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The Effects of Climate on Dengue Occurrence in Matale, Sri Lanka: Generalized Linear Models

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ABSTRACT

Dengue fever is an arboviral disease caused by four dengue virus serotypes. It is transmitted by the bite of an infected female mosquito of the genus Aedes. Over the years, dengue has become a major health issue in Sri Lanka. Since climate affects both virus incubation and mosquito development, studying the distribution of dengue fever with its relevant climate factors would be useful. This paper aims to measure the role of climate variables alone on the occurrence of dengue while eliminating the weight from past lags. The selected area for the study is the Matale district, and the study period is from 2005 to 2020. The dengue cases were first differentiated to remove the series dependence. Monthly differentiated dengue and climate variables were log-transformed to stabilize the variance and to normalize the data sets for modeling. Cross-correlation functions (CCF) were used to measure the lag-wise correlation between dengue and climate. The causal relationship was further analyzed through a multiple-regression approach. For that, Generalized Linear Models (GLM) were built with the Gaussian family. Two models were built considering different time lags of climate variables. The results exhibited that rainfall and average temperature positively affected dengue occurrence. Although the regression coefficients were significant, the models indicated that climate has minimal effect. However, models fitted well during epidemic periods. Adding more variables to the model to obtain more precise predictions would be useful.

1. Introduction

Dengue fever (DF) and Dengue Hemorrhagic Fever (DHF) are arboviral diseases caused by four dengue virus serotypes: dengue 1, 2, 3, and 4. Aedes mosquitos, abundant in tropical and subtropical areas worldwide, transmit the virus. Dengue fever has spread substantially over the last few decades, and the disease is now endemic in various parts of the world [1].

Dengue has been endemic in Sri Lanka for the last 40 years. Since the early 1990s, significant epidemics of severe and fatal DHF have occurred at regular intervals. The magnitude of DF and DHF epidemics in Sri Lanka continued to increase during the 2000s, with a major outbreak in 2009 of 35,008 suspected cases [2]. Dengue became a serious public health issue in the country between 2010 and 2016, with cases progressively increasing. In 2017, the Central Epidemiology Unit of the Ministry of Health in Sri Lanka received reports of 186,101 suspected cases and 440 dengue-related deaths. This is the highest amount of cases reported in a year in Sri Lanka since dengue fever was declared a notifiable disease in 1996. Dengue fever became a serious public health issue in the United States between 2010 and 2016, with cases progressively increasing (from 28,473 in 2011 to 55,150 in 2016) across the country [3]. In 2019, the second-greatest cases (105,049 dengue cases) were reported. Initially, dengue fever spread in urban regions but has since expanded to rural and hilly countries.

Numerous studies have discovered the relationship between climate and dengue transmission. Increased temperature can promote dengue risk by improving vector development rate and shortening the viral incubation period. On the other hand, extreme hot temperatures reduce dengue transmission by increasing the mosquito mortality rate. Rainfall may provide a habitat for *Aedes Aegypti* and *Aedes Albopictus* larvae and pupae, but heavy rainfall will flush them away [5]. As a result, studies on the relationship between climate variables and dengue are important for deciding dengue outbreaks.

This paper aimed to determine the impacts of climatic conditions on dengue transmission in a selected district of Sri Lanka. A lag-wise correlation was observed between climate variables and dengue cases. The critical climate variables were recognized with their affecting time lags. Thereafter, the degree of their influence was assessed using a Generalized Linear Model (GLM). In addition, the association between climate and dengue epidemic was measured by fitting the model on dengue outbreaks. This study estimates the effects of climate alone, which is valuable for evaluating its function on different dengue patterns.

2. Material and Methods

2.1. Study area

The research was conducted in the Matale District of the central province of Sri Lanka. The land area of Matale is 1,993 km^2 and is divided into 11 divisional Secretariats divisions. The estimated population of the area was 484,531 in 2012, including urban, semi-urban, and rural areas [12]. Matale is the second-highest dengue-affected area in the central province.

2.2. Data

Monthly dengue cases from 2005 to 2020 were obtained from the Regional Director of Health Services (RDHS) in Matale with the permission of the Provincial Director of Health Services in the Central Province. Climatic data was obtained from the Department of Meteorology of Sri Lanka.

2.3. Methodology

Monthly aggregated dengue and climatic variables were used to analyze the association between dengue cases and climate. Rainfall, minimum temperature, maximum temperature, average temperature, and humidity were considered climatic variables. Dengue cases were first differentiated to remove the series' dependence on time. Then, the variables were log-transformed to stabilize the variance and to normalize the data sets for the modeling [6].

Pearson correlation coefficient was used in cross-correlation functions, and lagged correlations between dengue and climate variables were observed. A multiple regression approach examined the impact of climatic variables on dengue cases. For that, Generalized Linear Models (GLM) were built with the Gaussian family. GLM consists of a random component specifying the conditional distribution of the response variable, Yi (for the i^{th} lag of independently sampled dengue cases), given the values of the explanatory variables in the model. Yi and explanatory variables are the members of the Gaussian family that are continuous, decimal data with normal distribution [7,8].

The monthly lags of climate variables used as explanatory variables were determined from cross-correlation functions (CCF). We built two models, and the best model was determined based on the lowest Akaike's information criterion (AIC), Bayesian information criterion (BIC), and residual sum of squares (RSS) [9].

Model-1: A generalized Linear Model (GLM) was fitted using $\log_{10}$ (differentiated cases) as the response variable and $\log_{10}$ (climatic variables) with only the highest correlated lagged terms as the explanatory variables.

Model-2: All the