in many disease endemic settings, including Vietnam (Cuong et al., 2011), currently rely on targeted spraying of adulticides to reduce vector populations in and around the homes of reported patients. These activities are usually complemented with public health outreach and some routine activities to reduce vector breeding sites, within the constraints of limited public health budgets. Understanding the spatial dynamics and timing of dengue epidemics might enhance the implementation of current and future interventions by improved targeting to avert high-incidence dengue seasons. Results of this study provides a foundation for further investigation into the social and environmental factors responsible for changing disease patterns and provides data to inform program planning for dengue prevention control.

REFERENCE LIST

Alshehri, M. S. A. (2013). Dengue Fever outburst and its relationship with climatic factors. World Applied Sciences Journal, 22(4), 506-515.

An, D. T. M., & Rocklöv, J. (2014). Epidemiology of dengue fever in Hanoi from 2002 to 2010 and its meteorological determinants. Global health action, 7

Banu, S. (2013). Examining the impact of climate change on dengue transmission in the Asia-Pacific region.

Briët, O. J., Amerasinghe, P. H., & Vounatsou, P. (2013). Generalized seasonal autoregressive integrated moving average models for count data with application to malaria time series with low case numbers. PloS one, 8(6), e65761.

Castillo, K. C., Körbl, B., Stewart, A., Gonzalez, J. F., & Ponce, F. (2011). Application of spatial analysis to the examination of dengue fever in Guayaquil, Ecuador. Procedia Environmental Sciences, 7, 188-193.

Cazelles, B., Cazelles, K., & Chavez, M. (2014). Wavelet analysis in ecology and epidemiology: impact of statistical tests. Journal of The Royal Society Interface, 11(91), 20130585.

Cazelles, B., Chavez, M., McMichael, A. J., & Hales, S. (2005). Nonstationary influence of El Nino on the synchronous dengue epidemics in Thailand. PLoS medicine, 2(4), e106.

Chaves, L. F., & Koenraadt, C. J. (2010). Climate change and highland malaria: fresh air for a hot debate. The Quarterly Review of Biology, 85(1), 27-55.

Chen, S. C., Liao, C. M., Chio, C. P., Chou, H. H., You, S. H., & Cheng, Y. H. (2010). Lagged temperature effect with mosquito transmission potential explains dengue variability in southern Taiwan: insights from a statistical analysis. Science of the total environment, 408(19), 4069-4075.

Cheong, Y. L., Burkart, K., Leitão, P. J., & Lakes, T. (2013). Assessing weather effects on dengue disease in Malaysia. International journal of environmental research and public health, 10(12), 6319-6334.

Colón-González, F. J., Lake, I. R., & Bentham, G. (2011). Climate variability and dengue fever in warm and humid Mexico. The American journal of tropical medicine and hygiene, 84(5), 757-763.

Cuong, H. Q., Hien, N. T., Duong, T. N., Phong, T. V., Cam, N. N., Farrar, J., ... & Horby, P. (2011). Quantifying the emergence of dengue in Hanoi, Vietnam: 1998–2009. PLoS neglected tropical diseases, 5(9), e1322.

Dengue battle costs billions- so why the soaring deaths?.(201, February 09). *The Sunday Times,* p. A4

Descloux, E., Mangeas, M., Menkes, C. E., Lengaigne, M., Leroy, A., Tehei, T., ... & De Lamballerie, X. (2012). Climate-based models for understanding and forecasting dengue epidemics. PLoS neglected tropical diseases, 6(2), e1470.

Fairos, W. W., Azaki, W. W., Alias, L. M., & Wah, Y. B. (2010). Modelling Dengue Fever (DF) and Dengue Haemorrhagic Fever (DHF) Outbreak Using Poisson and Negative Binomial Model. Int J Math Comput Sci Eng, 4, 809-814.

Fansiri, T., Fontaine, A., Diancourt, L., Caro, V., Thaisomboonsuk, B., Richardson, J. H., ... & Lambrechts, L. (2013). Genetic mapping of specific interactions between Aedes aegypti mosquitoes and dengue viruses. PLoS genetics, 9(8), e1003621.

Focks, D. A., Alexander, N., Villegas, E., & World Health Organization. (2006). Multicountry study of Aedes aegypti pupal productivity survey methodology: findings and recommendations.

Gasparrini, A., Armstrong, B., & Kenward, M. G. (2010). Distributed lag non-linear models. Statistics in medicine, 29(21), 2224-2234.

Gharbi, M., Quenel, P., Gustave, J., Cassadou, S., Ruche, G. L., Girdary, L., & Marrama, L. (2011). Time series analysis of dengue incidence in Guadeloupe, French West Indies: forecasting models using climate variables as predictors. BMC infectious diseases, 11(1), 166.

Grinsted, A., Moore, J. C., & Jevrejeva, S. (2004). Application of the cross wavelet transform and wavelet coherence to geophysical time series. Nonlinear processes in geophysics, 11(5/6), 561-566.

Harris, E., Videa, E., Pérez, L., Sandoval, E., Téllez, Y., Perez, M. L., ... & Balmaseda, A. (2000). Clinical, epidemiologic, and virologic features of dengue in the 1998 epidemic in Nicaragua. The American journal of tropical medicine and hygiene, 63(1), 5-11.

Hii, Y. L. (2013). Climate and dengue fever: early warning based on temperature and rainfall.

Hu, W., Clements, A., Williams, G., & Tong, S. (2010). Dengue fever and El Nino/Southern Oscillation in Queensland, Australia: a time series predictive model. Occupational and environmental medicine, 67(5), 307-311.

Hu, W., Tong, S., Mengersen, K., & Connell, D. (2007). Weather variability and the incidence of cryptosporidiosis: comparison of time series poisson regression and SARIMA models. Annals of epidemiology, 17(9), 679-688.

Jeefoo, P. (2012). Spatial Temporal Dynamics and Risk Zonation of Dengue Fever, Dengue Hemorrhagic Fever, and Dengue Shock Syndrome in Thailand. International Journal of Modern Education and Computer Science (IJMECS), 4(9), 58.

Johansson, M. A., Cummings, D. A., & Glass, G. E. (2009). Multiyear climate variability and dengue—El Nino southern oscillation, weather, and dengue incidence in Puerto Rico, Mexico, and Thailand: a longitudinal data analysis. PLoS medicine, 6(11), e1000168.

Killick, R., & Eckley, I. A. (2011). Changepoint: an R package for changepoint analysis. R package version 0.6, URL http://CRAN. R-project. org/package= changepoint

Kim, Y. M., Park, J. W., & Cheong, H. K. (2012). Estimated effect of climatic variables on the transmission of Plasmodium vivax malaria in the Republic of Korea. Environmental health perspectives, 120(9), 131

Lam, P. K., Tam, D. T. H., Diet, T. V., Tam, C. T., Tien, N. T. H., Kieu, N. T. T., ... & Wills, B. (2013). Clinical characteristics of dengue shock syndrome in Vietnamese children: a 10-year prospective study in a single hospital. Clinical infectious diseases, 57(11), 1577-1586.

Lowe, R., Bailey, T. C., Stephenson, D. B., Graham, R. J., Coelho, C. A., Carvalho, M. S., & Barcellos, C. (2011). Spatio-temporal modelling of climate-sensitive disease risk: Towards an early warning system for dengue in Brazil. Computers & Geosciences, 37(3), 371-381.

Luz, P. M., Vanni, T., Medlock, J., Paltiel, A. D., & Galvani, A. P. (2011). Dengue vector control strategies in an urban setting: an economic modelling assessment. The Lancet, 377(9778), 1673-1680.

Ma, W., Sun, X., Song, Y., Tao, F., Feng, W., He, Y., ... & Yuan, Z. (2013). Applied mixed generalized additive model to assess the effect of temperature on the incidence of bacillary dysentery and its forecast. PloS one, 8(4), e62122.

Martinez, E. Z., & Silva, E. A. S. D. (2011). Predicting the number of cases of dengue infection in Ribeirão Preto, São Paulo State, Brazil, using a SARIMA model. Cadernos de saude publica, 27(9), 1809-1818.

Messer, W. B., Vitarana, U. T., Sivananthan, K., Elvtigala, J., Preethimala, L. D., Ramesh, R., ... & De Silva, A. M. (2002). Epidemiology of dengue in Sri Lanka before and after the emergence of epidemic dengue hemorrhagic fever. The American journal of tropical medicine and hygiene, 66(6), 765-773.

Morin, C. W., Comrie, A. C., & Ernst, K. (2013). Climate and dengue transmission: evidence and implications. Environmental health perspectives, 121(11-12), 1264-1272.

Nakhapakorn, K., & Tripathi, N. K. (2005). An information value based analysis of physical and climatic factors affecting dengue fever and dengue haemorrhagic fever incidence. International Journal of Health Geographics, 4(1), 13.

Packages, R., & Pretty, R. wtc {biwavelet} Compute wavelet coherence.

Pascual, M., Cazelles, B., Bouma, M. J., Chaves, L. F., & Koelle, K. (2008). Shifting patterns: malaria dynamics and rainfall variability in an African highland. Proceedings of the Royal Society B: Biological Sciences, 275(1631), 123-132.

Pathirana, S., Kawabata, M., & Goonatilake, R. (2009). Study of potential risk of dengue disease outbreak in Sri Lanka using GIS and statistical modelling. Journal of Rural and Tropical Public Health, 8, 8.

Pham, H. V., Doan, H. T., Phan, T. T., & Minh, N. N. T. (2011). Ecological factors associated with dengue fever in a central highlands Province, Vietnam. BMC infectious diseases, 11(1), 172.

Pinto, E., Coelho, M., Oliver, L., & Massad, E. (2011). The influence of climate variables on dengue in Singapore. International journal of environmental health research, 21(6), 415-426.

Prates, M. O., Dey, D. K., & Lachos, V. H. (2012). A dengue fever study in the state of.

Seng, S. B., Chong, A. K., & Moore, A. (2005). Geostatistical modelling, analysis and mapping of epidemiology of dengue fever in Johor State, Malaysia.

Serfling, R. E. (1963). Methods for current statistical analysis of excess pneumonia-influenza deaths. Public health reports, 78(6), 494.

Thai, K. T., Cazelles, B., Van Nguyen, N., Vo, L. T., Boni, M. F., Farrar, J., ... & de Vries, P. J. (2010). Dengue dynamics in Binh Thuan province, southern Vietnam: periodicity, synchronicity and climate variability. PLoS neglected tropical diseases, 4(7), e747.

Tissera, H. A., Ooi, E. E., Gubler, D. J., Tan, Y., Logendra, B., Wahala, W. M. P. B., ... & De Silva, A. D. (2011). New dengue virus type 1 genotype in Colombo, Sri Lanka. Emerging infectious diseases, 17(11), 2053-2055.

Torrence, C., & Compo, G. P. (1998). A practical guide to wavelet analysis. Bulletin of the American Meteorological society, 79(1), 61-78.

Wu, P. C., Guo, H. R., Lung, S. C., Lin, C. Y., & Su, H. J. (2007). Weather as an effective predictor for occurrence of dengue fever in Taiwan. Acta tropica, 103(1), 50-57.

Wu, P. C., Lay, J. G., Guo, H. R., Lin, C. Y., Lung, S. C., & Su, H. J. (2009). Higher temperature and urbanization affect the spatial patterns of dengue fever transmission in subtropical Taiwan. Science of the total environment, 407(7), 2224-2233.

Xiao, H., Tian, H. Y., Cazelles, B., Li, X. J., Tong, S. L., Gao, L. D., ... & Zhang, X. X. (2013). Atmospheric moisture variability and transmission of hemorrhagic fever with renal syndrome in changsha city, mainland china, 1991–2010. PLoS neglected tropical diseases, 7(6), e2260.

Yang, L., Qin, G., Zhao, N., Wang, C., & Song, G. (2012). Using a generalized additive model with autoregressive terms to study the effects of daily temperature on mortality. BMC medical research methodology, 12(1), 165.

Yusof, Y., & Mustaffa, Z. (2011). Dengue outbreak prediction: A least squares support vector machines approach. International Journal of Computer Theory and Engineering, 3(4), 489-493.

Zacarias, O. P., & Andersson, M. (2010). Mapping malaria incidence distribution that accounts for environmental factors in Maputo Province-Mozambique. *Malar J*, *9*, 79.

Appendix A: Wavelet analyses of Dengue Cases by Districts

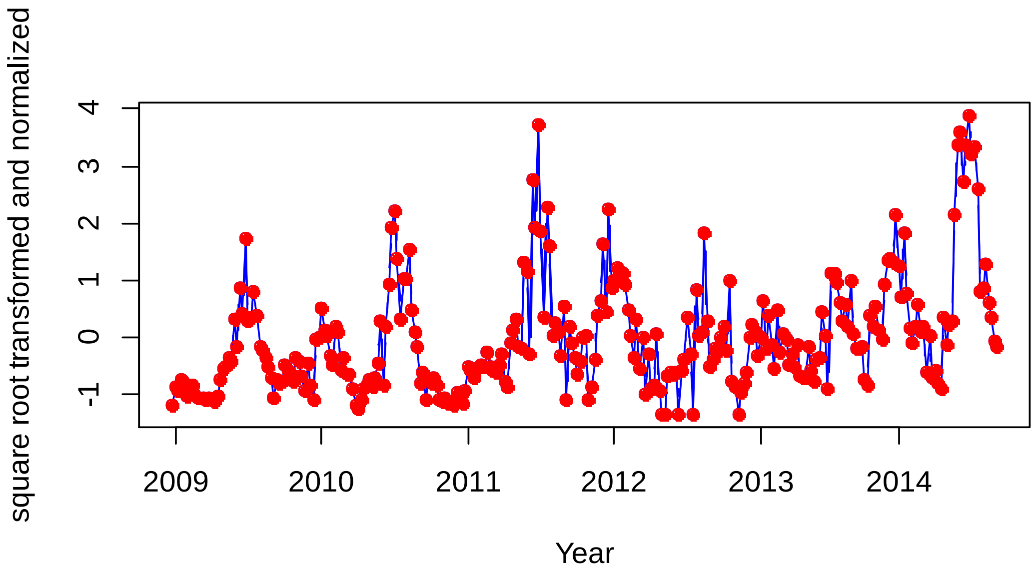


Figure A1: Time series plot of square root transformed and normalized aggregated dengue incidence in Colombo District, 2009 – September, 2014.

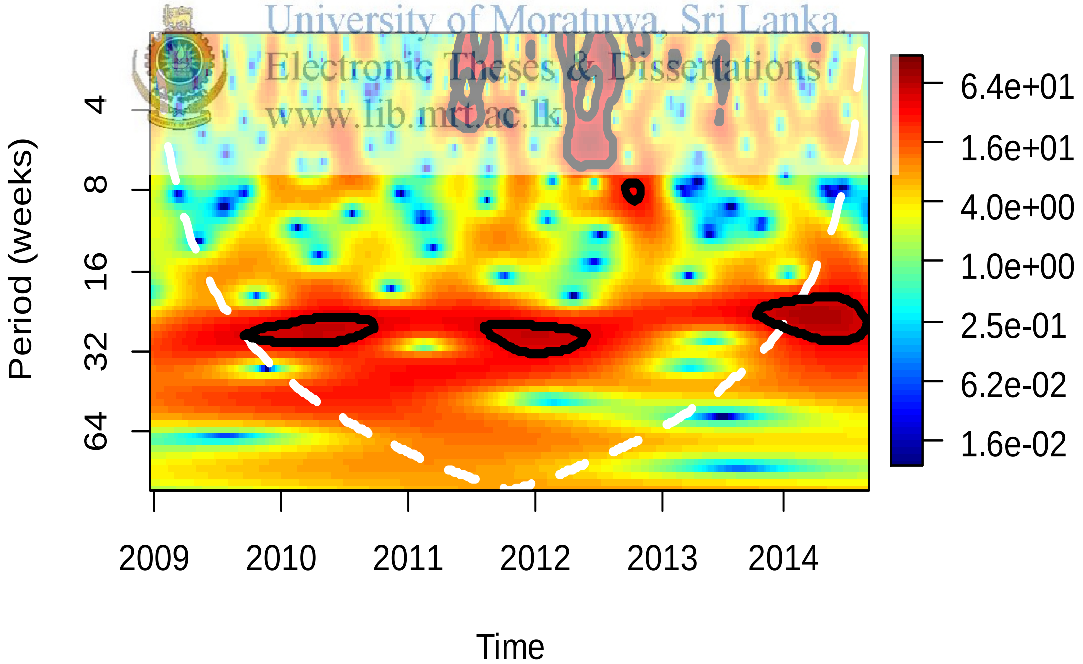


Figure A2: Wavelet power spectrum of dengue incidence in Colombo district from 2009 to September, 2014.

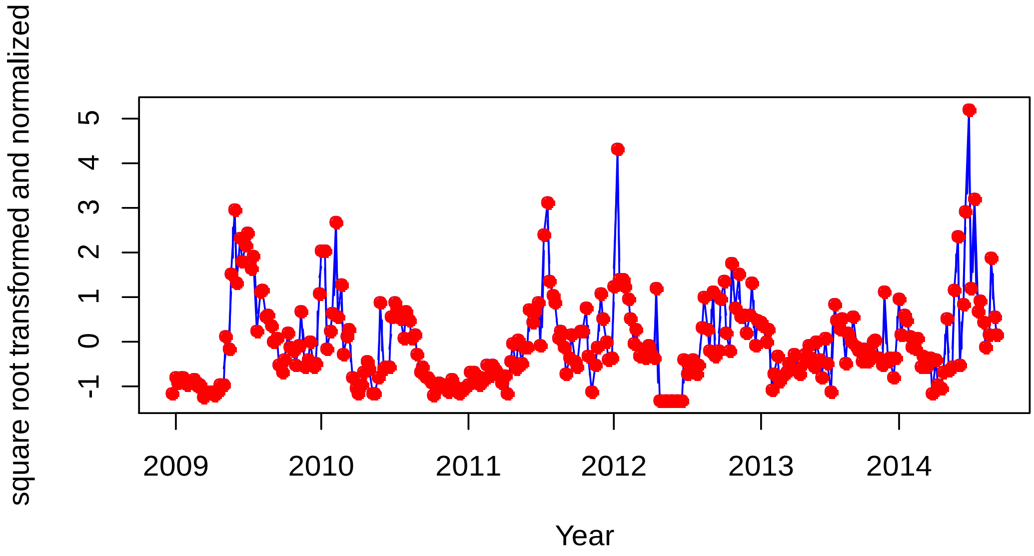


Figure A3: Time series plot of square root transformed and normalized aggregated dengue incidence in Gampaha District, 2009 – September, 2014.

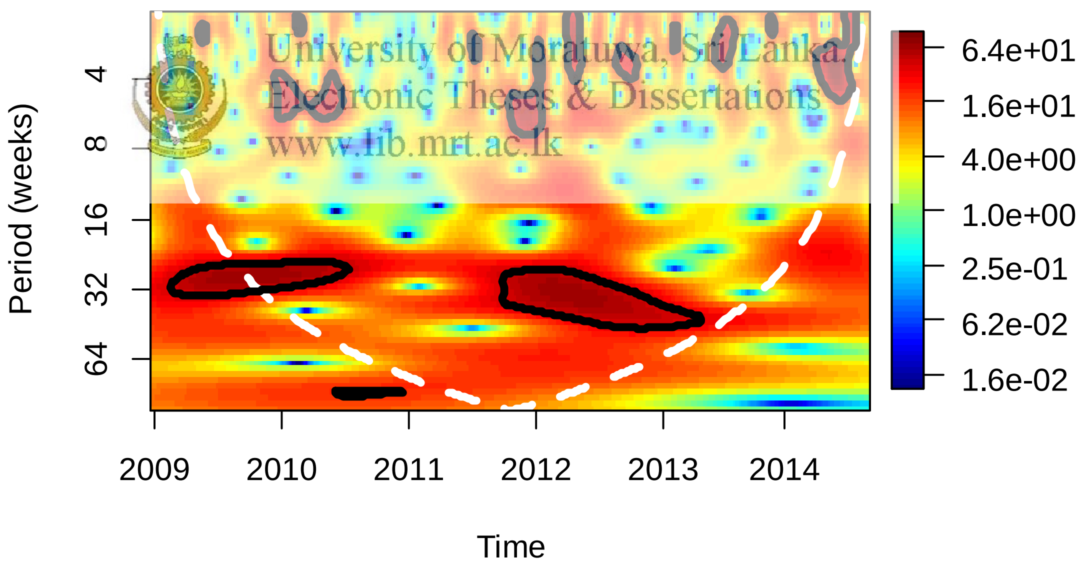


Figure A4: wavelet power spectrum of dengue incidence in Gampaha district from 2009 to September, 2014.

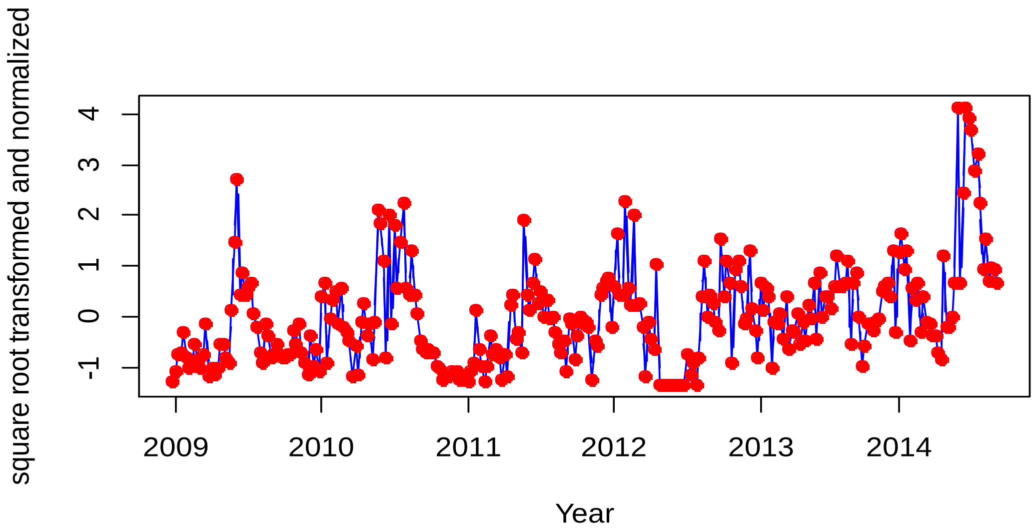


Figure A5: Time series plot of square root transformed and normalized aggregated dengue incidence in Kalutara District, 2009 – September, 2014.

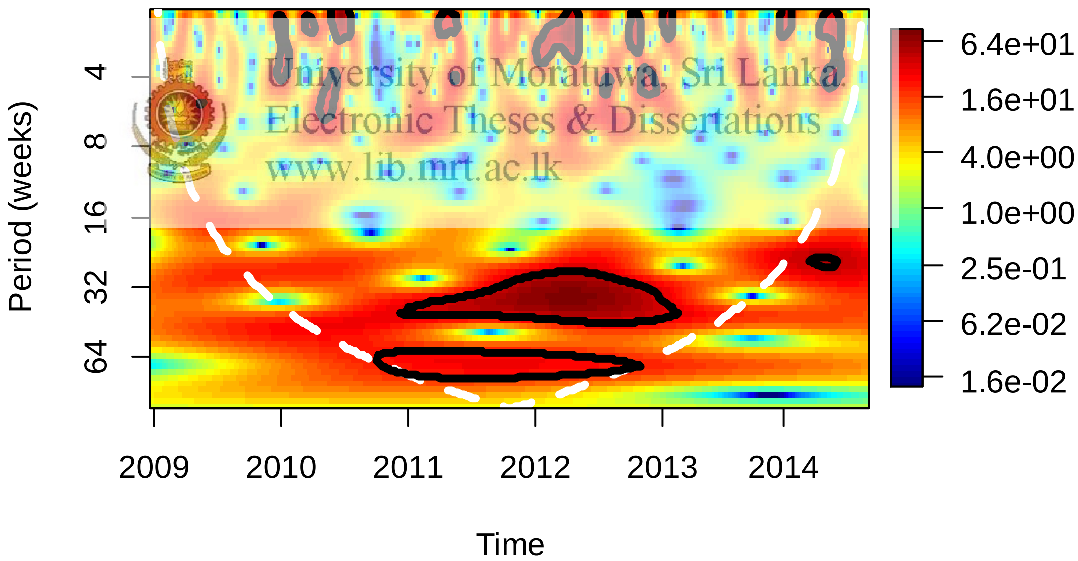


Figure A6: wavelet power spectrum of dengue incidence in Kalutara district from 2009 to September, 2014

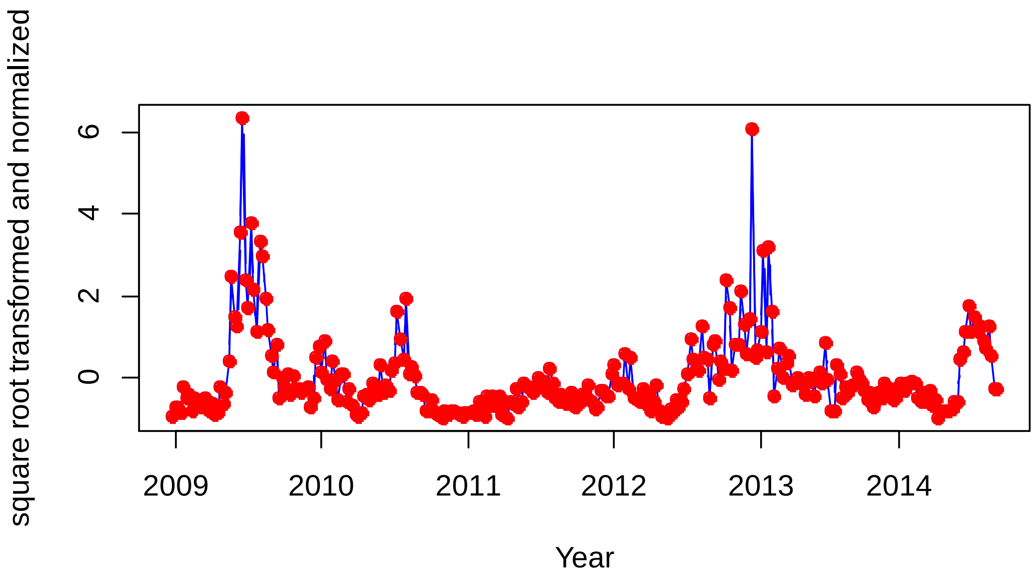


Figure A7: Time series plot of square root transformed and normalized aggregated dengue incidence in Kurunagala District, 2009 – September, 2014.

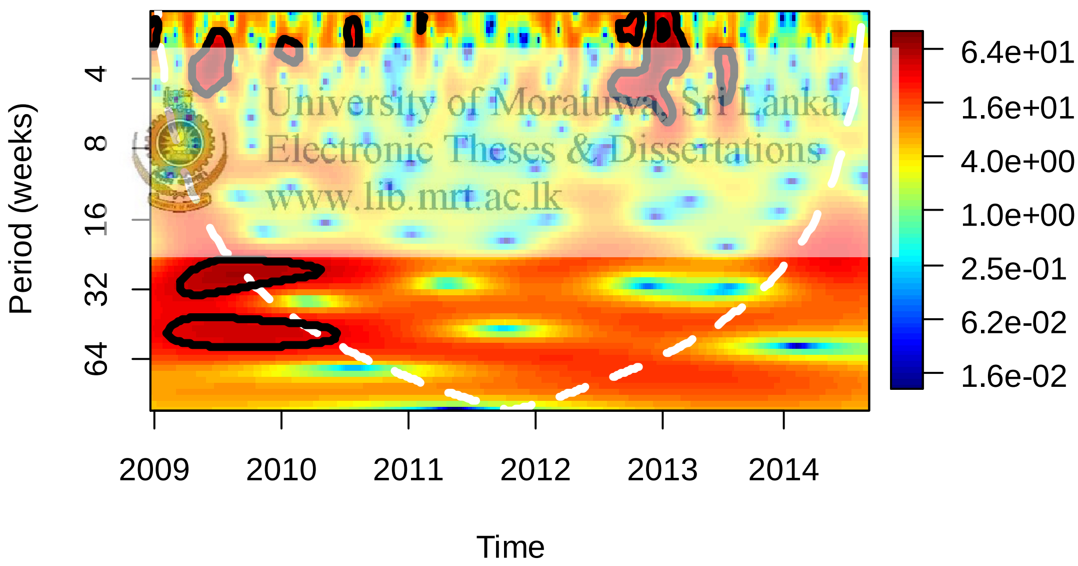


Figure A8: wavelet power spectrum of dengue incidence in Kurunalaga district from 2009 to September, 2014

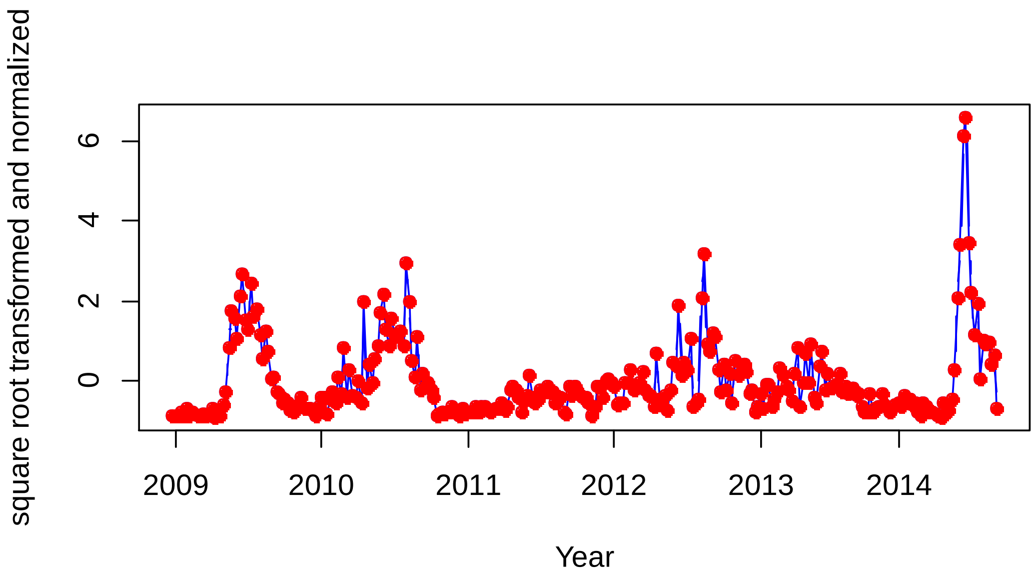


Figure A9: Time series plot of square root transformed and normalized aggregated dengue incidence in Rathnapura District, 2009 – September, 2014.

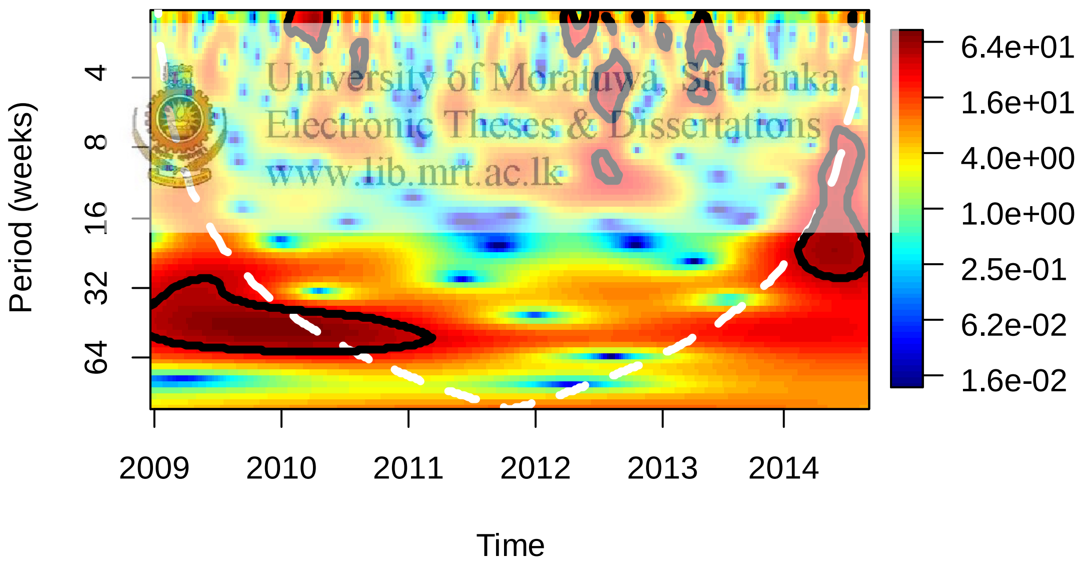


Figure A10: wavelet power spectrum of dengue incidence in Rathnapura district from 2009 to September, 2014

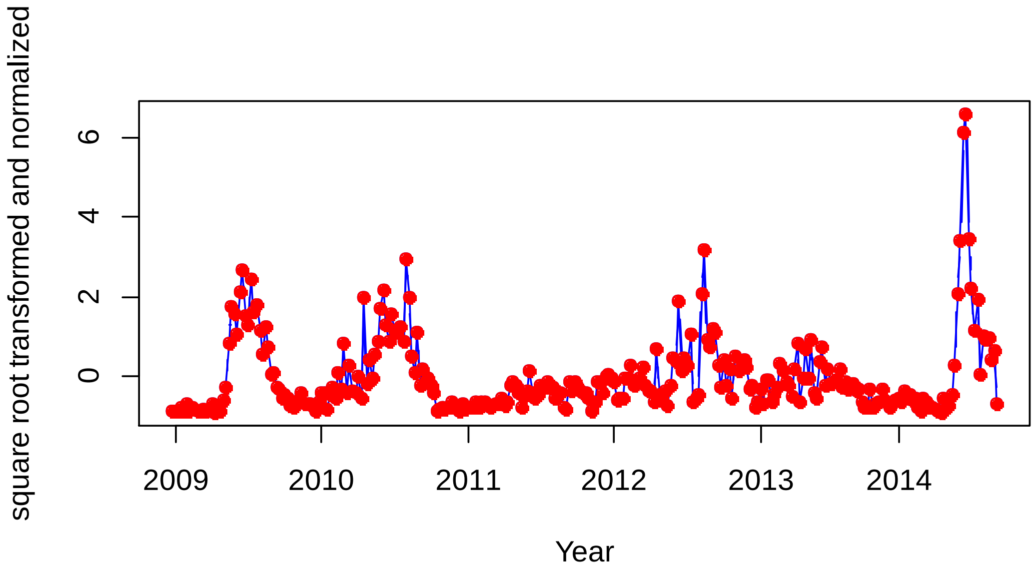


Figure A11: Time series plot of square root transformed and normalized aggregated dengue incidence in Kandy District, 2009 – September, 2014.

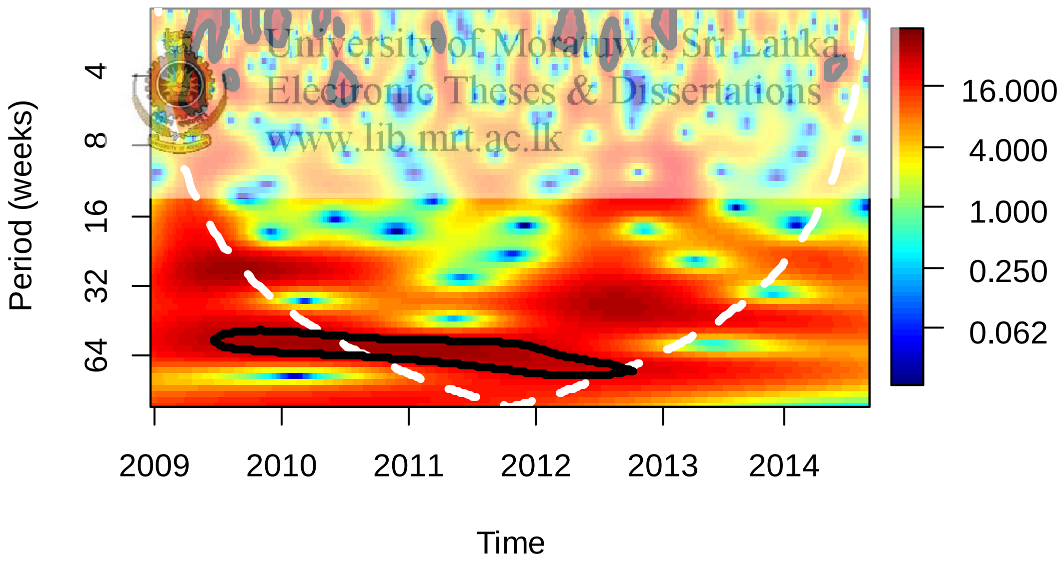


Figure A12: wavelet power spectrum of dengue incidence in Kandy district from 2009 to September, 2014

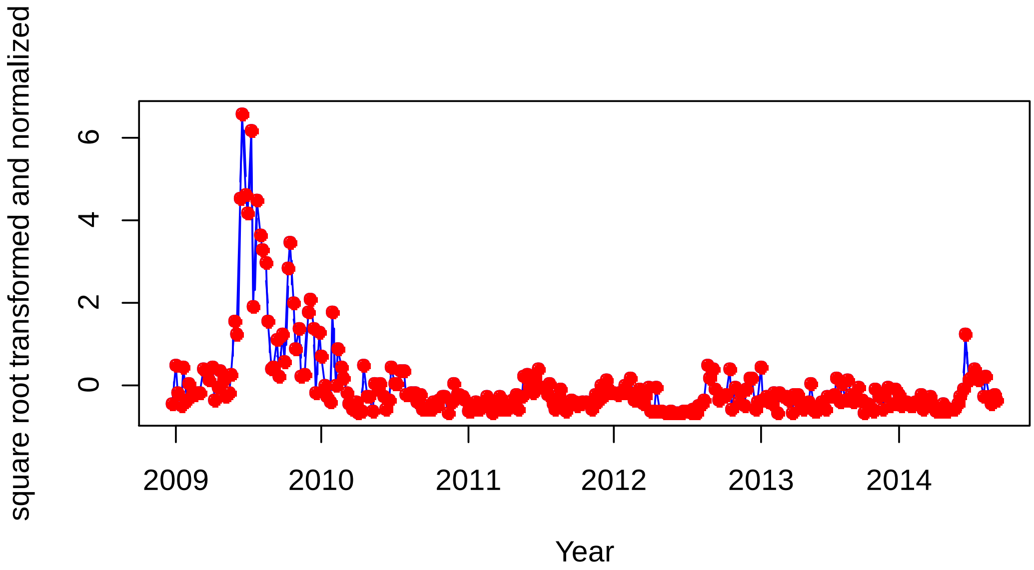


Figure A13: Time series plot of square root transformed and normalized aggregated dengue incidence in Matale District, 2009 – September, 2014.

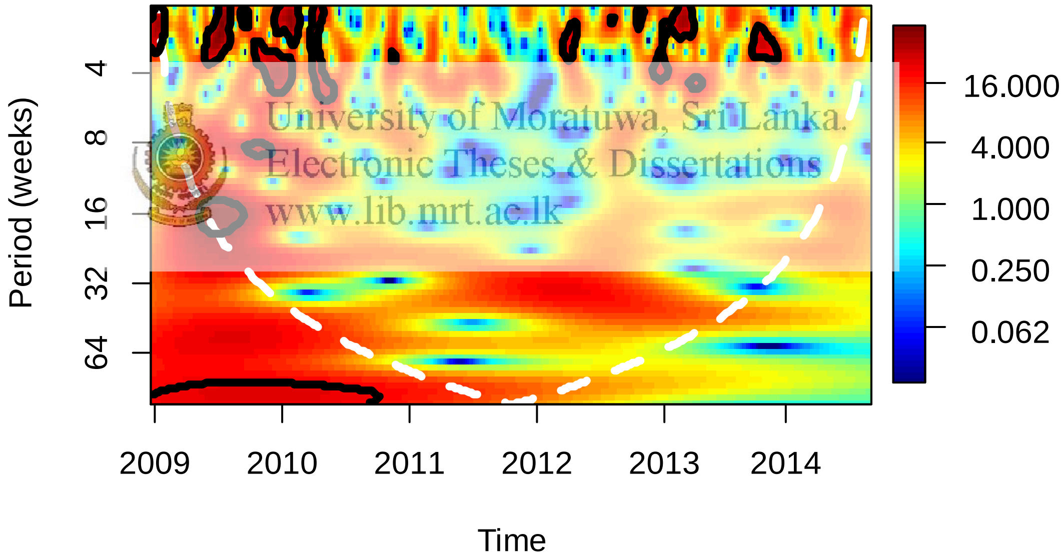


Figure A14: wavelet power spectrum of dengue incidence in Matale district from 2009 to September, 2014

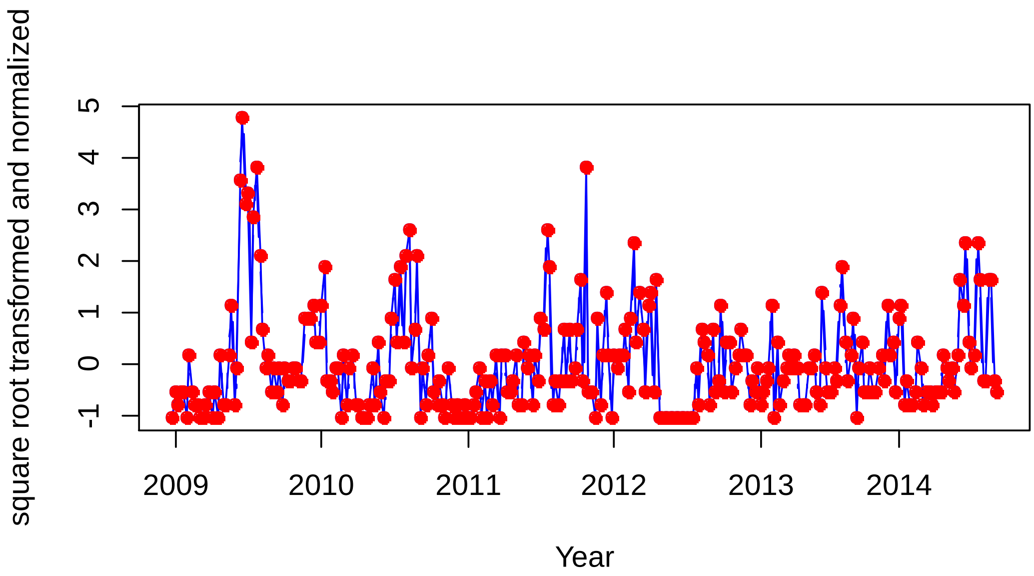


Figure A15: Time series plot of square root transformed and normalized aggregated dengue incidence in Nuwara Eliya District, 2009 – September, 2014.

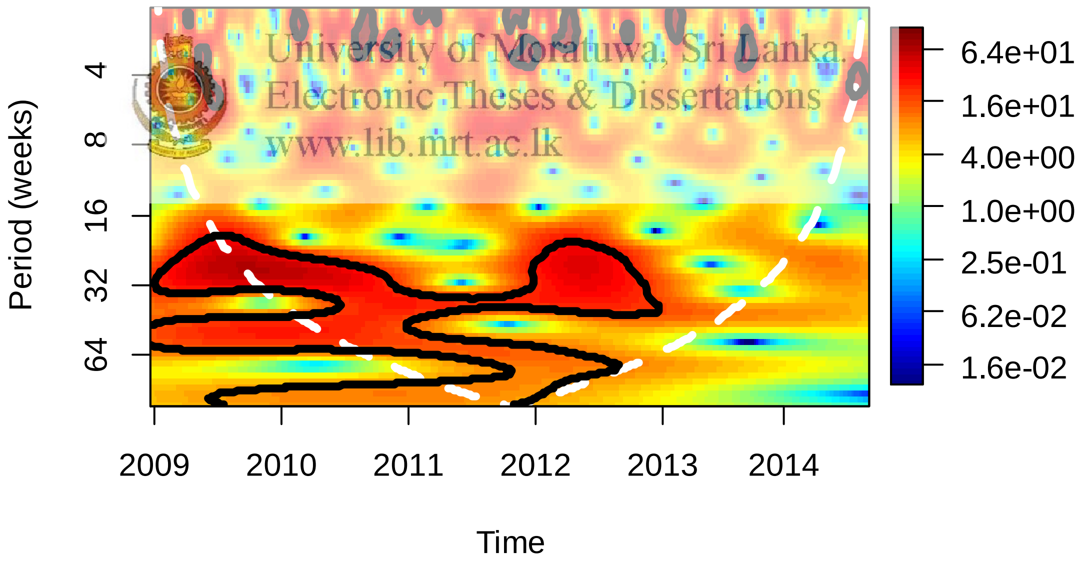


Figure A16: wavelet power spectrum of dengue incidence in Nuwara Eliya district from 2009 to September, 2014

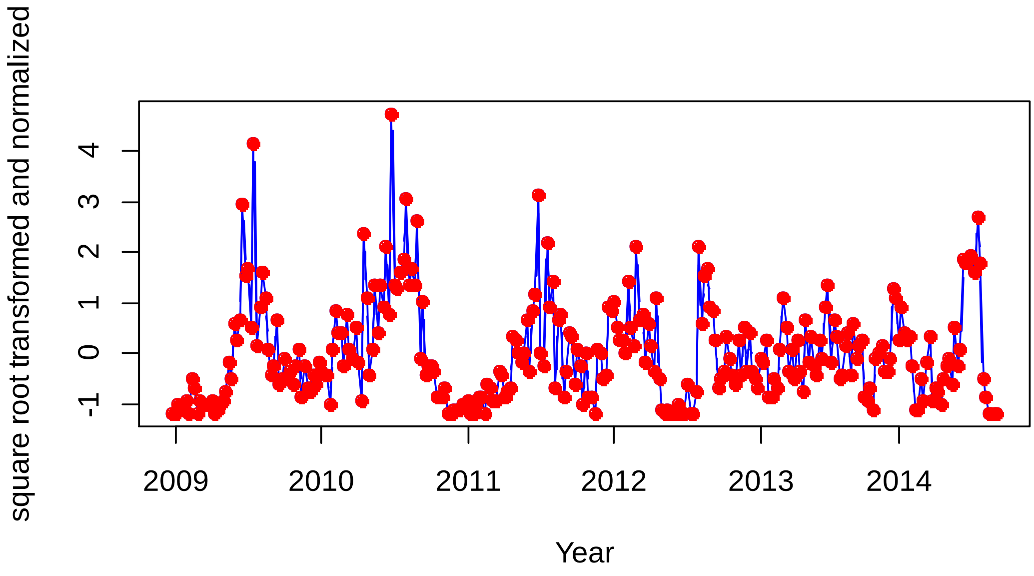


Figure A17: Time series plot of square root transformed and normalized aggregated dengue incidence in Galle District, 2009 – September, 2014.

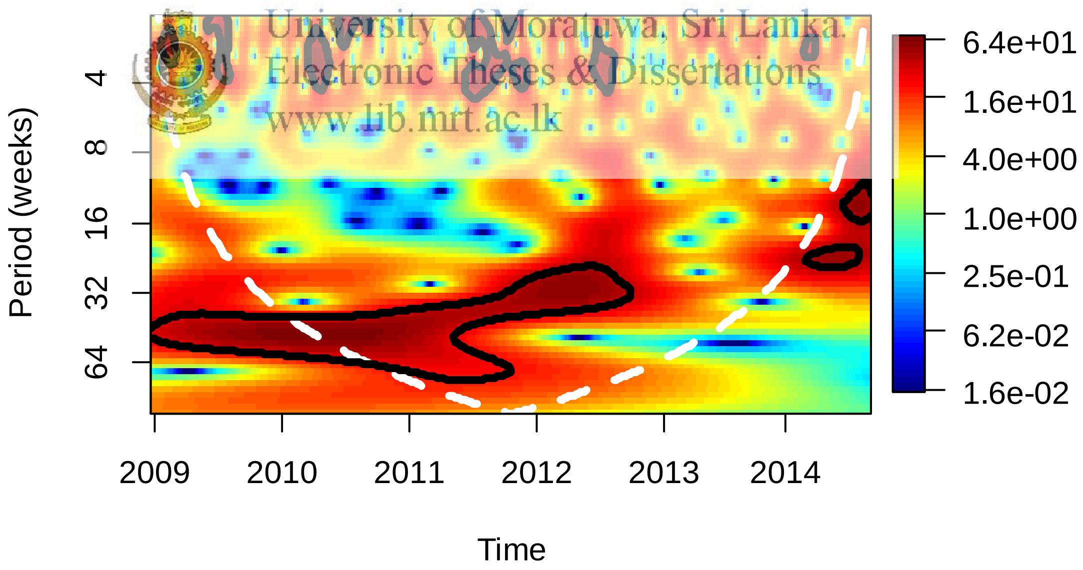


Figure A18: wavelet power spectrum of dengue incidence in Galle district from 2009 to September, 2014

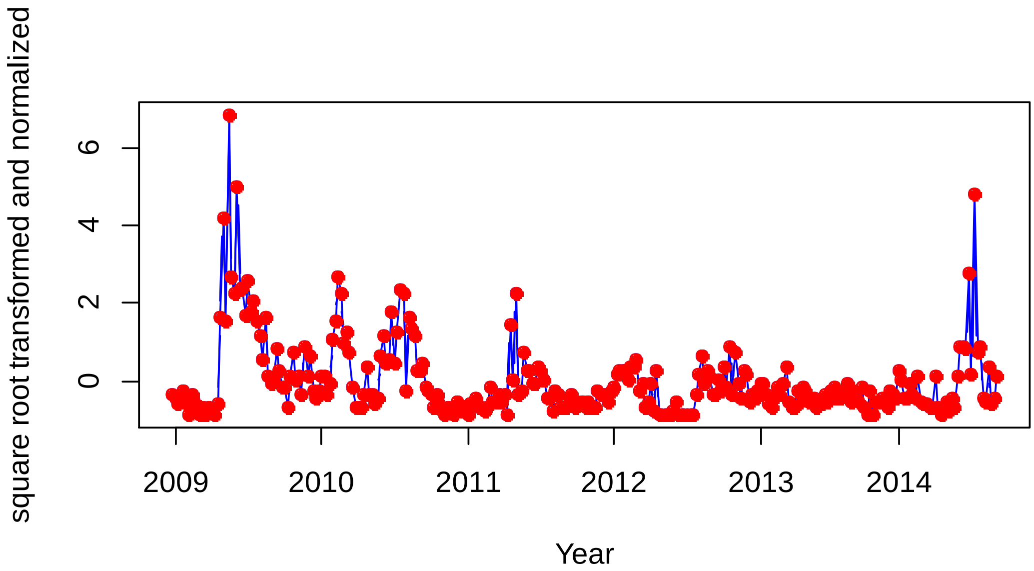


Figure A19: Time series plot of square root transformed and normalized aggregated dengue incidence in Hambantota District, 2009 – September, 2014.

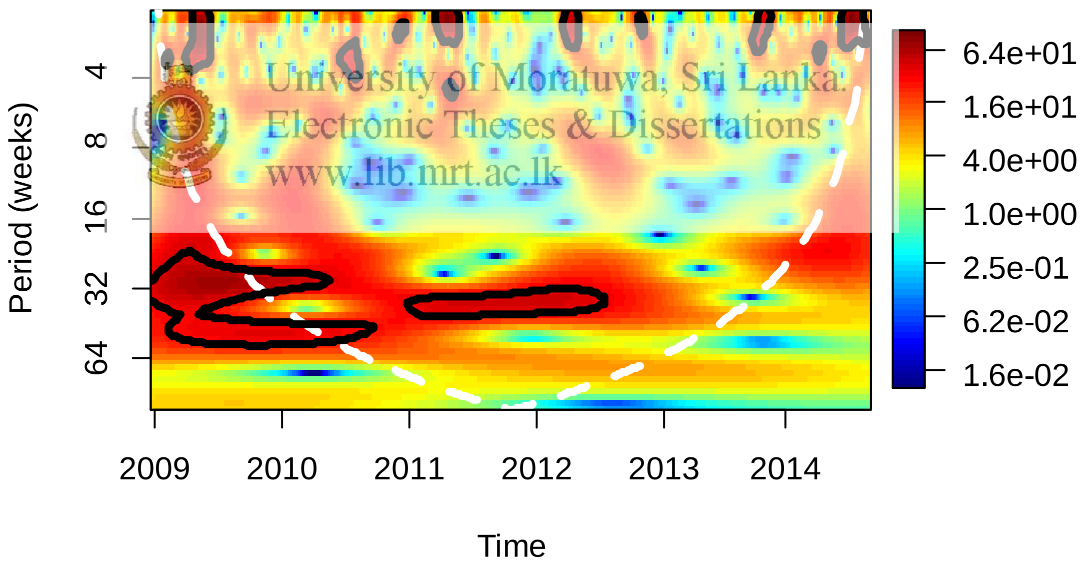


Figure A20: wavelet power spectrum of dengue incidence in Hambantota district from 2009 to September, 2014

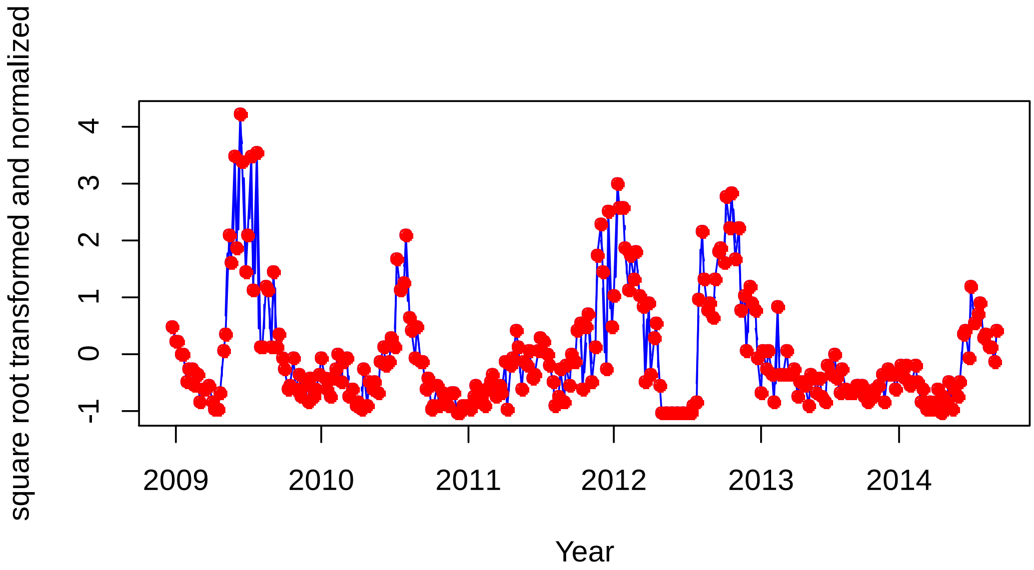


Figure A21: Time series plot of square root transformed and normalized aggregated dengue incidence in Matara District, 2009 – September, 2014.

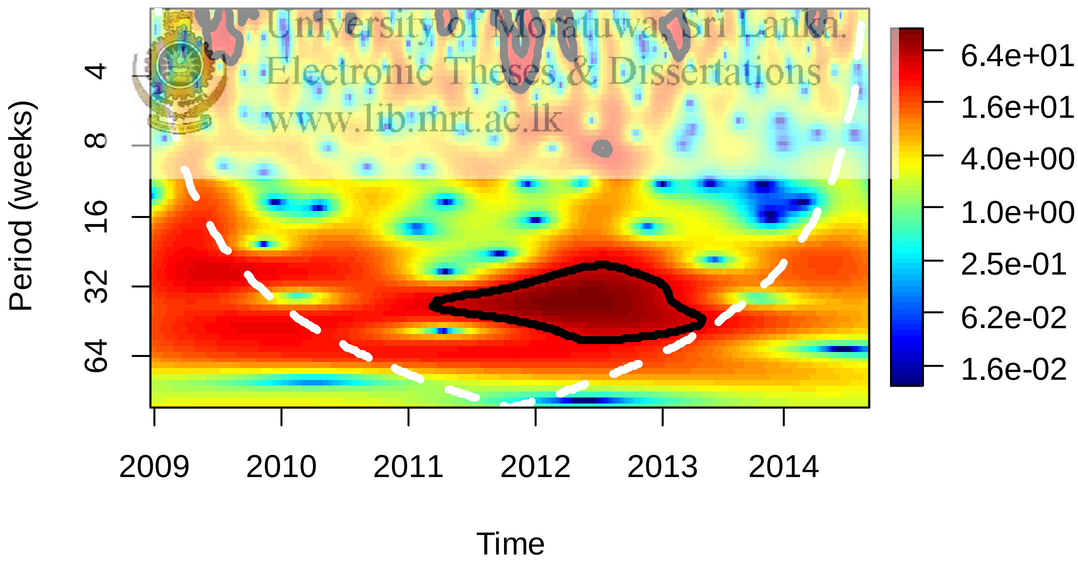


Figure A22: wavelet power spectrum of dengue incidence in Matara district from 2009 to September, 2014

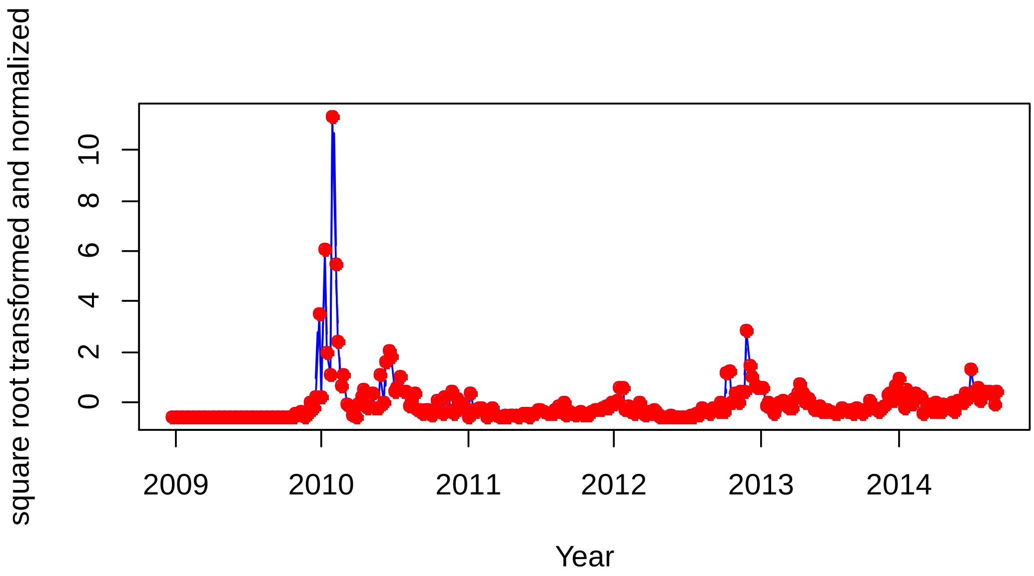


Figure A23: Time series plot of square root transformed and normalized aggregated dengue incidence in Jaffna District, 2009 – September, 2014.

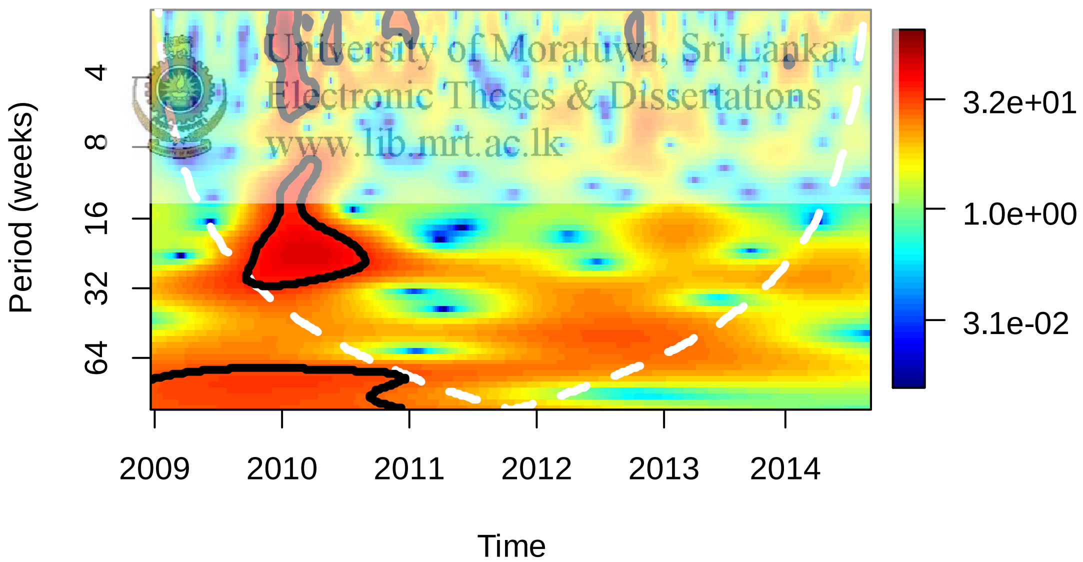


Figure A24: wavelet power spectrum of dengue incidence in Jaffna district from 2009 to September, 2014

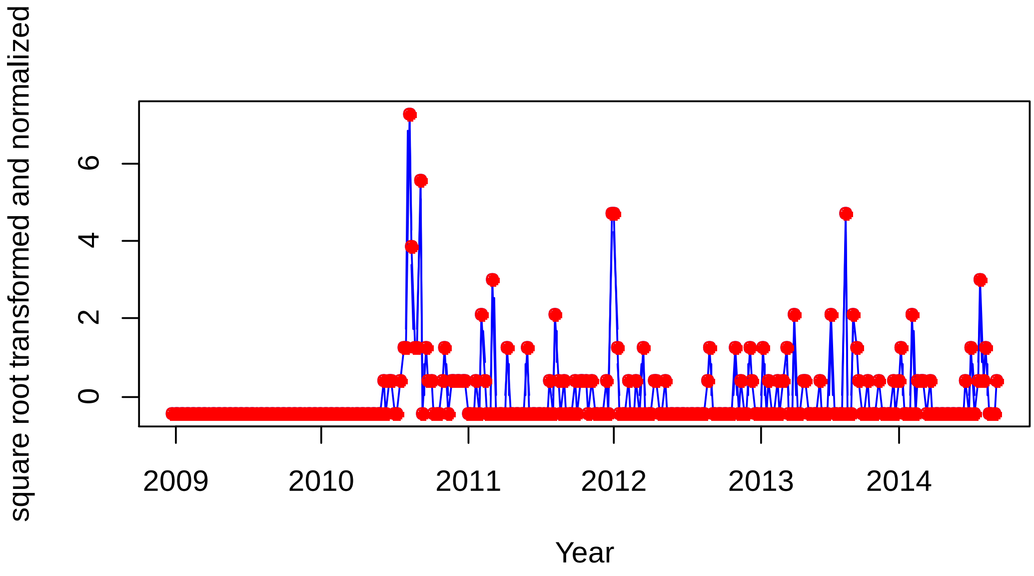


Figure A25: Time series plot of square root transformed and normalized aggregated dengue incidence in Killinochchie District, 2009 – September, 2014.

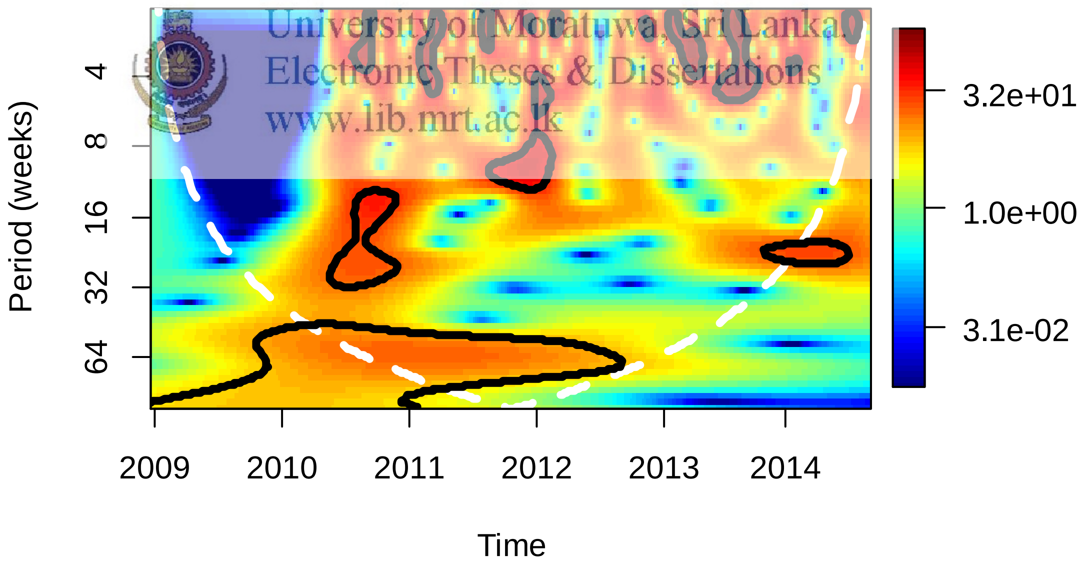


Figure A26: wavelet power spectrum of dengue incidence in Killinochchie district from 2009 to September, 2014

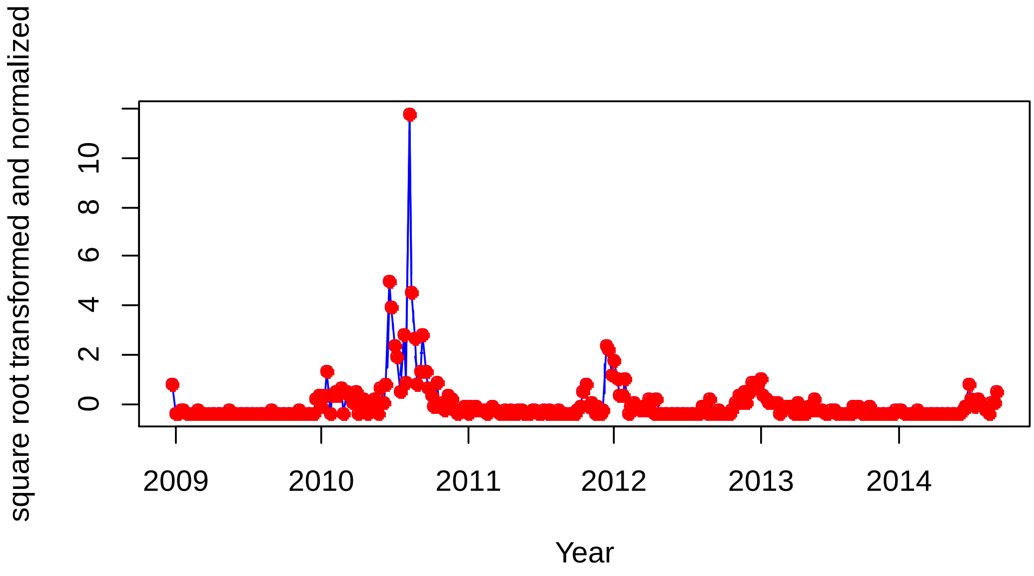


Figure A27: Time series plot of square root transformed and normalized aggregated dengue incidence in Mannar District, 2009 – September, 2014.

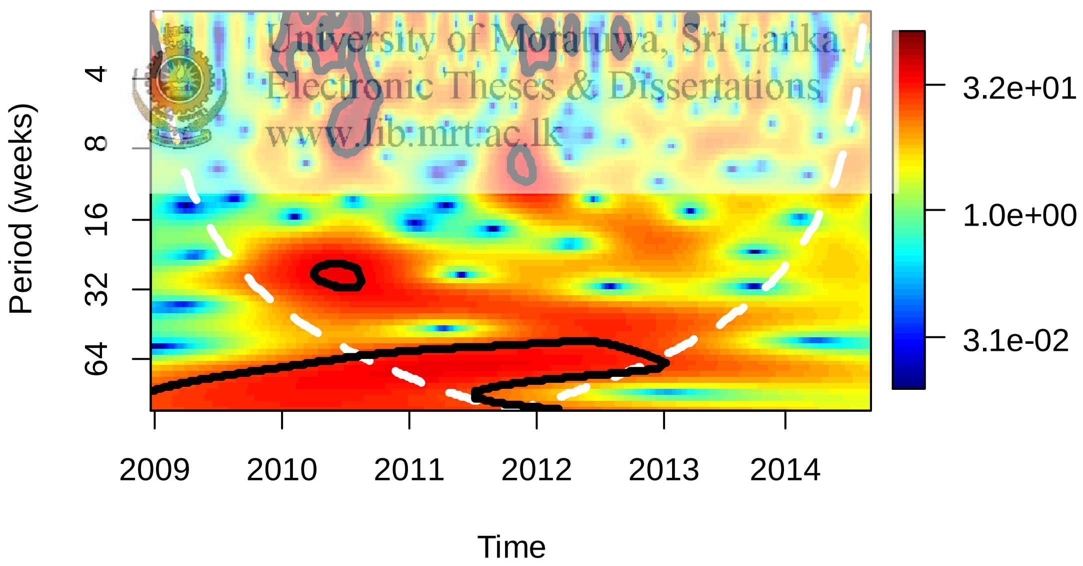


Figure A28: wavelet power spectrum of dengue incidence in Mannar district from 2009 to September, 2014

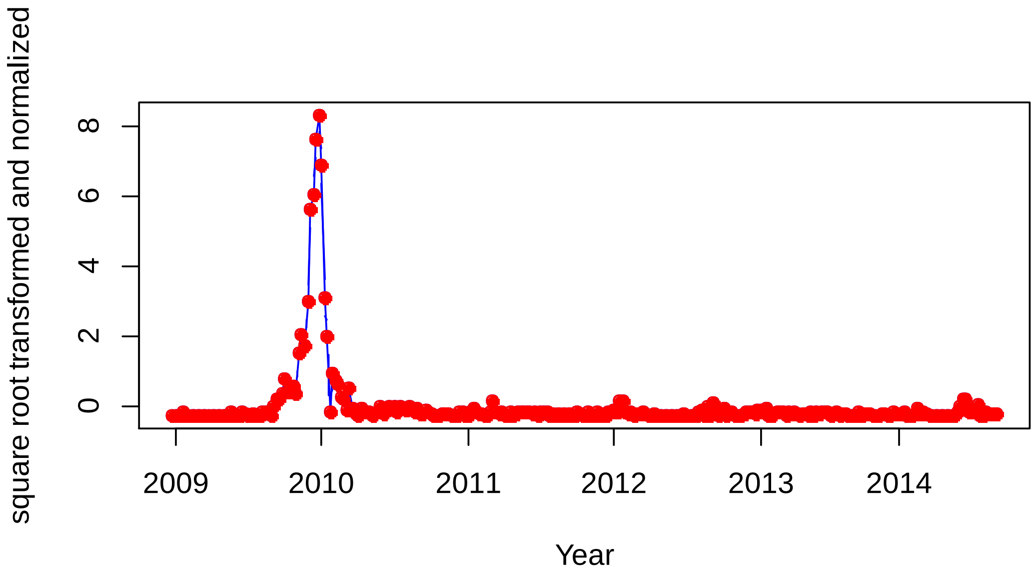


Figure A29: Time series plot of square root transformed and normalized aggregated dengue incidence in Vavuniya District, 2009 – September, 2014.

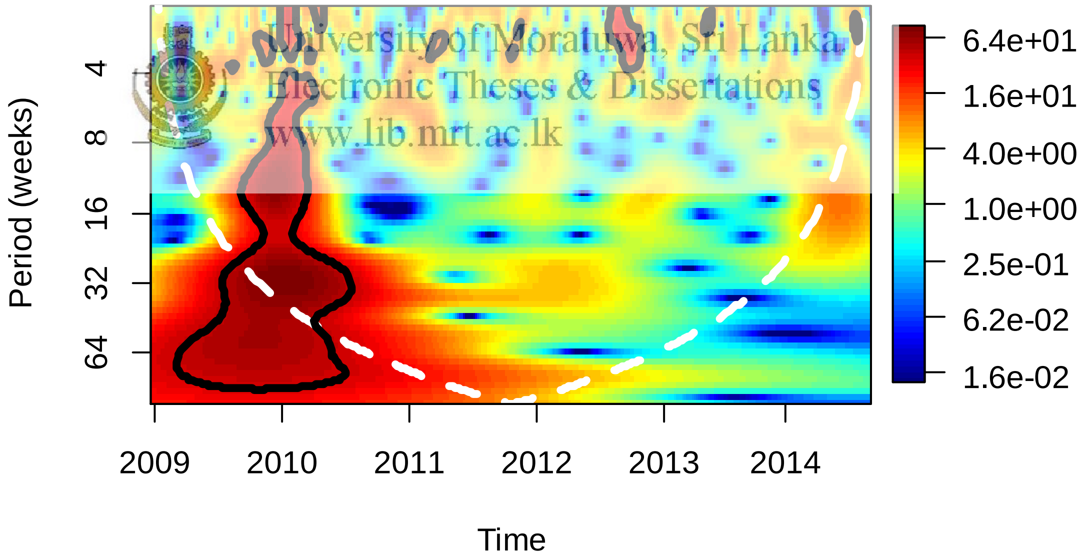


Figure A30: wavelet power spectrum of dengue incidence in Vavuniya district from 2009 to September, 2014

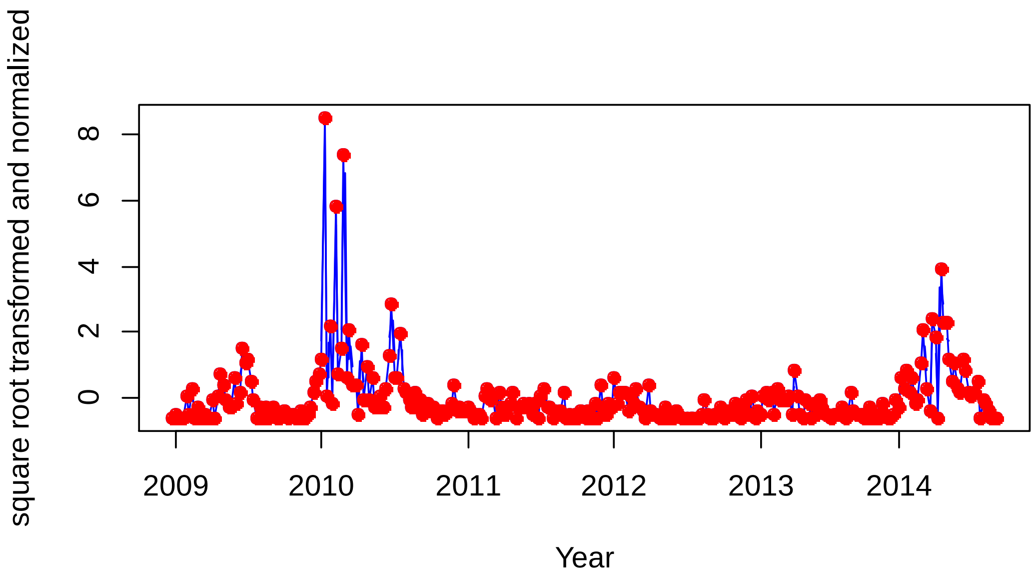


Figure A31: Time series plot of square root transformed and normalized aggregated dengue incidence in Trincomalee District, 2009 – September, 2014.

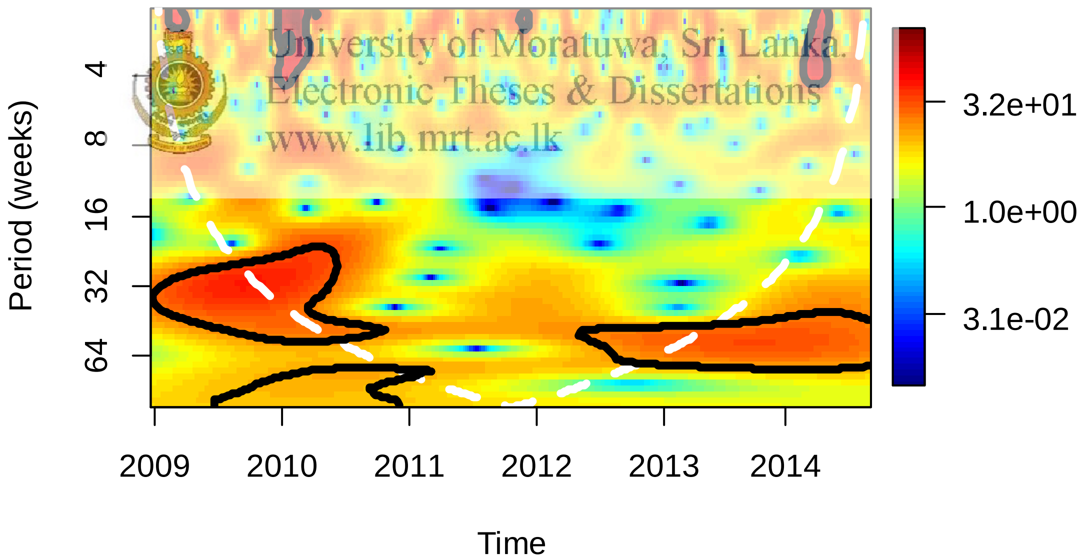


Figure A32: wavelet power spectrum of dengue incidence in Trincomalee district from 2009 to September, 2014

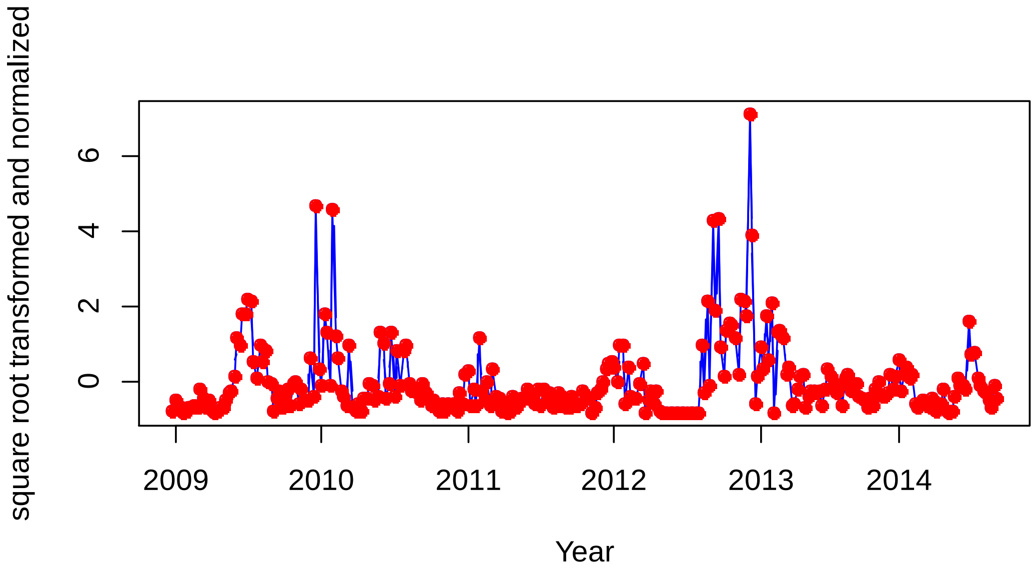


Figure A33: Time series plot of square root transformed and normalized aggregated dengue incidence in Puttalam District, 2009 – September, 2014.

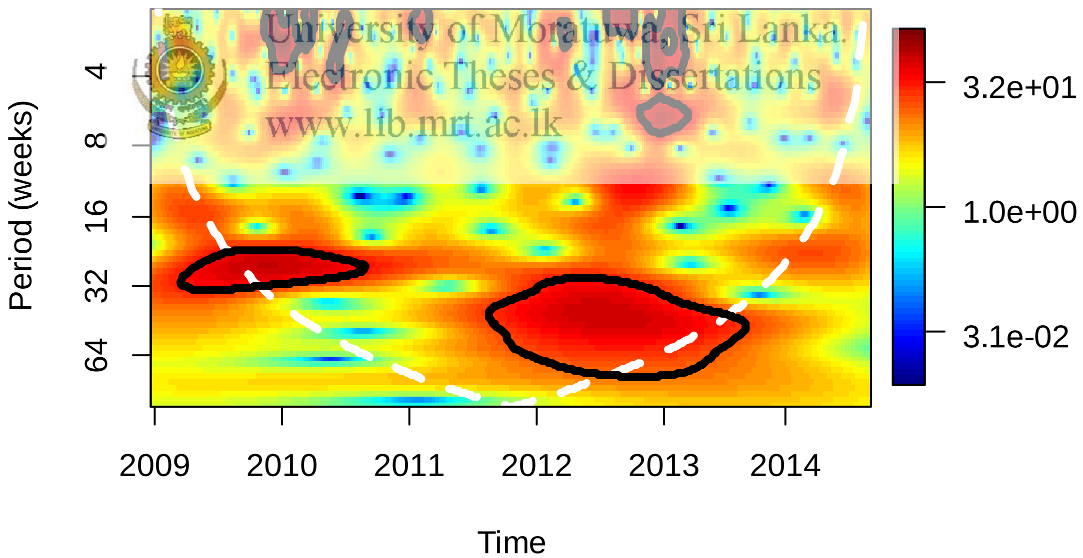


Figure A34: wavelet power spectrum of dengue incidence in Puttalam district from 2009 to September, 2014

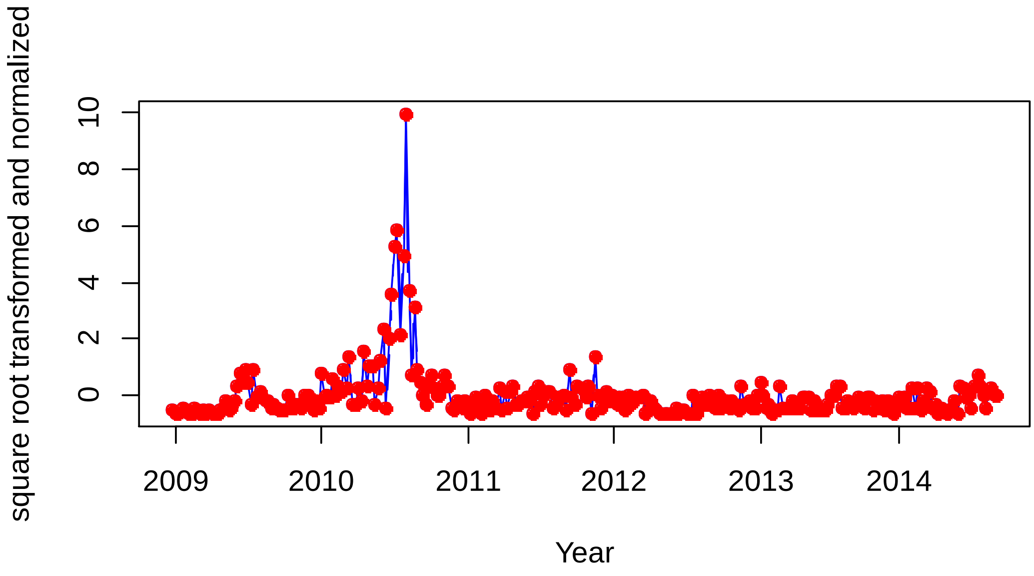


Figure A35: Time series plot of square root transformed and normalized aggregated dengue incidence in Monaragala District, 2009 – September, 2014.

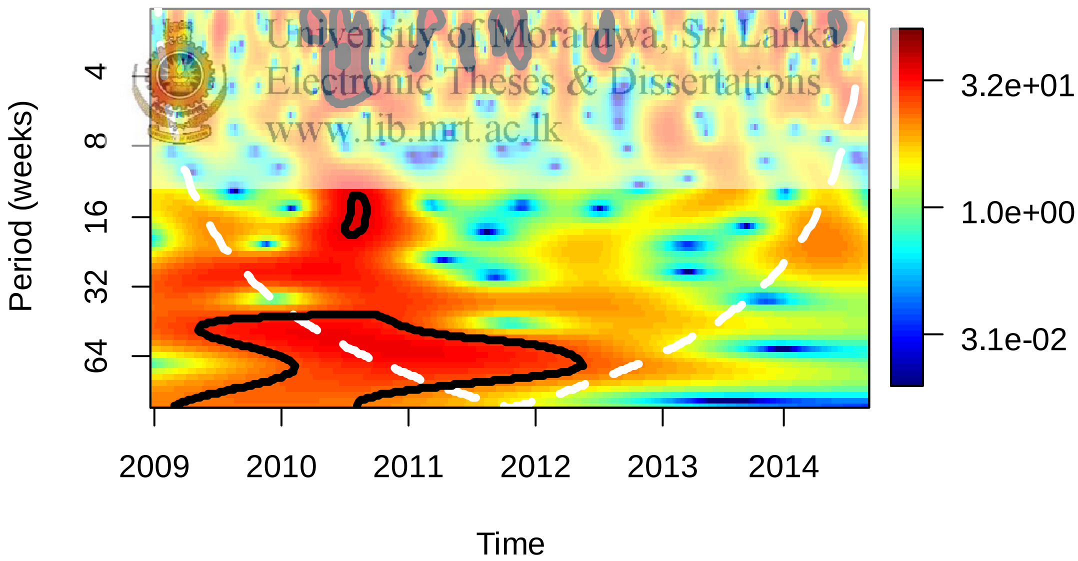


Figure A36: wavelet power spectrum of dengue incidence in Monaragala district from 2009 to September, 2014

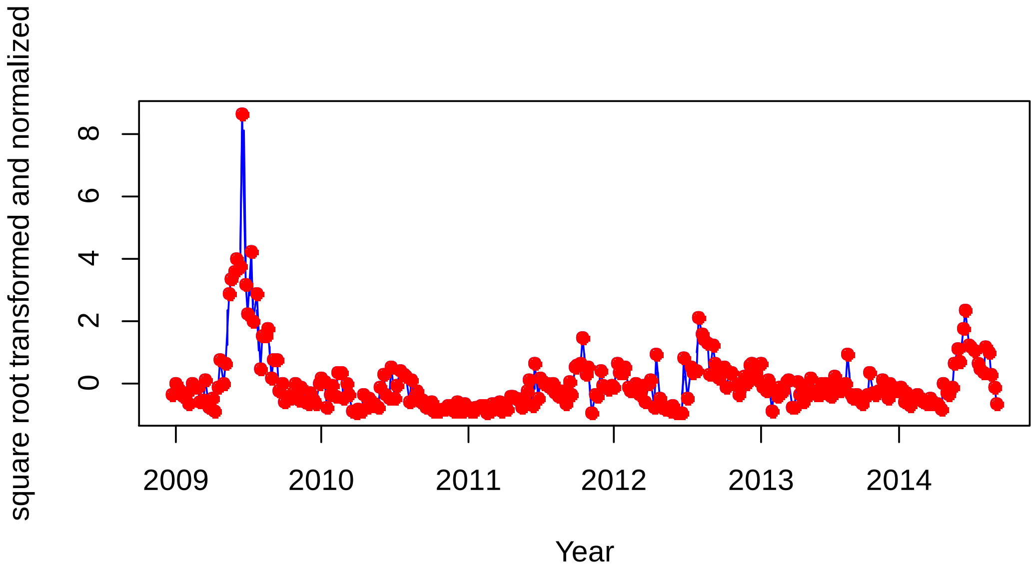


Figure A37: Time series plot of square root transformed and normalized aggregated dengue incidence in Kegalle District, 2009 – September, 2014.

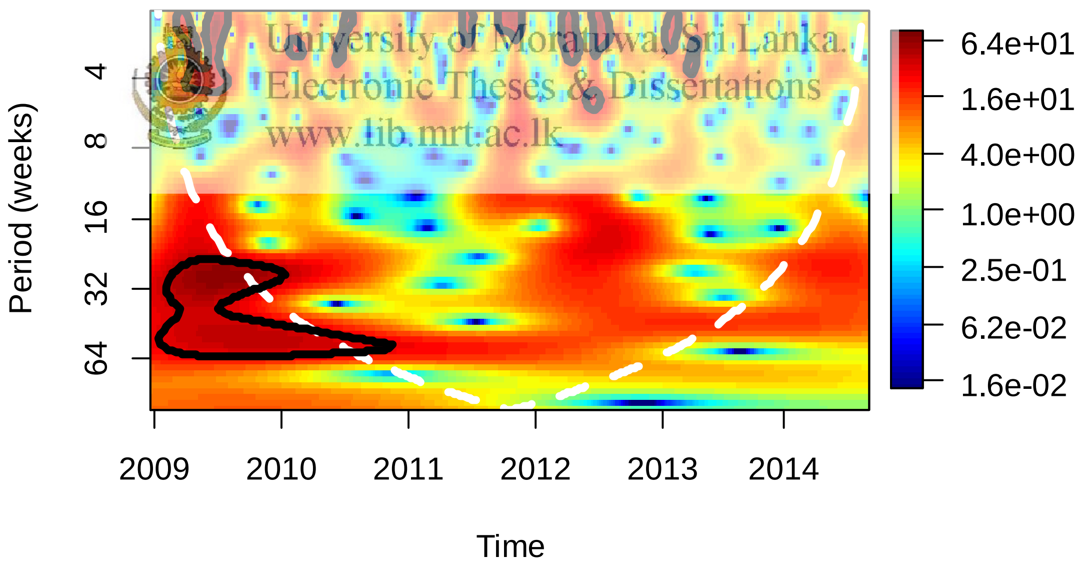


Figure A38: wavelet power spectrum of dengue incidence in Kegalle district from 2009 to September, 2014

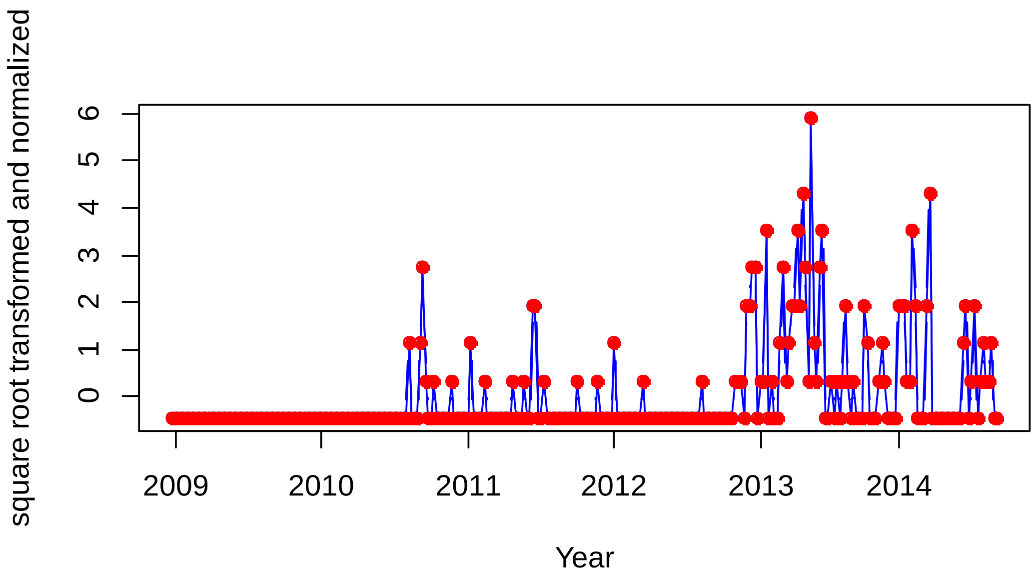


Figure A39: Time series plot of square root transformed and normalized aggregated dengue incidence in Mulative District, 2009 – September, 2014.

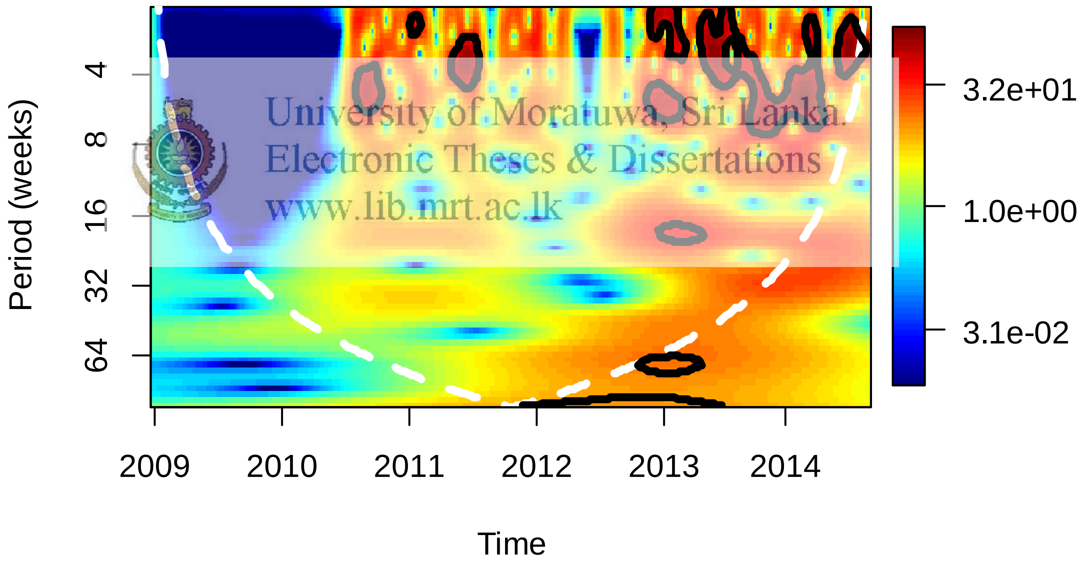


Figure A40: wavelet power spectrum of dengue incidence in Mulative district from 2009 to September, 2014

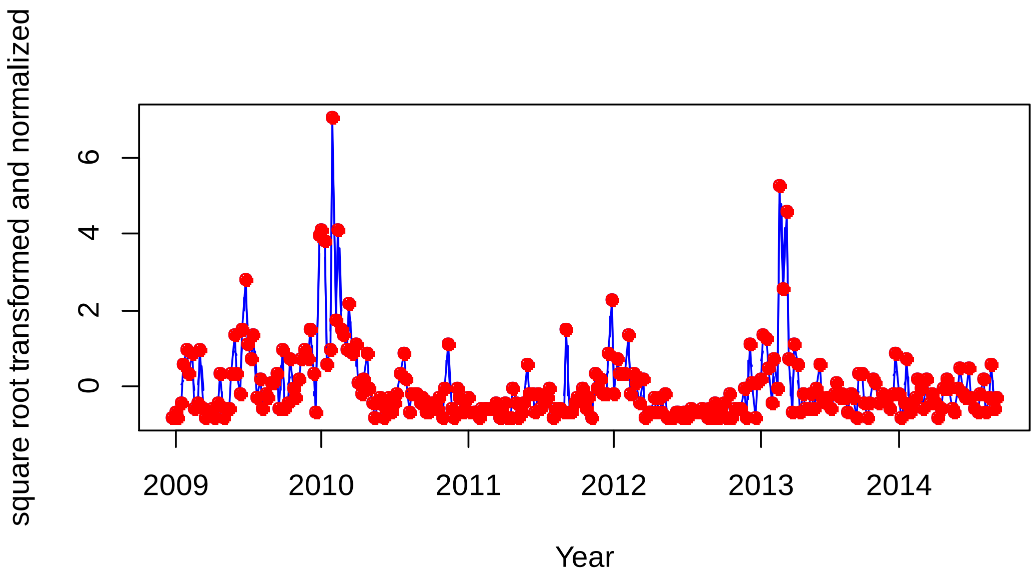


Figure A41: Time series plot of square root transformed and normalized aggregated dengue incidence in Ampara District, 2009 – September, 2014.

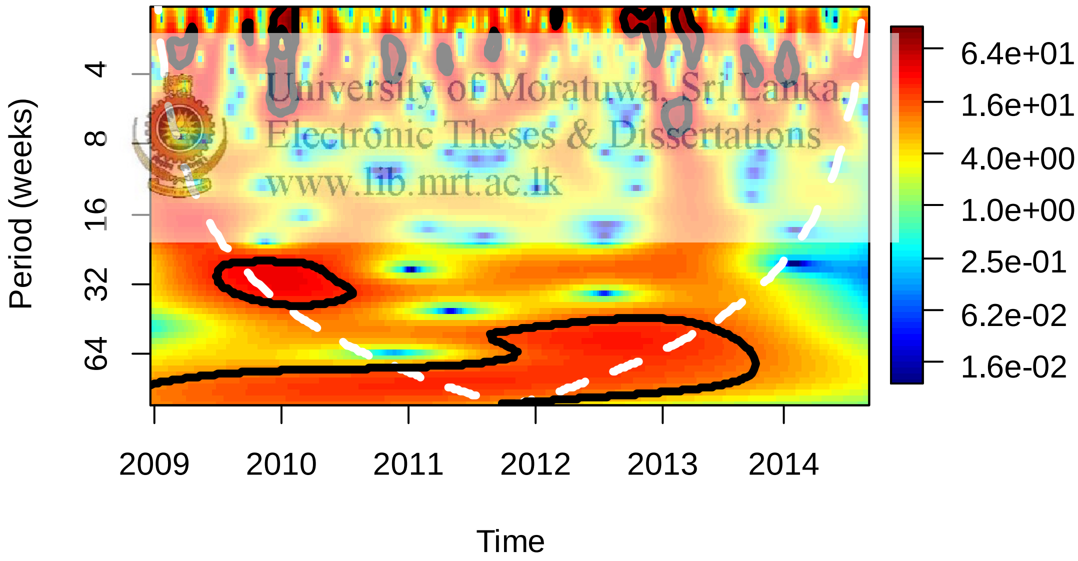


Figure A42: wavelet power spectrum of dengue incidence in Ampara district from 2009 to September, 2014

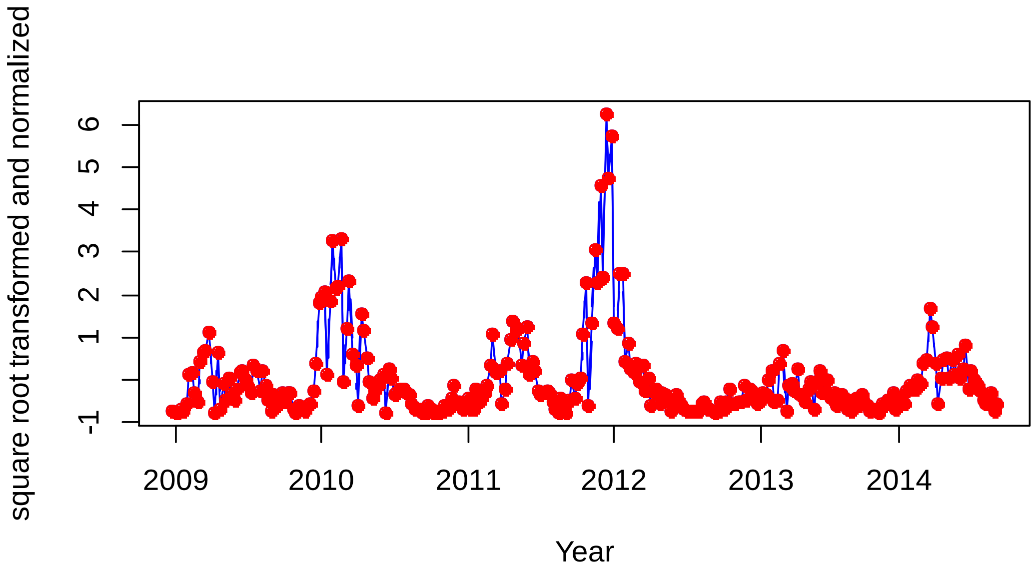


Figure A43: Time series plot of square root transformed and normalized aggregated dengue incidence in Batticalo District, 2009 – September, 2014.

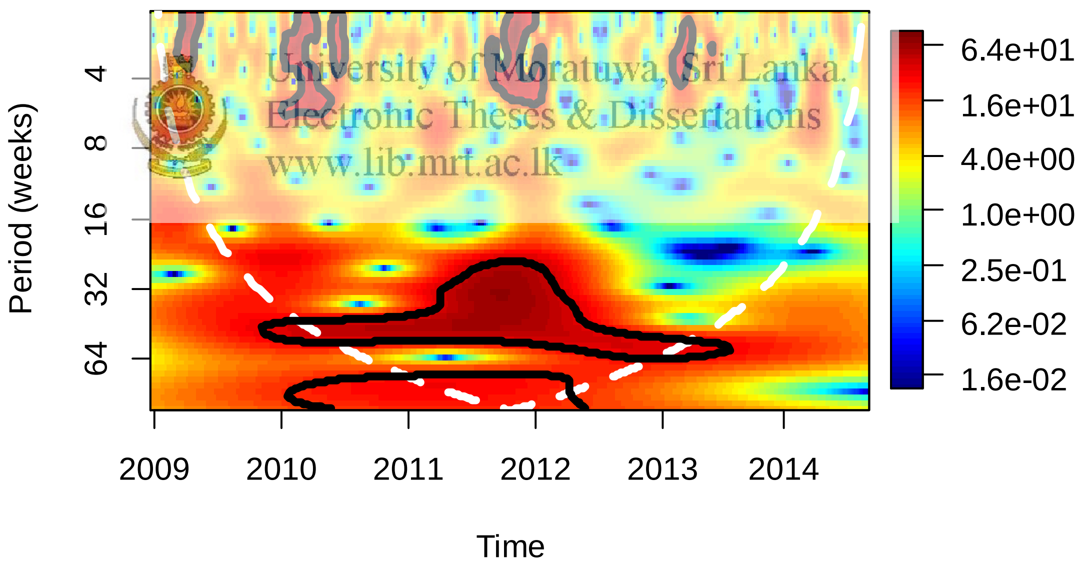


Figure A44: wavelet power spectrum of dengue incidence in Batticalo district from 2009 to September, 2014

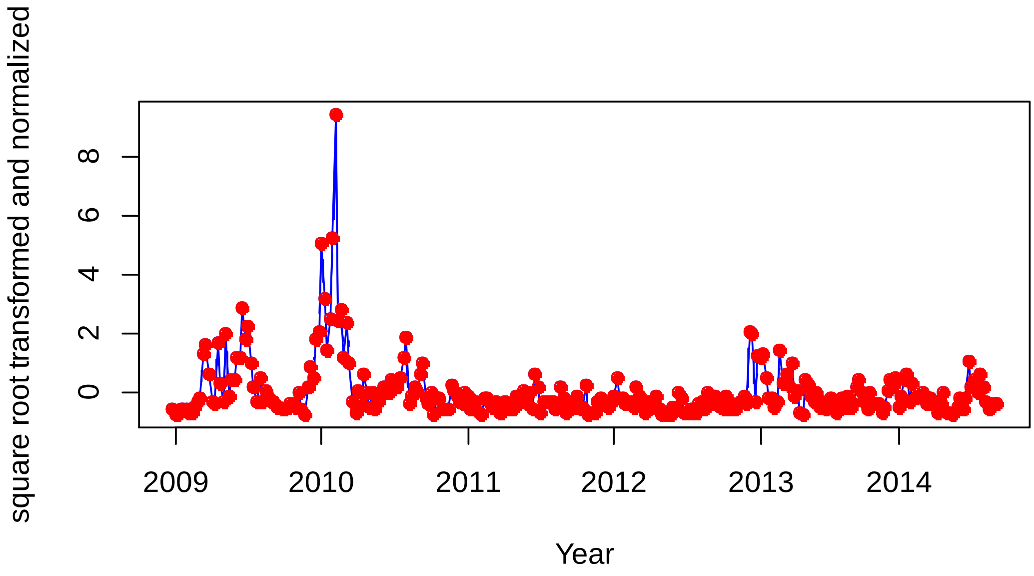


Figure A45: Time series plot of square root transformed and normalized aggregated dengue incidence in Anuradapura District, 2009 – September, 2014.

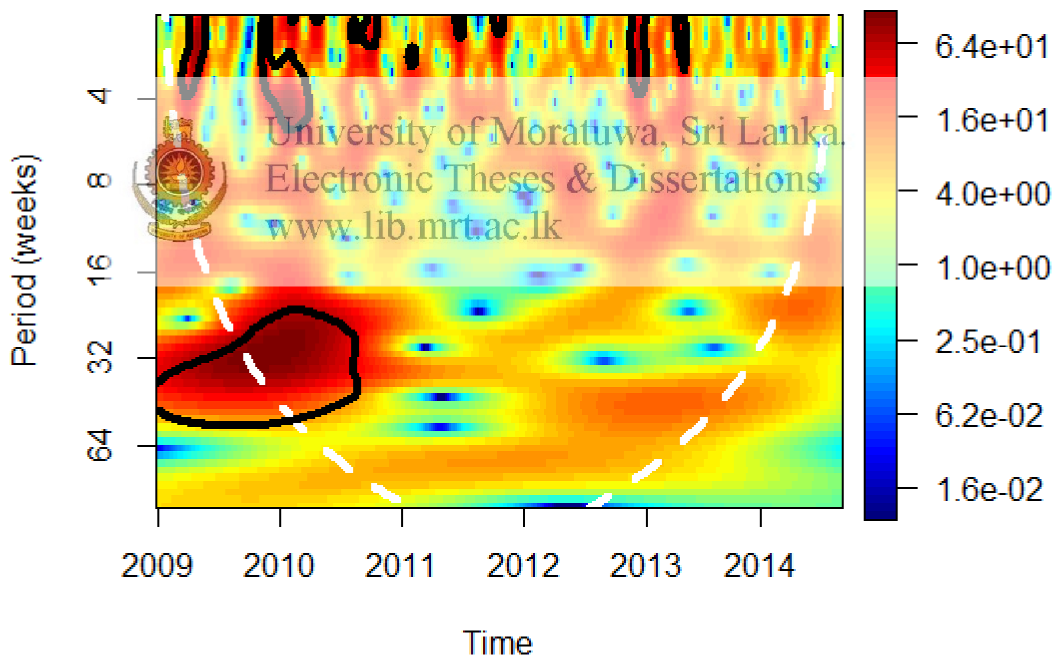


Figure A46: wavelet power spectrum of dengue incidence in Anuradapura district from 2009 to September, 2014

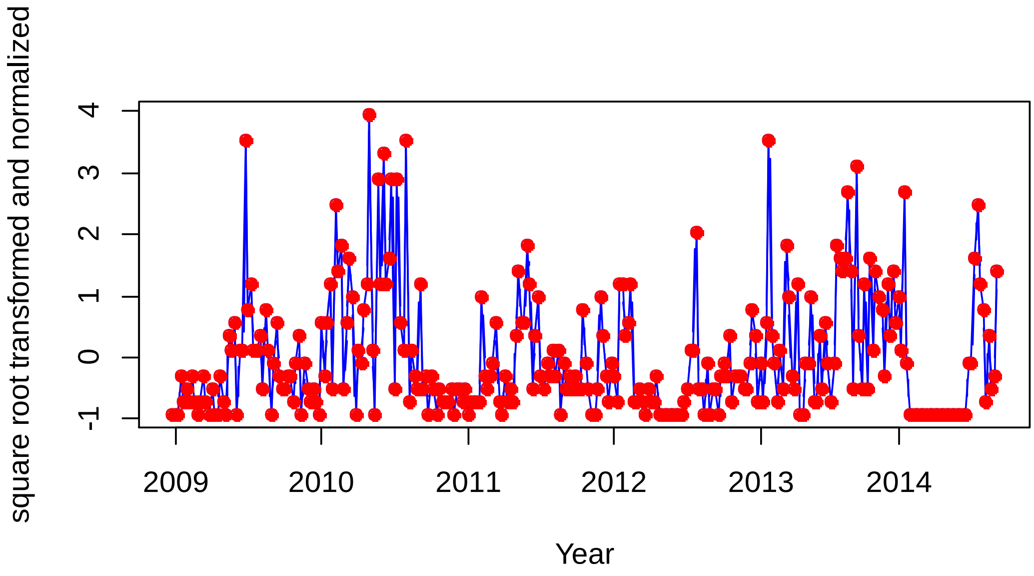


Figure A47: Time series plot of square root transformed and normalized aggregated dengue incidence in Polonnaruwa District, 2009 – September, 2014.

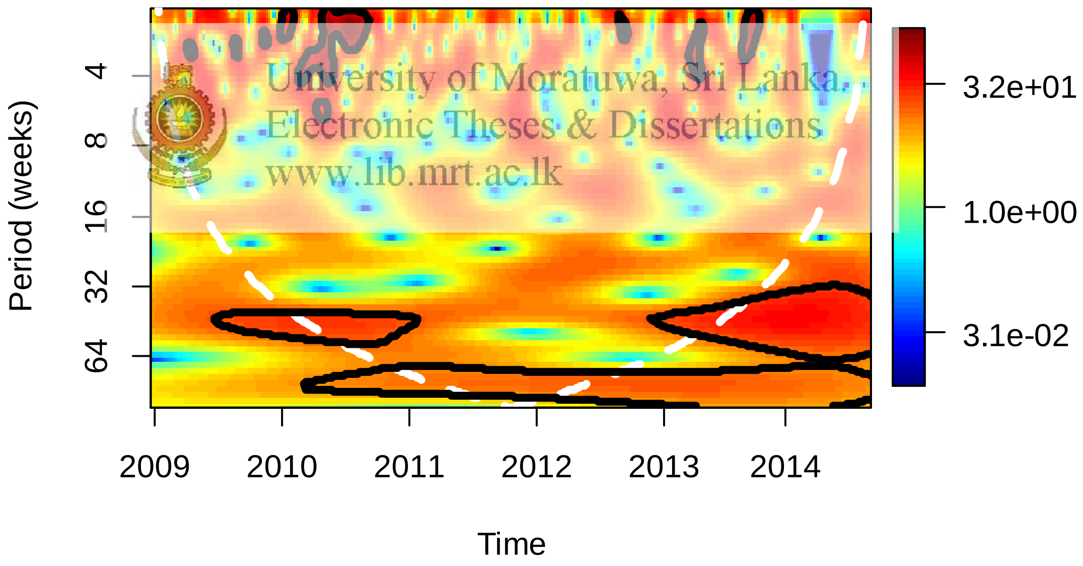


Figure A48: wavelet power spectrum of dengue incidence in Plonnaruwa district from 2009 to September, 2014

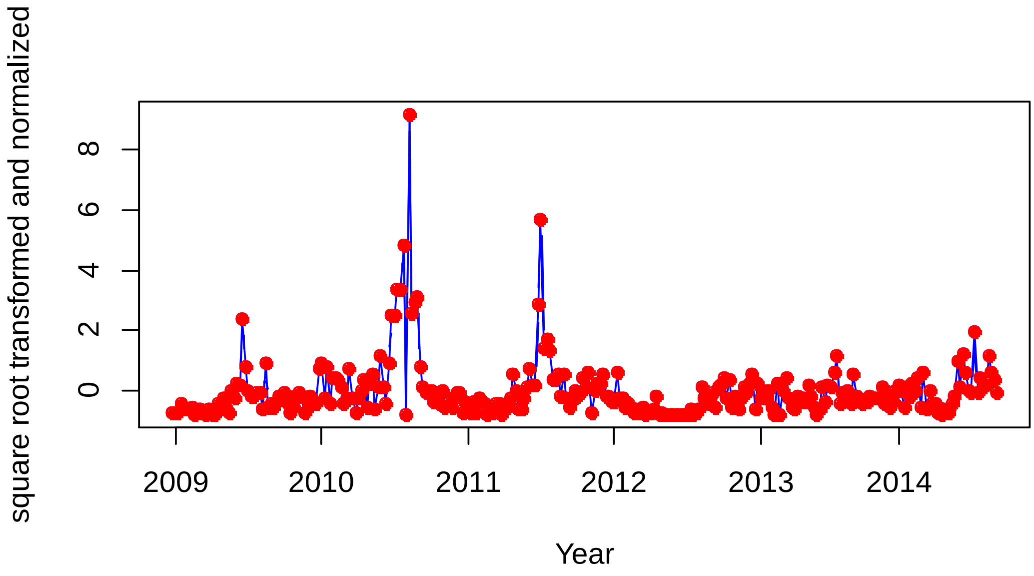


Figure A49: Time series plot of square root transformed and normalized aggregated dengue incidence in Badulla District, 2009 – September, 2014.

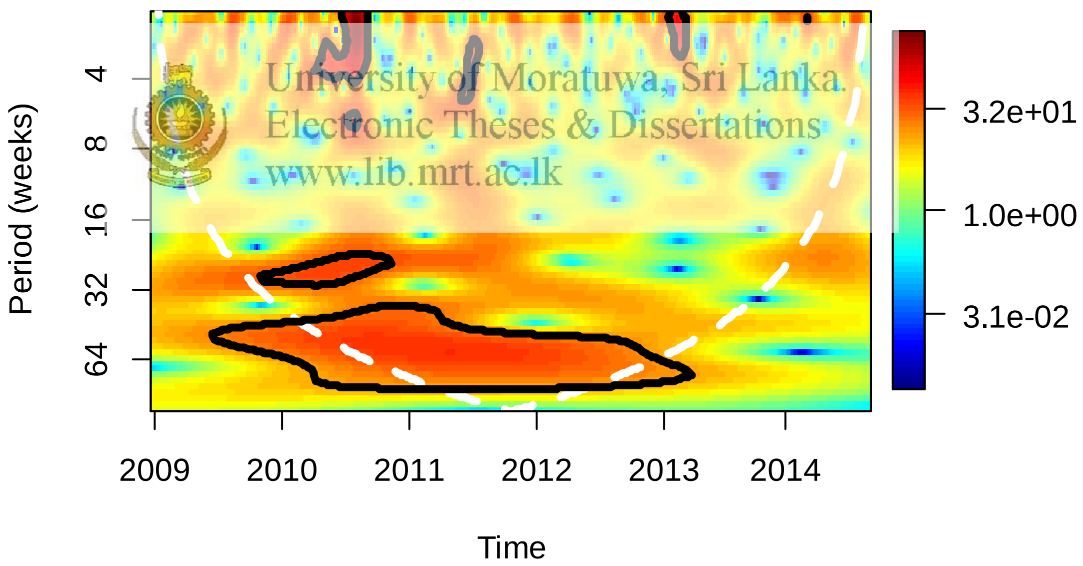


Figure A50: wavelet power spectrum of dengue incidence in Badulla district from 2009 to September, 2014

Appendix B: Wavelet analyses of Climatic Variables

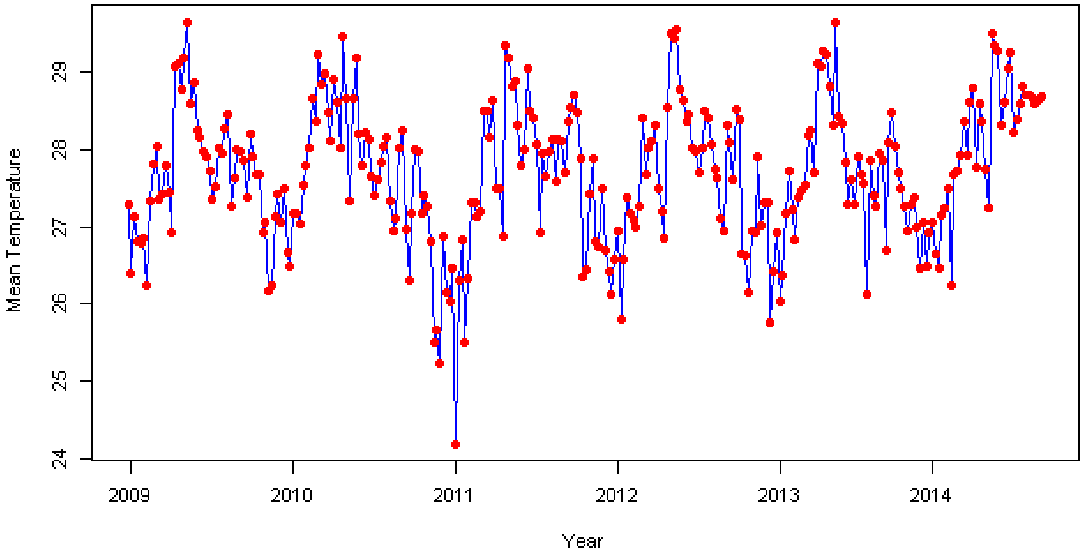


Figure B1: Time series plot of weekly mean temperature (^{0}C) from January 2009 – September 2014

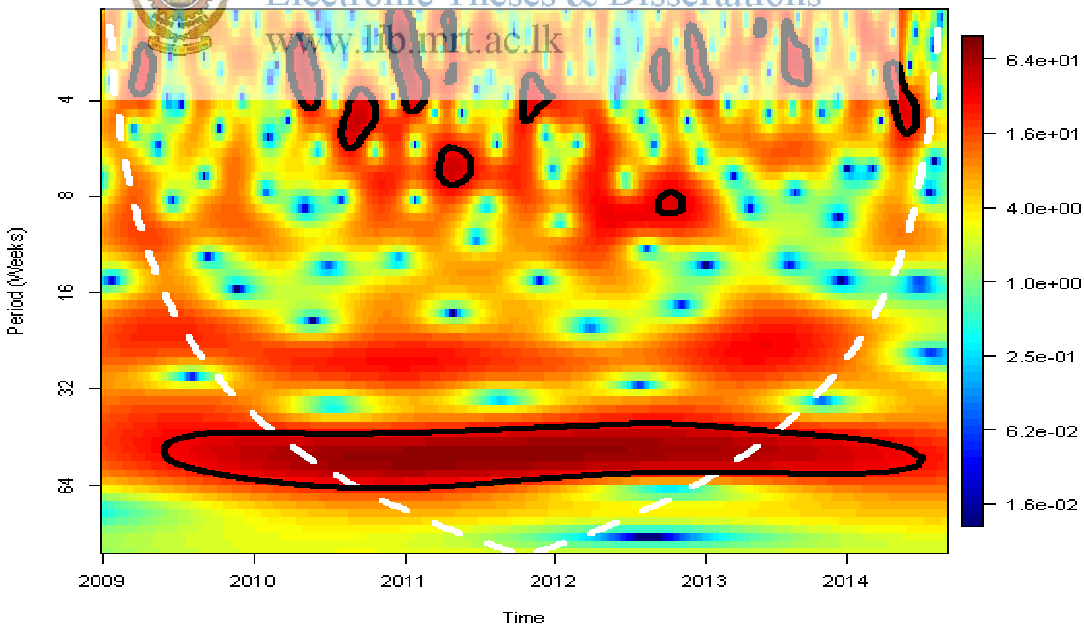


Figure B2: Wavelet power spectrum of mean temperature in Colombo district from 2009 to September, 2014

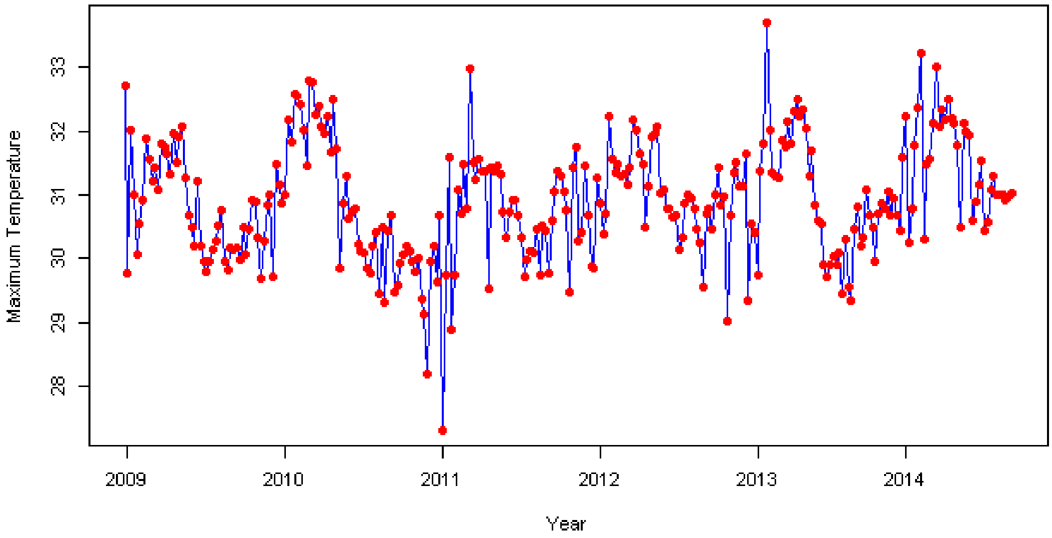


Figure B3: Time series plot of weekly maximum temperature (^{0}C) from January 2009 – September 2014

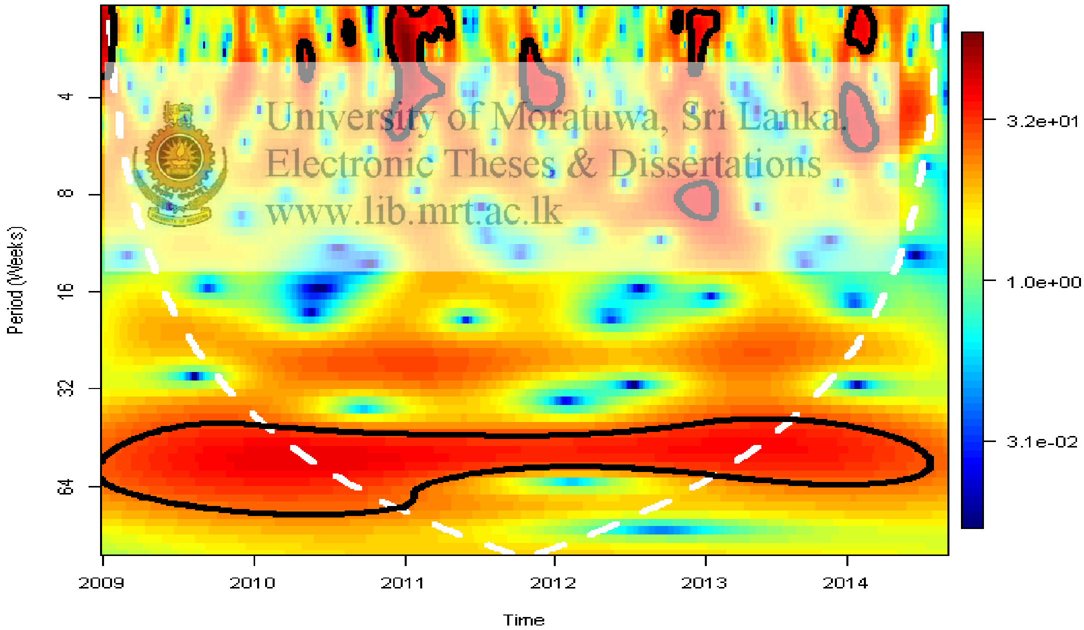


Figure B4: Wavelet power spectrum of maximum temperature in Colombo district from 2009 to September, 2014

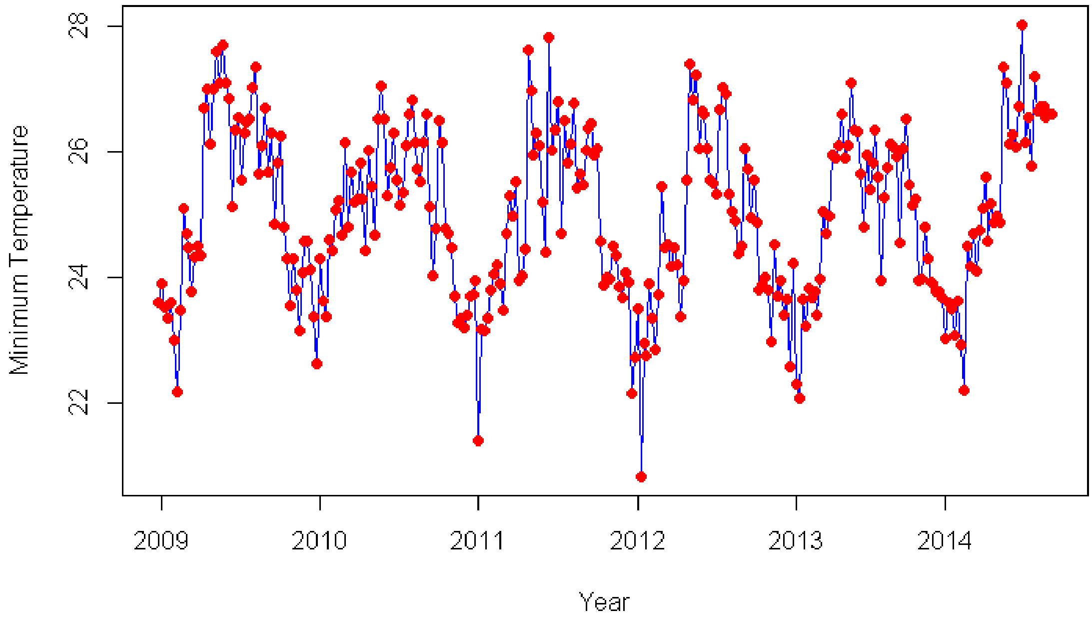


Figure B5: Time series plot of weekly minimum temperature (^{0}C) from January 2009 – September 2014

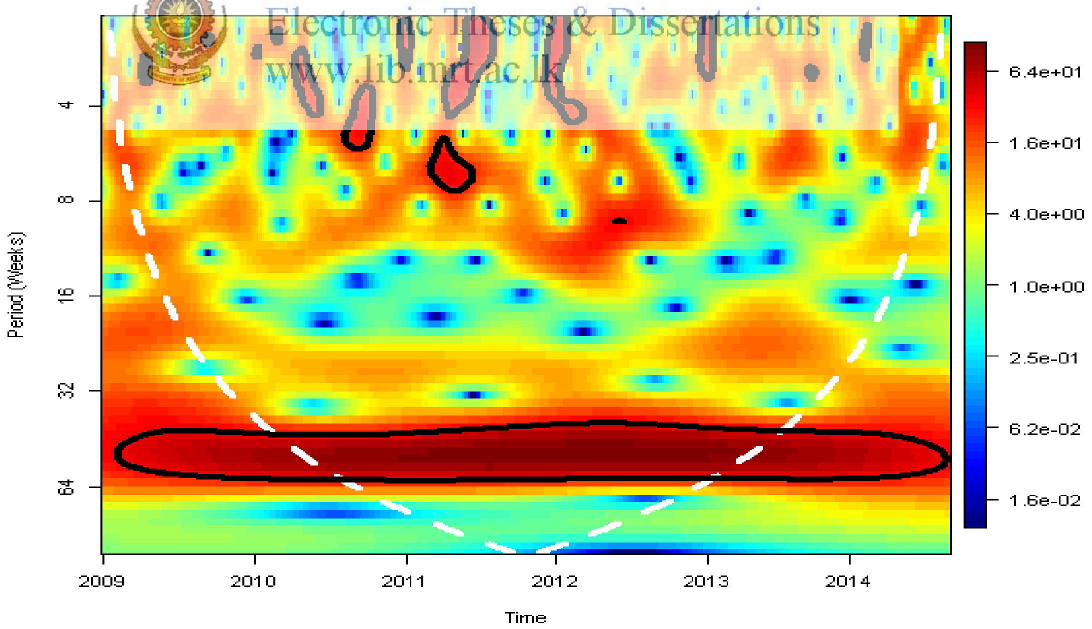


Figure B6: Wavelet power spectrum of minimum temperature in Colombo district from 2009 to September, 2014

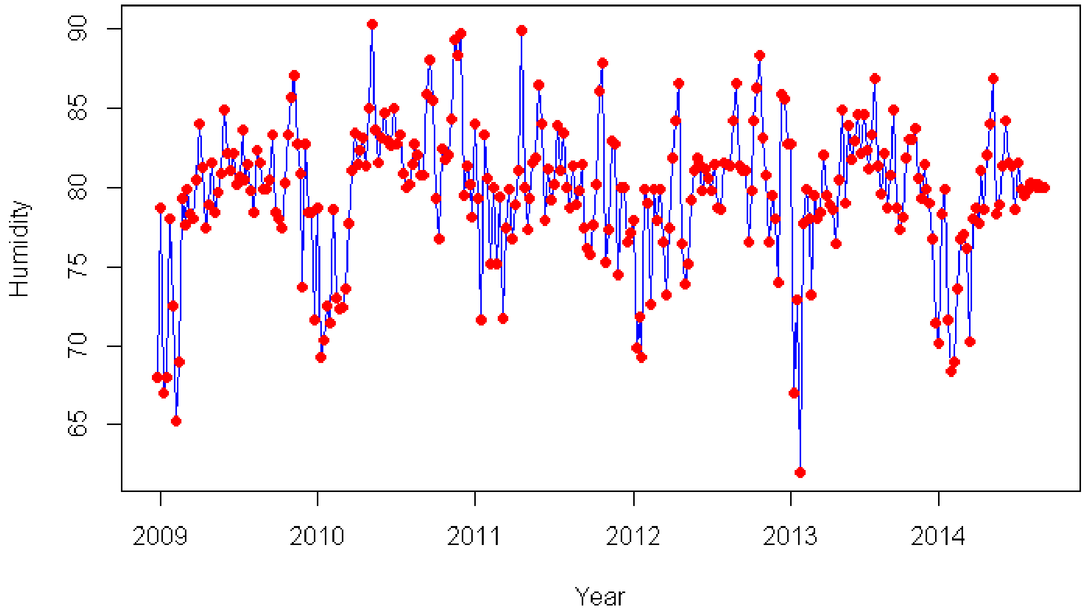


Figure B7: Time series plot of weekly relative humidity (%) from January 2009 – September 2014

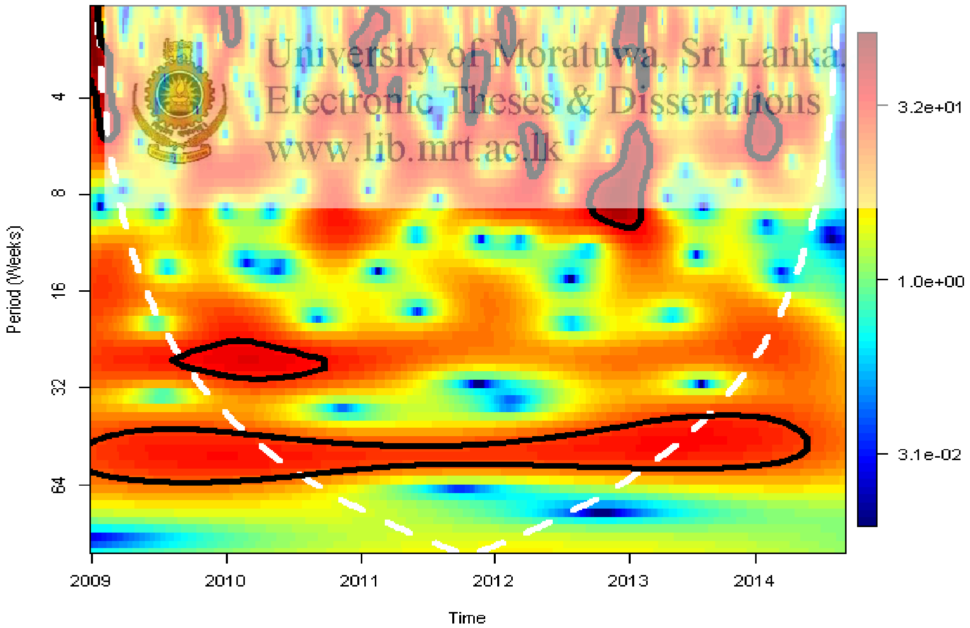


Figure B8: Wavelet power spectrum of humidity in Colombo district from 2009 to September, 2014

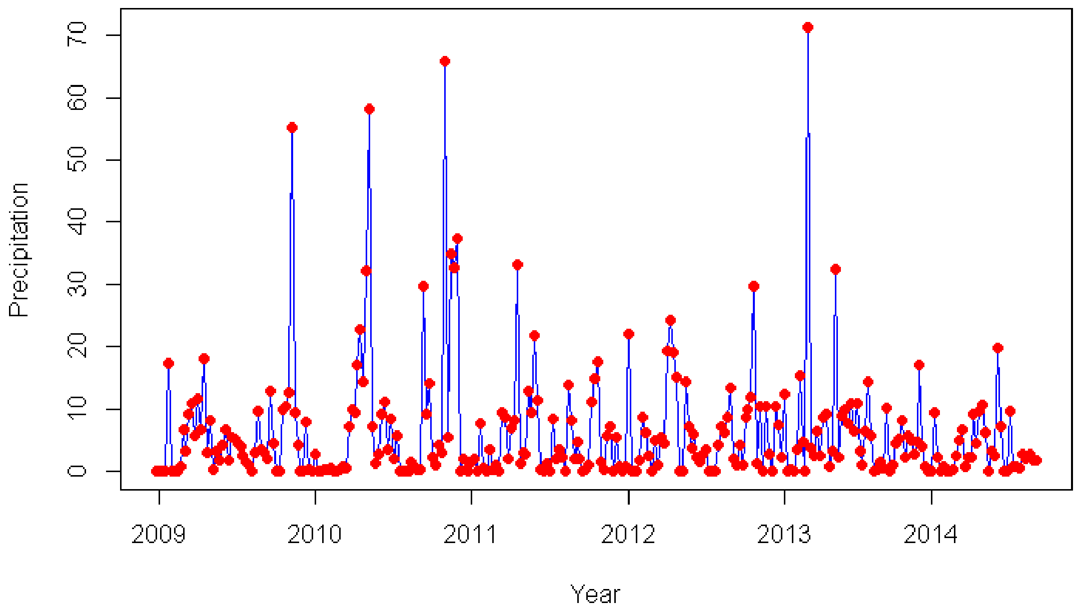


Figure B9: Time series plot of weekly precipitation (mm) from January 2009 – September 2014

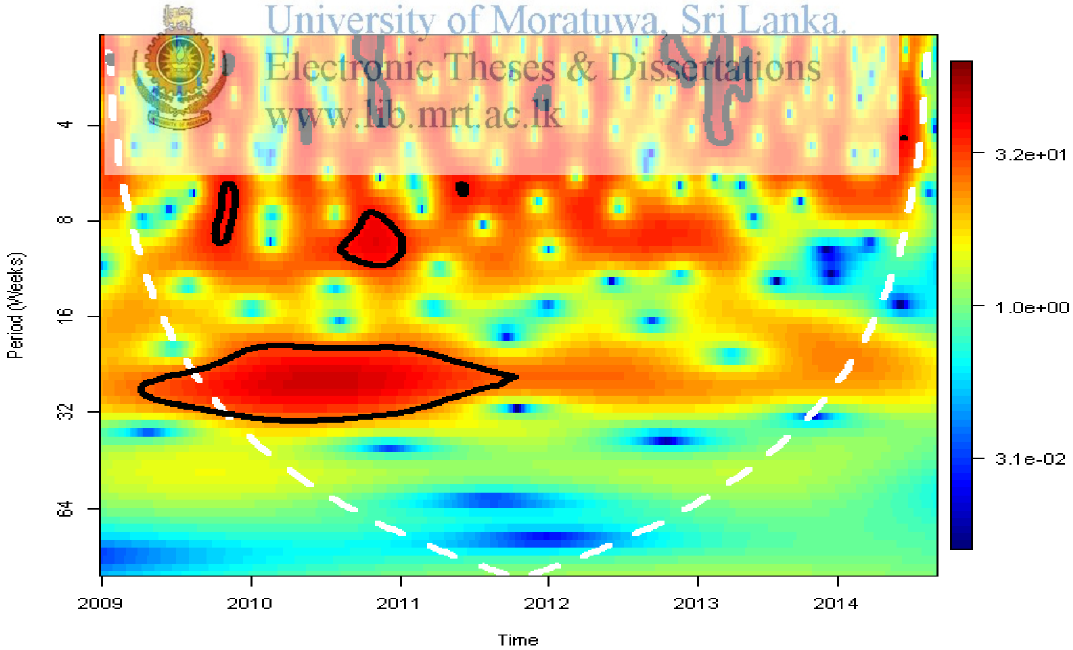


Figure B10: Wavelet power spectrum of precipitation in Colombo district from 2009 to September, 2014

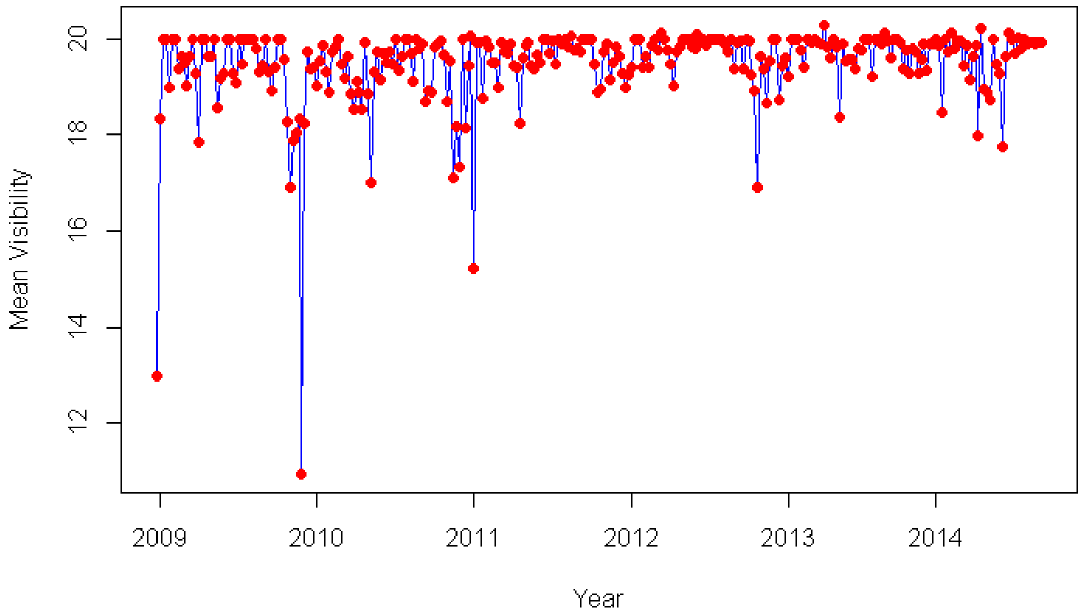


Figure B11: Time series plot of weekly mean visibility (km) from January 2009 – September 2014

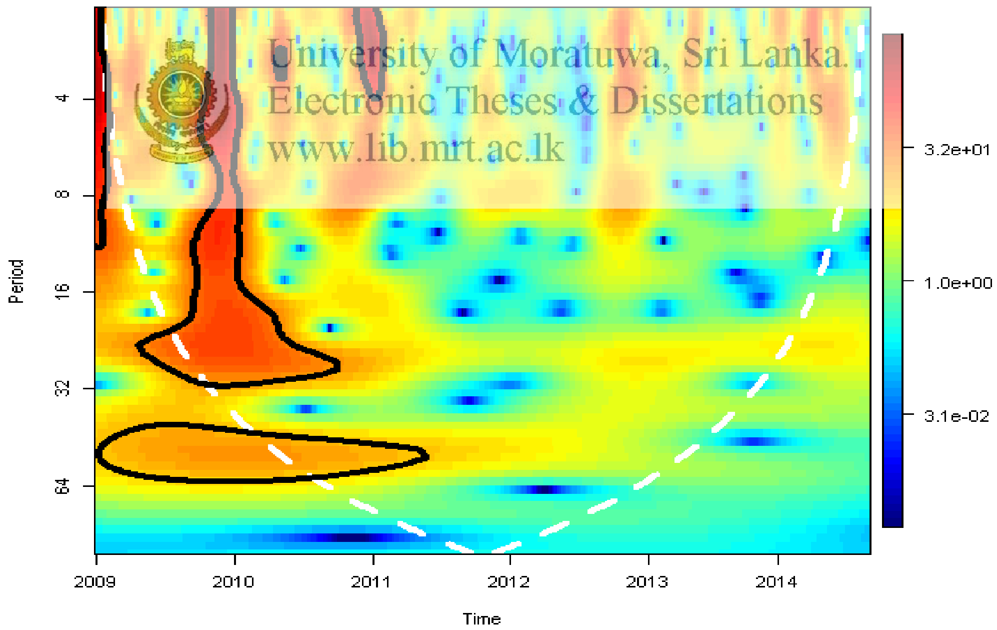


Figure B12: Wavelet power spectrum of mean visibility in Colombo district from 2009 to September, 2014

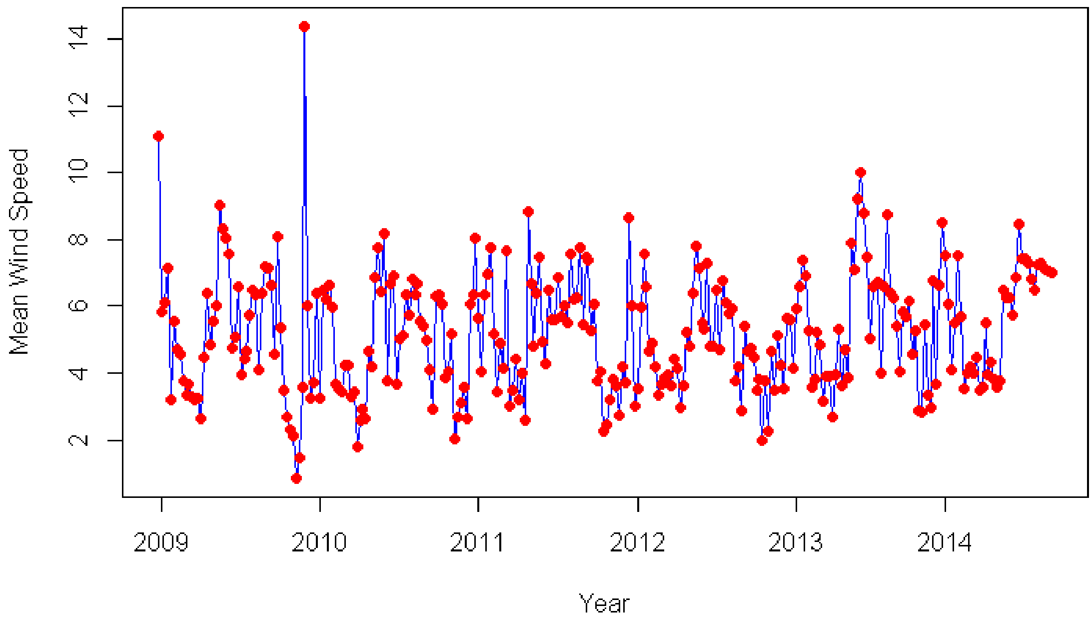


Figure B13: Time series plot of weekly mean wind speed (km/h) from January 2009 – September 2014

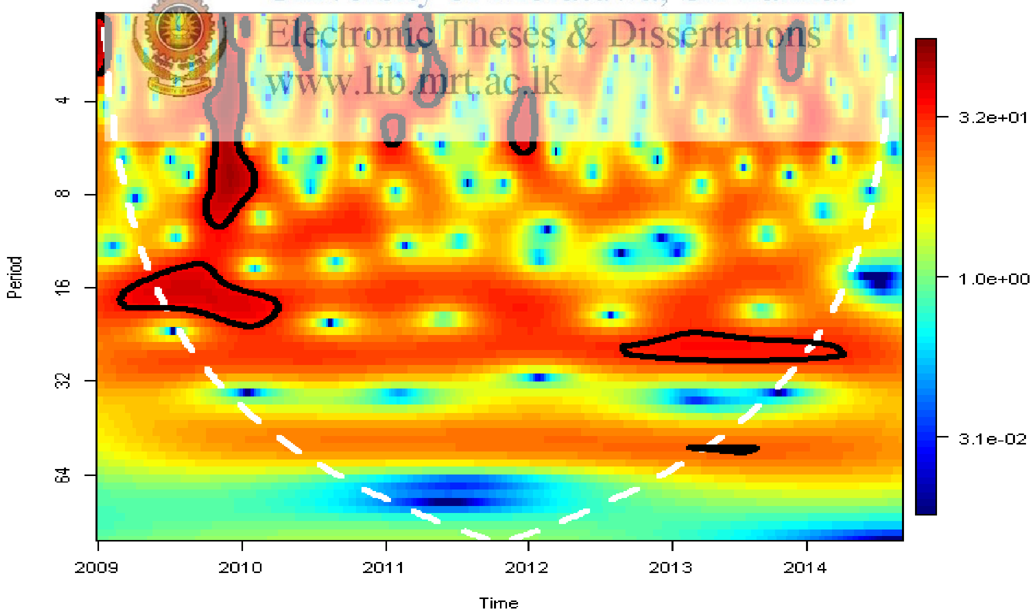


Figure B14: Wavelet power spectrum of mean wind speed in Colombo district from 2009 to September, 2014

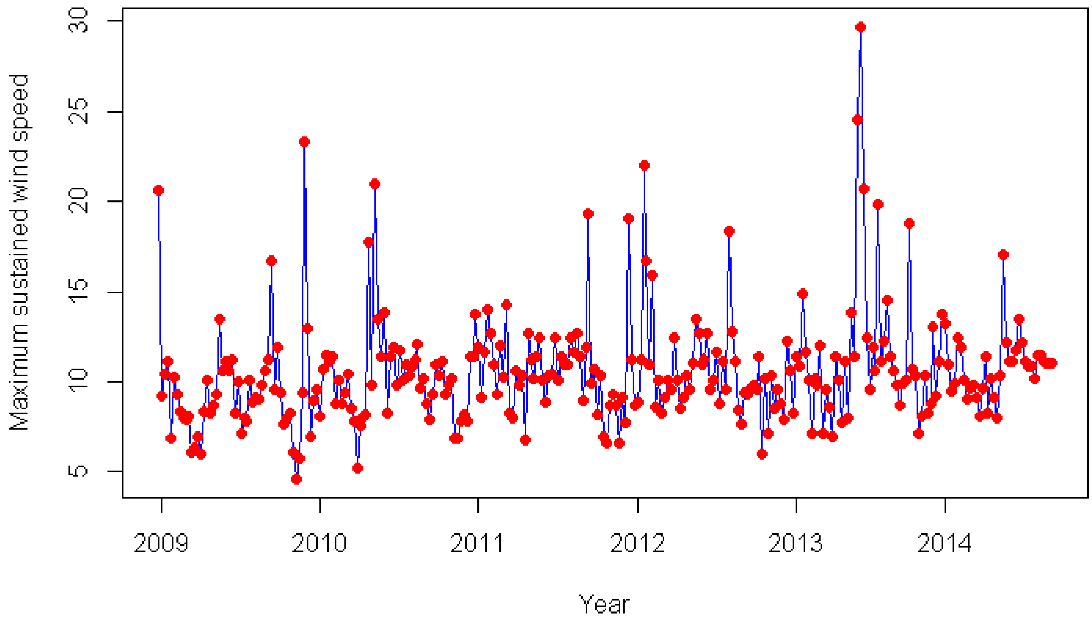


Figure B15: Time series plot of weekly maximum sustained wind speed (km/h) from January 2009 – September 2014

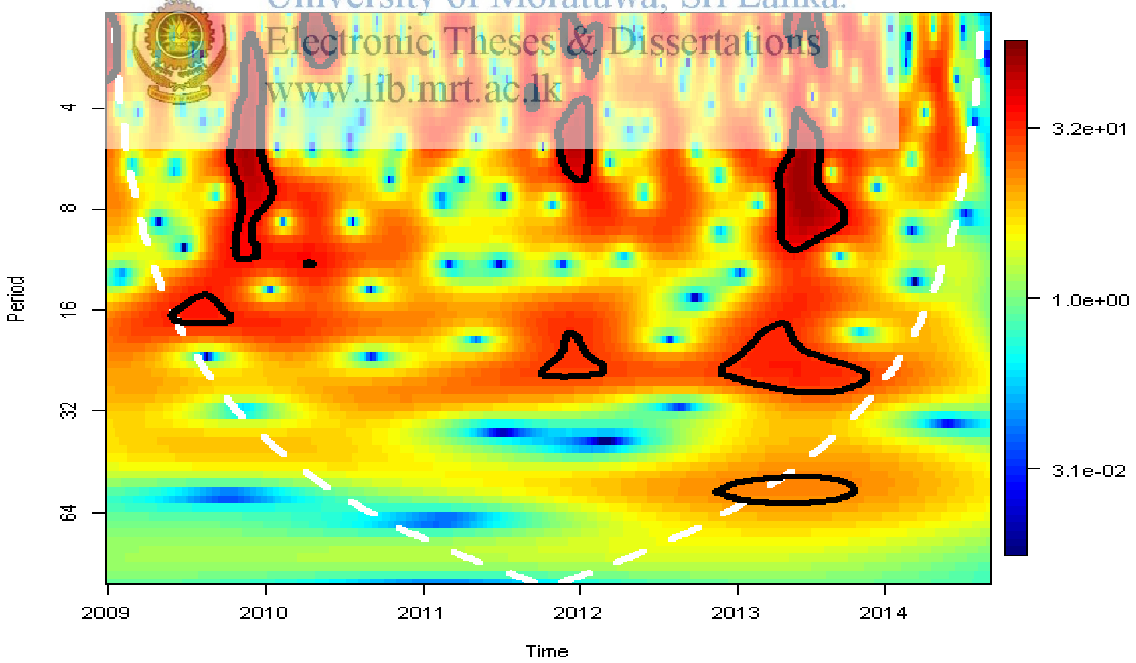


Figure B16: Wavelet power spectrum of maximum sustained wind speed (km/ h) in Colombo district from 2009 to September, 2014

Appendix C: Results of DLNM

```
Call:

glm(formula = Cases ~ cb.TEM + cb.TMAX + cb.PP + cb.H4 + cb.VM
+ cb.VV + as.factor(Year) + as.factor(Week), family =
quasipoisson())

Deviance Residuals:

     Min         1Q     Median        3Q        Max

-12.9271   -1.8347   -0.2185    1.9783    8.4264

Coefficients:

                      Estimate Std. Error t value Pr(>|t|)

(Intercept)           2.575496   2.454822   1.049   0.2959

cb.TEMv1.l1           0.161887   1.021405   0.158   0.8743

cb.TEMv1.l2          -0.808253   1.337494  -0.604   0.5466

cb.TEMv1.l3           1.318652   1.326758   0.994   0.3220

cb.TEMv1.l4           0.717818   1.106650   0.649   0.5176

cb.TEMv1.l5           0.071412   0.746380   0.096   0.9239

cb.TMAXv1.l1         -0.731850   0.986271  -0.742   0.4593

cb.TMAXv1.l2          1.303715   1.944450   0.670   0.5037

cb.TMAXv1.l3         -2.274978   1.438795  -1.581   0.1161

cb.TMAXv1.l4         -0.514038   0.953365  -0.539   0.5906

cb.TMAXv1.l5         -0.318340   0.698409  -0.456   0.6492

cb.PPv1.l1           -0.041687   0.134587  -0.310   0.7572

cb.PPv2.l1            0.576822   0.473007   1.219   0.2247

cb.PPv3.l1           -0.521393   1.222512  -0.426   0.6704

cb.PPv4.l1           -1.490459   1.849657  -0.806   0.4217

cb.PPv5.l1            0.283484   0.596299   0.475   0.6352

cb.PPv1.l2            1.560629   1.495528   1.044   0.2985

cb.PPv2.l2            0.819295   6.726087   0.122   0.9032

cb.PPv3.l2           -0.900930  15.944428  -0.057   0.9550
```

cb.PPv4.l2	8.612236	20.806189	0.414	0.6796	
cb.PPv5.l2	10.366726	6.301800	1.645	0.1022	
cb.PPv1.l3	-2.927583	3.337170	-0.877	0.3818	
cb.PPv2.l3	-1.226584	15.875310	-0.077	0.9385	
cb.PPv3.l3	1.146546	38.276038	0.030	0.9761	
cb.PPv4.l3	1.181488	51.652315	0.023	0.9818	
cb.PPv5.l3	-33.969521	17.556674	-1.935	0.0550	.
cb.PPv1.l4	1.304292	2.122377	0.615	0.5399	
cb.PPv2.l4	-0.454676	10.018507	-0.045	0.9639	
cb.PPv3.l4	0.899360	24.426967	0.037	0.9707	
cb.PPv4.l4	-7.648432	34.500371	-0.222	0.8249	
cb.PPv5.l4	23.198909	12.206558	1.901	0.0594	.
cb.H4v1.l1	-0.087631	0.988158	-0.089	0.9295	
cb.H4v2.l1	-0.405079	0.562179	-0.721	0.4724	
cb.H4v1.l2	-0.537331	1.273626	-0.422	0.6738	
cb.H4v2.l2	-0.920131	0.558005	-1.649	0.1014	
cb.H4v1.l3	3.137602	1.557569	2.014	0.0459	*
cb.H4v2.l3	0.531748	0.719368	0.739	0.4610	
cb.H4v1.l4	-3.336076	1.448590	-2.303	0.0228	*
cb.H4v2.l4	-2.058437	1.065131	-1.933	0.0553	.
cb.H4v1.l5	-0.200602	1.317641	-0.152	0.8792	
cb.H4v2.l5	-0.707887	0.693928	-1.020	0.3094	
cb.H4v1.l6	0.701396	0.883439	0.794	0.4286	
cb.H4v2.l6	-0.142374	0.455941	-0.312	0.7553	
cb.VMv1.l1	-0.596839	0.598257	-0.998	0.3202	
cb.VMv2.l1	0.216810	0.528602	0.410	0.6823	
cb.VMv1.l2	0.079761	0.669837	0.119	0.9054	
cb.VMv2.l2	0.583206	0.635194	0.918	0.3601	
cb.VMv1.l3	0.233236	1.110923	0.210	0.8340	

cb.VMv2.l3	0.811982	0.858955	0.945	0.3461	
cb.VMv1.l4	0.009704	0.964934	0.010	0.9920	
cb.VMv2.l4	-1.035043	0.614454	-1.684	0.0943	.
cb.VMv1.l5	0.581911	0.722671	0.805	0.4221	
cb.VMv2.l5	1.177928	0.565911	2.081	0.0392	*
cb.VMv1.l6	0.492381	0.636870	0.773	0.4408	
cb.VMv2.l6	-0.602758	0.465919	-1.294	0.1979	
cb.VVv1.l1	3.050401	2.194891	1.390	0.1668	
cb.VVv2.l1	0.223482	0.523647	0.427	0.6702	
cb.VVv1.l2	1.749661	2.526520	0.693	0.4898	
cb.VVv2.l2	-0.843500	0.544625	-1.549	0.1237	
cb.VVv1.l3	5.409396	3.032733	1.784	0.0766	.
cb.VVv2.l3	0.123604	0.763015	0.162	0.8715	
cb.VVv1.l4	-0.802995	4.068487	-0.197	0.8438	
cb.VVv2.l4	-1.217167	0.917718	-1.326	0.1869	
cb.VVv1.l5	5.448858	2.415345	2.256	0.0256	*
cb.VVv2.l5	-1.045113	0.543457	-1.923	0.0565	.
cb.VVv1.l6	0.361965	1.913471	0.189	0.8502	
cb.VVv2.l6	-0.112037	0.563082	-0.199	0.8426	
as.factor(Year)2010	0.644255	0.969502	0.665	0.5074	
as.factor(Year)2011	1.015308	0.900469	1.128	0.2614	
as.factor(Year)2012	1.554259	1.042632	1.491	0.1383	
as.factor(Year)2013	2.288741	1.246380	1.836	0.0684	.
as.factor(Year)2014	2.249348	1.506726	1.493	0.1377	
as.factor(Week)2	0.044785	0.332218	0.135	0.8930	
as.factor(Week)3	0.191546	0.556413	0.344	0.7312	
as.factor(Week)4	0.154200	0.838943	0.184	0.8544	
as.factor(Week)5	0.069523	1.110472	0.063	0.9502	
as.factor(Week)6	0.271021	1.376369	0.197	0.8442	

as.factor(Week)7	0.644636	1.648196	0.391	0.6963
as.factor(Week)8	0.714294	1.924640	0.371	0.7111
as.factor(Week)9	1.003582	2.191565	0.458	0.6477
as.factor(Week)10	0.779856	2.379966	0.328	0.7436
as.factor(Week)11	0.609344	2.564880	0.238	0.8126
as.factor(Week)12	0.484967	2.730466	0.178	0.8593
as.factor(Week)13	0.204299	2.874102	0.071	0.9434
as.factor(Week)14	-0.129080	2.988529	-0.043	0.9656
as.factor(Week)15	-0.659673	3.061023	-0.216	0.8297
as.factor(Week)16	-0.210571	3.113451	-0.068	0.9462
as.factor(Week)17	-0.167475	3.145608	-0.053	0.9576
as.factor(Week)18	-0.409174	3.151776	-0.130	0.8969
as.factor(Week)19	-0.395857	3.084539	-0.128	0.8981
as.factor(Week)20	0.104383	2.999590	0.035	0.9723
as.factor(Week)21	0.949203	2.924290	0.325	0.7460
as.factor(Week)22	1.153124	2.833597	0.407	0.6847
as.factor(Week)23	1.202118	2.783027	0.432	0.6664
as.factor(Week)24	1.725927	2.675882	0.645	0.5200
as.factor(Week)25	1.917063	2.511227	0.763	0.4465
as.factor(Week)26	2.572721	2.362135	1.089	0.2780
as.factor(Week)27	2.664733	2.274028	1.172	0.2433
as.factor(Week)28	2.752624	2.176142	1.265	0.2080
as.factor(Week)29	2.632909	2.130308	1.236	0.2186
as.factor(Week)30	2.924052	2.106576	1.388	0.1673
as.factor(Week)31	2.813014	2.105265	1.336	0.1837
as.factor(Week)32	2.923913	2.124817	1.376	0.1710
as.factor(Week)33	2.902987	2.179235	1.332	0.1850
as.factor(Week)34	2.577762	2.229195	1.156	0.2495
as.factor(Week)35	2.224697	2.317001	0.960	0.3386

as.factor(Week)36	1.658310	2.360789	0.702	0.4836
as.factor(Week)37	2.137877	2.386563	0.896	0.3719
as.factor(Week)38	1.695302	2.360851	0.718	0.4739
as.factor(Week)39	1.818521	2.388858	0.761	0.4478
as.factor(Week)40	1.731428	2.384401	0.726	0.4690
as.factor(Week)41	1.342164	2.345245	0.572	0.5680
as.factor(Week)42	1.451757	2.277326	0.637	0.5249
as.factor(Week)43	1.155952	2.206702	0.524	0.6012
as.factor(Week)44	0.538456	2.143537	0.251	0.8020
as.factor(Week)45	0.737854	2.029040	0.364	0.7167
as.factor(Week)46	0.704693	1.895953	0.372	0.7107
as.factor(Week)47	0.833471	1.713526	0.486	0.6274
as.factor(Week)48	0.740750	1.510222	0.490	0.6246
as.factor(Week)49	0.879011	1.238490	0.710	0.4790
as.factor(Week)50	0.469140	0.980194	0.479	0.6330
as.factor(Week)51	0.348745	0.742414	0.470	0.6393
as.factor(Week)52	0.332881	0.502842	0.662	0.5091
as.factor(Week)53	0.245855	0.831679	0.296	0.7680


```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for quasipoisson family taken to be 16.03292)

Null deviance: 16541.7  on 263  degrees of freedom
Residual deviance:  2501.7  on 140  degrees of freedom

Number of Fisher Scoring iterations: 5
```

Appendix D: R codes

```
# Exploratory Data Analysis - Time series plots of dengue
# incidence

C_District=read.csv(file.choose(),header=T)

attach(C_District)

a=as.matrix(C_District)

rr=as.ts(a,start=c(2008,52),frequency=c(1,52,52,52,52,49,
36))

for (i in 5 to 29){

win.graph(width=6.5, height=2.5,pointsize=8)

plot(a[,i],type="b",bg=66,col="blue",ylab="Dengue
Cases",xaxt="n",xlab="Year")

lines( a[,i], col="blue")

points( a[,i], col="red", pch=19 )

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

}

#*********************************************************

# Chapter 5 - Wavelet Analyses

# Figure 5.1

C_District=read.csv(file.choose(),header=T)

attach(C_District)

a=as.matrix(C_District[30])

rr=as.ts(a,start=c(2008,52),frequency=c(1,52,52,52,52,49,
21))


All=sqrt(All)

ta=cbind(1:294, (All-mean(All))/sd(All))
```

```
rr2=as.ts(ta[,2],start=c(2008,52),frequency=c(1,52,52,52,
52,49,21))

win.graph(width=6.5, height=2.5,pointsize=8)

plot(rr2,type="b",bg=66,col="blue",ylab="square root
transformed and normalized",xaxt="n")

lines( rr2, col="blue")

points( rr2, col="red", pch=19 )

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

#*********************************************************

#Wavelet transformation of dengue cases

C_District=read.csv(file.choose(),header=T)

attach(C_District)

##--------------- Compute wavelet spectra------------------

library(biwavelet)

Colombo=sqrt(Colombo)

Gampaha=sqrt(Gampaha)

Kalutara=sqrt(Kalutara)

Kandy=sqrt(Kandy)

Matale=sqrt(Matale)

Nuwara.Eliya=sqrt(Nuwara.Eliya)

Galle=sqrt(Galle)

Hambantota=sqrt(Hambantota)

Matara=sqrt(Matara)

Jaffna=sqrt(Jaffna)

Kilinochchi=sqrt(Kilinochchi)

Mannar=sqrt(Mannar)
```

```
Vavuniya=sqrt(Vavuniya)

Mulative=sqrt(Mulative)

Batticalo=sqrt(Batticalo)

Ampara=sqrt(Ampara)

Trincomalee=sqrt(Trincomalee)

Kurunagala=sqrt(Kurunagala)

Puttalam=sqrt(Puttalam)

Anuradhapura=sqrt(Anuradhapura)

Polonnaruwa=sqrt(Polonnaruwa)

Badulla=sqrt(Badulla)

Monaragala=sqrt(Monaragala)

Ratnapura=sqrt(Ratnapura)

Kegalle=sqrt(Kegalle)
```



```
t1=cbind(1:294,(Colombo-mean(Colombo))/sd(Colombo))

t2=cbind(1:294,(Gampaha-mean(Gampaha))/sd(Gampaha))

t3=cbind(1:294, (Kalutara-mean(Kalutara))/sd(Kalutara))

t4=cbind(1:294, (Kandy-mean(Kandy))/sd(Kandy))

t5=cbind(1:294,(Matale-mean(Matale))/sd(Matale))

t6=cbind(1:294, (Nuwara.Eliya-
mean(Nuwara.Eliya))/sd(Nuwara.Eliya))

t7=cbind(1:294,(Galle-mean(Galle))/sd(Galle))

t8=cbind(1:294, (Hambantota-
mean(Hambantota))/sd(Hambantota))

t9=cbind(1:294,(Matara-mean(Matara))/sd(Matara))

t10=cbind(1:294,(Jaffna-mean(Jaffna))/sd(Jaffna))
```

```
t11=cbind(1:294,(Kilinochchi-
mean(Kilinochchi))/sd(Kilinochchi))

t12=cbind(1:294, (Mannar-mean(Mannar))/sd(Mannar))

t13=cbind(1:294,(Vavuniya-mean(Vavuniya))/sd(Vavuniya))

t14=cbind(1:294, (Mulative-mean(Mulative))/sd(Mulative))

t15=cbind(1:294, (Batticalo-
mean(Batticalo))/sd(Batticalo))

t16=cbind(1:294,(Ampara-mean(Ampara))/sd(Ampara))

t17=cbind(1:294, (Trincomalee-
mean(Trincomalee))/sd(Trincomalee))

t18=cbind(1:294, (Kurunagala-
mean(Kurunagala))/sd(Kurunagala))

t19=cbind(1:294,(Puttalam-mean(Puttalam))/sd(Puttalam))

t20=cbind(1:294, (Anuradhapura-
mean(Anuradhapura))/sd(Anuradhapura))

t21=cbind(1:294, (Polonnaruwa-
mean(Polonnaruwa))/sd(Polonnaruwa))

t22=cbind(1:294,(Badulla-mean(Badulla))/sd(Badulla))

t23=cbind(1:294,(Monaragala-
mean(Monaragala))/sd(Monaragala))

t24=cbind(1:294, (Ratnapura-
mean(Ratnapura))/sd(Ratnapura))

t25=cbind(1:294, (Kegalle-mean(Kegalle))/sd(Kegalle))


wt.t1=wt(t1)

wt.t2=wt(t2)

wt.t3=wt(t3)

wt.t4=wt(t4)

wt.t5=wt(t5)
```

```
wt.t6=wt(t6)

wt.t7=wt(t7)

wt.t8=wt(t8)

wt.t9=wt(t9)

wt.t10=wt(t10)

wt.t11=wt(t11)

wt.t12=wt(t12)

wt.t13=wt(t13)

wt.t14=wt(t14)

wt.t15=wt(t15)

wt.t16=wt(t16)

wt.t17=wt(t17)

wt.t18=wt(t18)

wt.t19=wt(t19)

wt.t20=wt(t20)

wt.t21=wt(t21)

wt.t22=wt(t22)

wt.t23=wt(t23)

wt.t24=wt(t24)

wt.t25=wt(t25)

# Figure 5.4

par(mfrow=c(4,2),mai=c(0.3,0.7,0.2,0.2))

plot(wt.t1, plot.cb=F,
plot.phase=F,xaxt="n",main="a",ylab="Period (weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))
```

```
plot(wt.t2, plot.cb=F,
plot.phase=FALSE,xaxt="n",main="b",ylab="Period (weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(wt.t3, plot.cb=F,
plot.phase=FALSE,xaxt="n",main="c",ylab="Period (weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(wt.t4, plot.cb=F,
plot.phase=FALSE,xaxt="n",main="d",ylab="Period (weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(wt.t5, plot.cb=F,
plot.phase=FALSE,xaxt="n",main="e",ylab="Period (weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(wt.t6, plot.cb=F,
plot.phase=FALSE,xaxt="n",main="f",ylab="Period (weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(wt.t7, plot.cb=F,
plot.phase=FALSE,xaxt="n",main="g",ylab="Period (weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(wt.t8, plot.cb=F,
plot.phase=FALSE,xaxt="n",main="h",ylab="Period (weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(wt.t9, plot.cb=F,
plot.phase=FALSE,xaxt="n",main="Matara",ylab="Period
(weeks)")
```

```
axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(wt.t10, plot.cb=F,
plot.phase=FALSE,xaxt="n",main="Jaffna",ylab="Period
(weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(wt.t11, plot.cb=F,
plot.phase=FALSE,xaxt="n",main="Killinochchi",ylab="Perio
d (weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(wt.t12, plot.cb=F,
plot.phase=FALSE,xaxt="n",main="Mannar",ylab="Period
(weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))
```



```
plot(wt.t13, plot.cb=F,
plot.phase=FALSE,xaxt="n",main="Vavuniya",ylab="Period
(weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(wt.t14, plot.cb=F,
plot.phase=FALSE,xaxt="n",main="Mulative",ylab="Period
(weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(wt.t15, plot.cb=F,
plot.phase=FALSE,xaxt="n",main="Batticalo",ylab="Period
(weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))
```

```
plot(wt.t16, plot.cb=F,
plot.phase=FALSE,xaxt="n",main="Ampara",ylab="Period
(weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(wt.t17, plot.cb=F,
plot.phase=FALSE,xaxt="n",main="Trincomalee",ylab="Period
(weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(wt.t18, plot.cb=F,
plot.phase=FALSE,xaxt="n",main="Kurunagala",ylab="Period
(weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))


plot(wt.t19, plot.cb=F,
plot.phase=FALSE,xaxt="n",main="Puttalam",ylab="Period
(weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(wt.t20, plot.cb=F,
plot.phase=FALSE,xaxt="n",main="Anuradhapura",ylab="Perio
d (weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(wt.t21, plot.cb=F,
plot.phase=FALSE,xaxt="n",main="Polonnaruwa",ylab="Period
(weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(wt.t22, plot.cb=F,
plot.phase=FALSE,xaxt="n",main="Badulla",ylab="Period
(weeks)")
```

```
axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011,2012,2013,2014))

plot(wt.t23, plot.cb=F, plot.phase=FALSE,xaxt="n",main="Monaragala",ylab="Period (weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011,2012,2013,2014))

plot(wt.t24, plot.cb=F, plot.phase=FALSE,xaxt="n",main="Ratnapura",ylab="Period (weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011,2012,2013,2014))


plot(wt.t25, plot.cb=F, plot.phase=FALSE,xaxt="n",main="Kegall",ylab="Period (weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011,2012,2013,2014))

#--------------------Figure 5.5-----------------------------------

par(mfrow=c(5,5),mai=c(0.3,0.3,0.2,0.2))

b=wt.t1$period

a=apply(wt.t1$power.corr,1,mean)

plot(b,a,type="l",main ="Colombo",mai=c(0.001,0.001,0.001,0.001))

b=wt.t2$period

a=apply(wt.t2$power.corr,1,mean)

plot(b,a,type="l",main ="Gampaha",mai=c(0.001,0.001,0.001,0.001))

b=wt.t3$period

a=apply(wt.t3$power.corr,1,mean)
```

```
plot(b,a,type="l",main
="Kalutara",mai=c(0.001,0.001,0.001,0.001))

b=wt.t4$period

a=apply(wt.t4$power.corr,1,mean)

plot(b,a,type="l",main
="Kandy",mai=c(0.001,0.001,0.001,0.001))

b=wt.t5$period

a=apply(wt.t5$power.corr,1,mean)

plot(b,a,type="l",main
="Matale",mai=c(0.001,0.001,0.001,0.001))

b=wt.t6$period

a=apply(wt.t6$power.corr,1,mean)

plot(b,a,type="l",main ="Nuwara
Eliya",mai=c(0.001,0.001,0.001,0.001))

b=wt.t7$period

a=apply(wt.t7$power.corr,1,mean)

plot(b,a,type="l",main
="Galle",mai=c(0.001,0.001,0.001,0.001))

b=wt.t8$period

a=apply(wt.t8$power.corr,1,mean)

plot(b,a,type="l",main
="Hambantota",mai=c(0.001,0.001,0.001,0.001))

b=wt.t9$period

a=apply(wt.t9$power.corr,1,mean)

plot(b,a,type="l",main
="Matara",mai=c(0.001,0.001,0.001,0.001))

b=wt.t10$period

a=apply(wt.t10$power.corr,1,mean)
```

```
plot(b,a,type="l",main
="Jaffna",mai=c(0.001,0.001,0.001,0.001))

b=wt.t11$period

a=apply(wt.t11$power.corr,1,mean)

plot(b,a,type="l",main
="Killinochchie",mai=c(0.001,0.001,0.001,0.001))

b=wt.t12$period

a=apply(wt.t12$power.corr,1,mean)

plot(b,a,type="l",main
="Mannar",mai=c(0.001,0.001,0.001,0.001))

b=wt.t13$period

a=apply(wt.t13$power.corr,1,mean)

plot(b,a,type="l",main
="Vavuniya",mai=c(0.001,0.001,0.001,0.001))

b=wt.t14$period

a=apply(wt.t14$power.corr,1,mean)

plot(b,a,type="l",main
="Mulative",mai=c(0.001,0.001,0.001,0.001))

b=wt.t15$period

a=apply(wt.t15$power.corr,1,mean)

plot(b,a,type="l",main
="Batticalo",mai=c(0.001,0.001,0.001,0.001))

b=wt.t16$period

a=apply(wt.t16$power.corr,1,mean)

plot(b,a,type="l",main
="Ampara",mai=c(0.001,0.001,0.001,0.001))

b=wt.t17$period

a=apply(wt.t17$power.corr,1,mean)
```

```
plot(b,a,type="l",main
="Trincomalee",mai=c(0.001,0.001,0.001,0.001))

b=wt.t18$period

a=apply(wt.t18$power.corr,1,mean)

plot(b,a,type="l",main
="Kurunagala",mai=c(0.001,0.001,0.001,0.001))


b=wt.t19$period

a=apply(wt.t19$power.corr,1,mean)

plot(b,a,type="l",main
="Puttalam",mai=c(0.001,0.001,0.001,0.001))

b=wt.t20$period

a=apply(wt.t20$power.corr,1,mean)

plot(b,a,type="l",main
="Anuradhapura",mai=c(0.001,0.001,0.001,0.001))

b=wt.t21$period

a=apply(wt.t21$power.corr,1,mean)

plot(b,a,type="l",main
="Polonnaruwa",mai=c(0.001,0.001,0.001,0.001))

b=wt.t22$period

a=apply(wt.t22$power.corr,1,mean)

plot(b,a,type="l",main
="Badulla",mai=c(0.001,0.001,0.001,0.001))

b=wt.t23$period

a=apply(wt.t23$power.corr,1,mean)

plot(b,a,type="l",main
="Monaragala",mai=c(0.001,0.001,0.001,0.001))

b=wt.t24$period

a=apply(wt.t24$power.corr,1,mean)
```

```
plot(b,a,type="l",main
="Rathnapura",mai=c(0.001,0.001,0.001,0.001))

b=wt.t25$period

a=apply(wt.t25$power.corr,1,mean)

plot(b,a,type="l",main
="Kegalle",mai=c(0.001,0.001,0.001,0.001))


# Wavelet Cluster Analysis

C_District=read.csv(file.choose(),header=T)

attach(C_District)

C_District=read.csv(file.choose(),header=T)

C_District[2]

names(C_District)

attach(C_District)

apply(C_District,2,length)

apply(C_District,2,mean,na.rm=T)


library(biwavelet)

Colombo=sqrt(Colombo)

Gampaha=sqrt(Gampaha)

Kalutara=sqrt(Kalutara)

Kandy=sqrt(Kandy)

Matale=sqrt(Matale)

Nuwara.Eliya=sqrt(Nuwara.Eliya)

Galle=sqrt(Galle)

Hambantota=sqrt(Hambantota)

Matara=sqrt(Matara)
```

```
Jaffna=sqrt(Jaffna)

Kilinochchi=sqrt(Kilinochchi)

Mannar=sqrt(Mannar)

Vavuniya=sqrt(Vavuniya)

Mulative=sqrt(Mulative)

Batticalo=sqrt(Batticalo)

Ampara=sqrt(Ampara)

Trincomalee=sqrt(Trincomalee)

Kurunagala=sqrt(Kurunagala)

Puttalam=sqrt(Puttalam)

Anuradhapura=sqrt(Anuradhapura)

Polonnaruwa=sqrt(Polonnaruwa)

Badulla=sqrt(Badulla)

Monaragala=sqrt(Monaragala)

Ratnapura=sqrt(Ratnapura)

Kegalle=sqrt(Kegalle)


t1=cbind(1:294, (Colombo-mean(Colombo))/sd(Colombo))

t2=cbind(1:294,(Gampaha-mean(Gampaha))/sd(Gampaha))

t3=cbind(1:294, (Kalutara-mean(Kalutara))/sd(Kalutara))

t4=cbind(1:294, (Kandy-mean(Kandy))/sd(Kandy))

t5=cbind(1:294,(Matale-mean(Matale))/sd(Matale))

t6=cbind(1:294, (Nuwara.Eliya-
mean(Nuwara.Eliya))/sd(Nuwara.Eliya))

t7=cbind(1:294,(Galle-mean(Galle))/sd(Galle))

t8=cbind(1:294, (Hambantota-
mean(Hambantota))/sd(Hambantota))
```

```
t9=cbind(1:294,(Matara-mean(Matara))/sd(Matara))

t10=cbind(1:294,(Jaffna-mean(Jaffna))/sd(Jaffna))

t11=cbind(1:294,(Kilinochchi-
mean(Kilinochchi))/sd(Kilinochchi))

t12=cbind(1:294, (Mannar-mean(Mannar))/sd(Mannar))

t13=cbind(1:294,(Vavuniya-mean(Vavuniya))/sd(Vavuniya))

t14=cbind(1:294, (Mulative-mean(Mulative))/sd(Mulative))

t15=cbind(1:294, (Batticalo-
mean(Batticalo))/sd(Batticalo))

t16=cbind(1:294,(Ampara-mean(Ampara))/sd(Ampara))

t17=cbind(1:294, (Trincomalee-
mean(Trincomalee))/sd(Trincomalee))

t18=cbind(1:294, (Kurunagala-
mean(Kurunagala))/sd(Kurunagala))

t19=cbind(1:294,(Puttalam-mean(Puttalam))/sd(Puttalam))

t20=cbind(1:294, (Anuradhapura-
mean(Anuradhapura))/sd(Anuradhapura))

t21=cbind(1:294, (Polonnaruwa-
mean(Polonnaruwa))/sd(Polonnaruwa))

t22=cbind(1:294,(Badulla-mean(Badulla))/sd(Badulla))

t23=cbind(1:294,(Monaragala-
mean(Monaragala))/sd(Monaragala))

t24=cbind(1:294, (Ratnapura-
mean(Ratnapura))/sd(Ratnapura))

t25=cbind(1:294, (Kegalle-mean(Kegalle))/sd(Kegalle))

wt.t1=wt(t1)

wt.t2=wt(t2)

wt.t3=wt(t3)

wt.t4=wt(t4)
```

```
wt.t5=wt(t5)

wt.t6=wt(t6)

wt.t7=wt(t7)

wt.t8=wt(t8)

wt.t9=wt(t9)

wt.t10=wt(t10)

wt.t11=wt(t11)

wt.t12=wt(t12)

wt.t13=wt(t13)

wt.t14=wt(t14)

wt.t15=wt(t15)

wt.t16=wt(t16)

wt.t17=wt(t17)

wt.t18=wt(t18)

wt.t19=wt(t19)

wt.t20=wt(t20)

wt.t21=wt(t21)

wt.t22=wt(t22)

wt.t23=wt(t23)

wt.t24=wt(t24)

wt.t25=wt(t25)

## Store all wavelet spectra into array

w.arr=array(NA, dim=c(25, NROW(wt.t1$wave),
NCOL(wt.t1$wave)))

w.arr[1, , ]=wt.t1$wave

w.arr[2, , ]=wt.t2$wave
```

```
w.arr[3, , ]=wt.t3$wave
w.arr[4, , ]=wt.t4$wave
w.arr[5, , ]=wt.t5$wave
w.arr[6, , ]=wt.t6$wave
w.arr[7, , ]=wt.t7$wave
w.arr[8, , ]=wt.t8$wave
w.arr[9, , ]=wt.t9$wave
w.arr[10, , ]=wt.t10$wave
w.arr[11, , ]=wt.t11$wave
w.arr[12, , ]=wt.t12$wave
w.arr[13, , ]=wt.t13$wave
w.arr[14, , ]=wt.t14$wave
w.arr[15, , ]=wt.t15$wave
w.arr[16, , ]=wt.t16$wave
w.arr[17, , ]=wt.t17$wave
w.arr[18, , ]=wt.t18$wave
w.arr[19, , ]=wt.t19$wave
w.arr[20, , ]=wt.t20$wave
w.arr[21, , ]=wt.t21$wave
w.arr[22, , ]=wt.t22$wave
w.arr[23, , ]=wt.t23$wave
w.arr[24, , ]=wt.t24$wave
w.arr[25, , ]=wt.t25$wave
## Compute dissimilarity and distance matrices
w.arr.dis=wclust(w.arr)
```

```
plot(hclust(w.arr.dis$dist.mat, method="ward"), sub="",
main="", ylab="Dissimilarity", hang=-1)

#Figure 5.8

par(mfrow=c(4,2),mai=c(0.3,0.7,0.2,0.2))

plot(wt.TEM, plot.cb=F,
plot.phase=F,xaxt="n",main="a",ylab="Period (weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(wt.TMAX, plot.cb=F,
plot.phase=FALSE,xaxt="n",main="b",ylab="Period (weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(wt.Tm, plot.cb=F,
plot.phase=FALSE,xaxt="n",main="c",ylab="Period (weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(wt.H, plot.cb=F,
plot.phase=FALSE,xaxt="n",main="d",ylab="Period (weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(wt.PP, plot.cb=F,
plot.phase=FALSE,xaxt="n",main="e",ylab="Period (weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(wt.VV, plot.cb=F,
plot.phase=FALSE,xaxt="n",main="f",ylab="Period (weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(wt.V, plot.cb=F,
plot.phase=FALSE,xaxt="n",main="g",ylab="Period (weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))
```

```
plot(wt.VM, plot.cb=F,
plot.phase=FALSE,xaxt="n",main="h",ylab="Period (weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

#Figure 5.9

par(mfrow=c(2,4),mai=c(0.3,0.3,0.2,0.2))

b=wt.TEM$period

a=apply(wt.TEM$power.corr,1,mean)

plot(b,a,type="l",main
="a",mai=c(0.001,0.001,0.001,0.001))

b=wt.TMAX$period

a=apply(wt.TMAX$power.corr,1,mean)

plot(b,a,type="l",main
="b",mai=c(0.001,0.001,0.001,0.001))

b=wt.Tm$period

a=apply(wt.Tm$power.corr,1,mean)

plot(b,a,type="l",main
="c",mai=c(0.001,0.001,0.001,0.001))

b=wt.H$period

a=apply(wt.H$power.corr,1,mean)

plot(b,a,type="l",main
="d",mai=c(0.001,0.001,0.001,0.001))

b=wt.PP$period

a=apply(wt.PP$power.corr,1,mean)

plot(b,a,type="l",main
="e",mai=c(0.001,0.001,0.001,0.001))

b=wt.VV$period

a=apply(wt.VV$power.corr,1,mean)
```

```
plot(b,a,type="l",main
="f",mai=c(0.001,0.001,0.001,0.001))

b=wt.Vperiod

a=apply(wt.V$power.corr,1,mean)

plot(b,a,type="l",main
="g",mai=c(0.001,0.001,0.001,0.001))

b=wt.VM$period

a=apply(wt.VM$power.corr,1,mean)

plot(b,a,type="l",main
="h",mai=c(0.001,0.001,0.001,0.001))


#Figure 5.10

rm(list=ls())

library(biwavelet)

Colombo=read.csv(file.choose(),header=T)

attach(Colombo)

head(Colombo)

names(Colombo)

attach(Colombo)

apply(Colombo1,2,length)

par(mfrow=c(4,2),mai=c(0.6,0.7,0.4,0.2))

#ccf(mdeaths, fdeaths, ylab = "cross-correlation")

ccf(TEM, Cases, main = "a", ylab = "cross-correlation",
xlab="lag")

ccf(TMAX, Cases, main = "b", ylab = "cross-correlation",
xlab="lag")

ccf(Tm, Cases, main = "c", ylab = "cross-correlation",
xlab="lag")
```

```
ccf(H, Cases, main = "d", ylab = "cross-correlation",
xlab="lag")

ccf(PP, Cases, main = "e", ylab = "cross-correlation",
xlab="lag")

ccf(VV, Cases, main = "f", ylab = "cross-correlation",
xlab="lag")

ccf(V, Cases, main = "g", ylab = "cross-correlation",
xlab="lag")

ccf(VM, Cases, main = "h", ylab = "cross-correlation",
xlab="lag")


#Figure 5.12 - Figure 5.26 and Appendix B

rm(list=ls())

library(biwavelet)

Colombo=read.csv(file.choose(),header=T)

attach(Colombo)

head(Colombo)

names(Colombo)

attach(Colombo)

apply(Colombo1,2,length)

TEM1=sqrt(TEM)

TMAX1=sqrt(TMAX)

Tm1=sqrt(Tm)

H1=sqrt(H)

PP1=sqrt(PP)

VV1=sqrt(VV)

V1=sqrt(V)

VM1=sqrt(VM)
```

```
Cases1=sqrt(Cases)

TEM2=cbind(1:294, (TEM1-mean(TEM1))/sd(TEM1))

TMAX2=cbind(1:294,(TMAX1-mean(TMAX1))/sd(TMAX1))

Tm2=cbind(1:294, (Tm1-mean(Tm1))/sd(Tm1))

H2=cbind(1:294,(H1-mean(H1))/sd(H1))

PP2=cbind(1:294, (PP1-mean(PP1))/sd(PP1))

VV2=cbind(1:294,(VV1-mean(VV1))/sd(VV1))

V2=cbind(1:294, (V1-mean(V1))/sd(V1))

VM2=cbind(1:294,(VM1-mean(VM1))/sd(VM1))

Cases2=cbind(1:294,(Cases1-mean(Cases1))/sd(Cases1))

wt.TEM=wt(TEM2)

wt.TMAX=wt(TMAX2)

wt.Tm=wt(Tm2)

wt.H=wt(H2)

wt.PP=wt(PP2)

wt.VV=wt(VV2)

wt.V=wt(V2)

wt.VM=wt(VM2)

wt.Cases=wt(Cases2)

## Store all wavelet spectra into array

w.arr=array(NA, dim=c(9, NROW(wt.TEM$wave),
NCOL(wt.TEM$wave)))

w.arr[1, , ]=wt.TEM$wave

w.arr[2, , ]=wt.TMAX$wave

w.arr[3, , ]=wt.Tm$wave

w.arr[4, , ]=wt.H$wave
```

```
w.arr[5, , ]=wt.PP$wave

w.arr[6, , ]=wt.VV$wave

w.arr[7, , ]=wt.V$wave

w.arr[8, , ]=wt.VM$wave

w.arr[9, , ]=wt.Cases$wave


# time series

plot(TEM,type="o",bg=66,col="blue",xlab="Year",ylab="
Mean Temperature",main = " ",xaxt="n")

points( TEM, col="red", pch=19 )

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(TMAX,type="o",bg=66,col="blue",xlab="Year",ylab="Max
imum Temperature",main = " ",xaxt="n")

points( TMAX, col="red", pch=19 )

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(Tm,type="o",bg=66,col="blue",xlab="Year",ylab="Minim
um Temperature",main = " ",xaxt="n")

points( Tm, col="red", pch=19 )

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(H,type="o",bg=66,col="blue",xlab="Year",ylab="Humidi
ty",main = " ",xaxt="n")

points( H, col="red", pch=19 )

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(PP,type="o",bg=66,col="blue",xlab="Year",ylab="Preci
pitation",main = " ",xaxt="n")
```

```
points( PP, col="red", pch=19 )

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(VV,type="o",bg=66,col="blue",xlab="Year",ylab="Mean
Visibility",main = " ",xaxt="n")

points( VV, col="red", pch=19 )

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(V,type="o",bg=66,col="blue",xlab="Year",ylab="Mean
Wind Speed",main = " ",xaxt="n")

points( V, col="red", pch=19 )

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(VM,type="o",bg=66,col="blue",xlab="Year",ylab="Maxim
um sustained wind speed",main = " ",xaxt="n")

points( VM, col="red", pch=19 )

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

#########################################################

#mean temperature

par(oma=c(0, 0, 0, 1), mar=c(5, 4, 4, 5) + 0.1)

plot(wt.TEM, plot.cb=TRUE,
plot.phase=FALSE,xaxt="n",ylab="Period (Weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

# maximum temperature

par(oma=c(0, 0, 0, 1), mar=c(5, 4, 4, 5) + 0.1)

plot(wt.TMAX, plot.cb=TRUE,
plot.phase=FALSE,xaxt="n",ylab="Period (Weeks)")
```

```
axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

# minimum temperature

par(oma=c(0, 0, 0, 1), mar=c(5, 4, 4, 5) + 0.1)

plot(wt.Tm, plot.cb=TRUE,
plot.phase=FALSE,xaxt="n",ylab="Period (Weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

#Humidity

par(oma=c(0, 0, 0, 1), mar=c(5, 4, 4, 5) + 0.1)

plot(wt.H, plot.cb=TRUE,
plot.phase=FALSE,xaxt="n",ylab="Period (Weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

# minimum precipitation
```



```
par(oma=c(0, 0, 0, 1), mar=c(5, 4, 4, 5) + 0.1)

plot(wt.PP, plot.cb=TRUE,
plot.phase=FALSE,xaxt="n",ylab="Period (Weeks)")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

#VV

par(oma=c(0, 0, 0, 1), mar=c(5, 4, 4, 5) + 0.1)

plot(wt.VV, plot.cb=TRUE, plot.phase=FALSE,xaxt="n")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

# V

par(oma=c(0, 0, 0, 1), mar=c(5, 4, 4, 5) + 0.1)

plot(wt.V, plot.cb=TRUE, plot.phase=FALSE,xaxt="n")
```

```
axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

#VM

par(oma=c(0, 0, 0, 1), mar=c(5, 4, 4, 5) + 0.1)

plot(wt.VM, plot.cb=TRUE, plot.phase=FALSE,xaxt="n")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

# Cases

par(oma=c(0, 0, 0, 1), mar=c(5, 4, 4, 5) + 0.1)

plot(wt.Cases, plot.cb=TRUE, plot.phase=FALSE,xaxt="n")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

########################################################

######## Cross-wavelet transform ######################

x <- 1:294

Cases <- Cases

par(mar = c(5, 4, 4, 4) + 0.3)  # Leave space for z axis

plot(x,Cases,type="o",xaxt="n",col="red",xlab="Year",pch=
20)

par(new = TRUE)

plot(x, TEM, type = "o", axes = FALSE, bty = "n", xlab =
"Year", ylab = "",xaxt="n",col="blue",pch=20)

axis(side=4, at = pretty(range(TEM)))

mtext("Mean temperature", side=4, line=3)

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

#---------------------------------------------------------

xwt.t1=xwt(Cases2,TEM2)
```

```
par(oma=c(0, 0, 0, 1), mar=c(5, 4, 4, 5) + 0.1)

plot(xwt.t1, plot.cb=TRUE,
plot.phase=TRUE,ylab="Period(Weeks)",xaxt="n")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

#*********************************************************

x <- 1:294

Cases <- Cases

## second data set on a very different scale

par(mar = c(5, 4, 4, 4) + 0.3)  # Leave space for z axis

plot(x,
Cases,type="o",xaxt="n",col="red",xlab="Year",pch=20) #
first plot

par(new = TRUE)

plot(x, Tm, type = "o", axes = FALSE, bty = "n", xlab =
"Year", ylab = "",xaxt="n",col="blue",pch=20)

axis(side=4, at = pretty(range(Tm)))

mtext("Minimum temperature", side=4, line=3)

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

#---------------------------------------------------------

xwt.t1=xwt(Cases2,Tm2)

par(oma=c(0, 0, 0, 1), mar=c(5, 4, 4, 5) + 0.1)

plot(xwt.t1, plot.cb=TRUE,
plot.phase=TRUE,ylab="Period(Weeks)",xaxt="n")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

#*********************************************************

x <- 1:294
```

```
Cases <- Cases

## second data set on a very different scale

par(mar = c(5, 4, 4, 4) + 0.3)  # Leave space for z axis

plot(x,
Cases,type="o",xaxt="n",col="red",xlab="Year",pch=20) #
first plot

par(new = TRUE)

plot(x, TMAX, type = "o", axes = FALSE, bty = "n", xlab =
"Year", ylab = "",xaxt="n",col="blue",pch=20)

axis(side=4, at = pretty(range(TMAX)))

mtext("Maximum temperature", side=4, line=3)

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

#---------------------------------------------------------

xwt.t1=xwt(Cases2,TMAX2)

par(oma=c(0, 0, 0, 1), mar=c(5, 4, 4, 5) + 0.1)

plot(xwt.t1, plot.cb=TRUE,
plot.phase=TRUE,ylab="Period(Weeks)",xaxt="n")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

#*********************************************************

x <- 1:294

Cases <- Cases

## second data set on a very different scale

par(mar = c(5, 4, 4, 4) + 0.3)  # Leave space for z axis

plot(x,
Cases,type="o",xaxt="n",col="red",xlab="Year",pch=20) #
first plot

par(new = TRUE)
```

```
plot(x,H, type = "o", axes = FALSE, bty = "n", xlab =
"Year", ylab = "",xaxt="n",col="blue",pch=20)

axis(side=4, at = pretty(range(H)))

mtext("Humidity", side=4, line=3)

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))


#---------------------------------------------------------

xwt.t1=xwt(Cases2,H2)

par(oma=c(0, 0, 0, 1), mar=c(5, 4, 4, 5) + 0.1)

plot(xwt.t1, plot.cb=TRUE,
plot.phase=TRUE,ylab="Period(Weeks)",xaxt="n")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

#*********************************************************

x <- 1:294

Cases <- Cases

## second data set on a very different scale

par(mar = c(5, 4, 4, 4) + 0.3)  # Leave space for z axis

plot(x,
Cases,type="o",xaxt="n",col="red",xlab="Year",pch=20) #
first plot

par(new = TRUE)

plot(x,PP, type = "o", axes = FALSE, bty = "n", xlab =
"Year", ylab = "",xaxt="n",col="blue",pch=20)

axis(side=4, at = pretty(range(PP)))

mtext("Precipitation", side=4, line=3)

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))
```

```
#---------------------------------------------------------

xwt.t1=xwt(Cases2,PP2)

par(oma=c(0, 0, 0, 1), mar=c(5, 4, 4, 5) + 0.1)

plot(xwt.t1, plot.cb=TRUE,
plot.phase=TRUE,ylab="Period(Weeks)",xaxt="n")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

#*********************************************************

x <- 1:294

Cases <- Cases

## second data set on a very different scale

par(mar = c(5, 4, 4, 4) + 0.3)  # Leave space for z axis

plot(x,
Cases,type="o",xaxt="n",col="red",xlab="Year",pch=20) #
first plot

par(new = TRUE)

plot(x,VV, type = "o", axes = FALSE, bty = "n", xlab =
"Year", ylab = "",xaxt="n",col="blue",pch=20)

axis(side=4, at = pretty(range(VV)))

mtext("Visibility", side=4, line=3)

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

#---------------------------------------------------------

xwt.t1=xwt(Cases2,VV2)

par(oma=c(0, 0, 0, 1), mar=c(5, 4, 4, 5) + 0.1)

plot(xwt.t1, plot.cb=TRUE,
plot.phase=TRUE,ylab="Period(Weeks)",xaxt="n")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))
```

```
#*******************************************************

x <- 1:294

Cases <- Cases

## second data set on a very different scale

par(mar = c(5, 4, 4, 4) + 0.3)  # Leave space for z axis

plot(x,
Cases,type="o",xaxt="n",col="red",xlab="Year",pch=20) #
first plot

par(new = TRUE)

plot(x,V, type = "o", axes = FALSE, bty = "n", xlab =
"Year", ylab = "",xaxt="n",col="blue",pch=20)

axis(side=4, at = pretty(range(V)))

mtext("Wind Speed", side=4, line=3)

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

#--------------------------------------------------------

xwt.t1=xwt(Cases2,V2)

par(oma=c(0, 0, 0, 1), mar=c(5, 4, 4, 5) + 0.1)

plot(xwt.t1, plot.cb=TRUE,
plot.phase=TRUE,ylab="Period(Weeks)",xaxt="n")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

#*******************************************************

x <- 1:294

Cases <- Cases

## second data set on a very different scale

par(mar = c(5, 4, 4, 4) + 0.3)  # Leave space for z axis
```

```
plot(x,
Cases,type="o",xaxt="n",col="red",xlab="Year",pch=20) #
first plot

par(new = TRUE)

plot(x,VM, type = "o", axes = FALSE, bty = "n", xlab =
"Year", ylab = "",xaxt="n",col="blue",pch=20)

axis(side=4, at = pretty(range(VM)))

mtext("Maximum Sustained Wind Speed", side=4, line=3)

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

#---------------------------------------------------------
xwt.t1=xwt(Cases2,VM2)

par(oma=c(0, 0, 0, 1), mar=c(5, 4, 4, 5) + 0.1)

plot(xwt.t1, plot.cb=TRUE,
plot.phase=TRUE,ylab="Period(Weeks)",xaxt="n")

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

#########################################################
##

# Change point analysis

rm(list=ls())

ls()


library(changepoint)

library(zoo)


cpdata=read.csv(file.choose(),header=T)

attach(cpdata)

head(cpdata)
```

```
##### change point detection using PELT method

Cases.pelt <- cpt.var(diff(Cases,difference=1),method =
"PELT")

TEM.pelt <- cpt.var(diff(TEM,difference=1),method =
"PELT")

TMAX.pelt <- cpt.var(diff(TMAX,difference=1),method =
"PELT")

Tm.pelt <- cpt.var(diff(Tm,difference=1),method = "PELT")

H.pelt <- cpt.var(diff(H,difference=1),method = "PELT")

PP.pelt <- cpt.var(diff(PP,difference=1),method = "PELT")

VV.pelt <- cpt.var(diff(VV,difference=1),method = "PELT")

V.pelt <- cpt.var(diff(V,difference=1),method = "PELT")

VM.pelt <- cpt.var(diff(VM,difference=1),method = "PELT")

logLik(Cases.pelt)

logLik(TEM.pelt)


#---------------------------------------------------------


par(mfrow=c(2,1))

plot(Cases.pelt,ylab="Dengue Cases" ,xlab="Time",main = "
",xaxt="n" )

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))


plot(TEM.pelt,ylab="Mean Temperature" ,xlab="Time",main =
" ",xaxt="n" )

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))
```

```
#---------------------------------------------------------

par(mfrow=c(2,1))

plot(Cases.pelt,ylab="Dengue Cases" ,xlab="Time",main = " ",xaxt="n" )

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011,2012,2013,2014))

plot(TMAX.pelt,ylab="Maximum Temperature" ,xlab="Time",main = " ",xaxt="n" )

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011,2012,2013,2014))

#---------------------------------------------------------

par(mfrow=c(2,1))

plot(Cases.pelt,ylab="Dengue Cases" ,xlab="Time",main = " ",xaxt="n" )

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011,2012,2013,2014))

plot(Tm.pelt,ylab="Minimum Temperature" ,xlab="Time",main = " ",xaxt="n" )

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011,2012,2013,2014))

#---------------------------------------------------------

par(mfrow=c(2,1))

plot(Cases.pelt,ylab="Dengue Cases" ,xlab="Time",main = " ",xaxt="n" )

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011,2012,2013,2014))

plot(H.pelt,ylab="Humidity" ,xlab="Time",main = " ",xaxt="n" )

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011,2012,2013,2014))
```

```
#--------------------------------------------------------

par(mfrow=c(2,1))

plot(Cases.pelt,ylab="Dengue Cases" ,xlab="Time",main = "
",xaxt="n" )

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(PP.pelt,ylab="Precipitation" ,xlab="Time",main = "
",xaxt="n" )

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))


#--------------------------------------------------------

par(mfrow=c(2,1))

plot(Cases.pelt,ylab="Dengue Cases" ,xlab="Time",main = "
",xaxt="n" )

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))


plot(VV.pelt,ylab="Visibility" ,xlab="Time",main = "
",xaxt="n" )

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

#--------------------------------------------------------

par(mfrow=c(2,1))

plot(Cases.pelt,ylab="Dengue Cases" ,xlab="Time",main = "
",xaxt="n" )

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))
```

```
plot(V.pelt,ylab="Wind Speed" ,xlab="Time",main = "
",xaxt="n" )

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))


#---------------------------------------------------------

par(mfrow=c(2,1))

plot(Cases.pelt,ylab="Dengue Cases" ,xlab="Time",main = "
",xaxt="n" )

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

plot(VM.pelt,ylab="Maximum Sustained Wind Speed"
,xlab="Time",main = " ",xaxt="n" )

axis(1,at=c(2,54,106,158,210,259),labels=c(2009,2010,2011
,2012,2013,2014))

##########################################################

# DLNM

########last model######################

rm(list=ls())

Colombo=read.csv(file.choose(),header=T)

attach(Colombo)

names(Colombo)

head(Colombo)

library(dlnm)

library(splines)

lagknots1 <- logknots(30, 4)

lagknots <- logknots(30, 3)
```

```
cb.PP <- crossbasis(PP,lag=25,
argvar=list("bs",df=5,degree=4,cen=median(PP)),arglag=lis
t(fun="poly",degree=3))

cb.TEM <- crossbasis(TEM, lag=30,
argvar=list(df=1,cen=median(TEM)),
arglag=list(knots=lagknots))

cb.TMAX <- crossbasis(TMAX, lag=30,
argvar=list(df=1,cen=median(TMAX)),

arglag=list(knots=lagknots))

cb.H4<- crossbasis(H, lag=20,
argvar=list(df=2,cen=median(H)),

arglag=list(knots=lagknots1))

cb.V<- crossbasis(V, lag=20,
argvar=list(df=2,cen=median(V)),

arglag=list(knots=lagknots1))

cb.VV<- crossbasis(VV, lag=20,
argvar=list(df=2,cen=median(VV)),

arglag=list(knots=lagknots1))

cb.VM<- crossbasis(VM, lag=20,
argvar=list(df=2,cen=median(VM)),

arglag=list(knots=lagknots1))

model5 <- glm(Cases ~
cb.TEM+cb.TMAX+cb.PP+cb.H4+cb.VM+cb.VV+as.factor(Year)+as
.factor(Week),family=quasipoisson())

AIC.cc<- -2*sum( dpois( model5$y, model5$fitted.values,
log=TRUE))+

2*summary(model5)$df[3]*summary(model5)$dispersion

AIC.cc

n=294

QIC.cc<- -2*sum( dpois( model5$y, model5$fitted.values,
log=TRUE))+
```

```
log(n)*summary(model5)$df[3]*summary(model5)$dispersion

QIC.cc

pred.TEM <- crosspred(cb.TEM, model5)

plot(pred.TEM, xlab="Mean Temperature", zlab="RR")

plot(pred.TEM, "contour", xlab="Mean Temperature",
key.title=title("RR"),

plot.title=title("Contour plot",xlab="Mean
Temperature",ylab="Lag"))

#pred.TEM2 <- crosspred(cb.TEM, model5,by=1)

#plot(pred.TEM2, "slices", var=27, ci="bars", type="p",
pch=19, ci.level=0.95,

#main="Association with a 1 - unit increase above
threshold (95%CI)",ylab="RR")


#---------MAximum Temperature -------------

pred.TMAX <- crosspred(cb.TMAX, model5)

plot(pred.TMAX, xlab="Maximum Temperature", zlab="RR")

plot(pred.TMAX, "contour", xlab="Maximum Temperature",
key.title=title("RR"),

plot.title=title("Contour plot",xlab="Maximum
Temperature",ylab="Lag"))

#plot(pred.TMAX, "slices", var=c(30,32,34),

#lag=c(15,20,25),ylab="RR")

#pred.TMAX2 <- crosspred(cb.TMAX, model5,by=1)

#plot(pred.TMAX2, "slices", var=30, ci="bars", type="p",
pch=19, ci.level=0.95,

#main="Association with a 1 - unit increase above
threshold (95%CI)",ylab="RR")
```

```
#----------Precipitation---------------

pred.PP <- crosspred(cb.PP, model5)

plot(pred.PP, xlab="Precipitation", zlab="RR")

plot(pred.PP, "contour", xlab="Precipitation",
key.title=title("RR"),

plot.title=title("Contour
plot",xlab="Precipitation",ylab="Lag"))

#pred.PP2 <- crosspred(cb.PP, model5,by=1)

#plot(pred.PP2, "slices", var=10, ci="bars", type="p",
pch=19, ci.level=0.95,

#main="Association with a 1 - unit increase above
threshold (95%CI)",ylab="RR")


#----------Humidity---------------

pred.H4 <- crosspred(cb.H4, model5)

plot(pred.H4, xlab="Humidity", zlab="RR")

plot(pred.H4, "contour", xlab="Humidity",
key.title=title("RR"),

plot.title=title("Contour
plot",xlab="Humidity",ylab="Lag"))

#pred.H42 <- crosspred(cb.H4, model5,by=1)

#plot(pred.H42, "slices", var=65, ci="bars", type="p",
pch=19, ci.level=0.95,

#main="Association with a 1 - unit increase above
threshold (95%CI)",ylab="RR")


#####################----------VV---------------

pred.VV <- crosspred(cb.VV, model5)

plot(pred.VV, xlab="Visibility", zlab="RR")
```

```
plot(pred.VV, "contour", xlab="Visibility",
key.title=title("RR"),

plot.title=title("Contour
plot",xlab="Visibility",ylab="Lag"))

pred.H42 <- crosspred(cb.H4, model5,by=1)

plot(pred.H42, "slices", var=65, ci="bars", type="p",
pch=19, ci.level=0.95,

main="Association with a 1 - unit increase above
threshold (95%CI)",ylab="RR")

####################----------VM--------------

pred.VM <- crosspred(cb.VM, model5)

plot(pred.VM, xlab="Maximum sustained wind speed",
zlab="RR")

plot(pred.VM, "contour", xlab="Maximum sustained wind
speed", key.title=title("RR"),

plot.title=title("Contour plot",xlab="Maximum sustained
wind speed",ylab="Lag"))

pred.H42 <- crosspred(cb.H4, model5,by=1)

plot(pred.H42, "slices", var=65, ci="bars", type="p",
pch=19, ci.level=0.95,

main="Association with a 1 - unit increase above
threshold (95%CI)",ylab="RR")

acf(model5$resid)

library(car)

qqPlot((model5$resid-
mean(model5$resid))/sd(model5$resid))

ks.test(rnorm(294),(model5$resid-
mean(model5$resid))/sd(model5$resid))
```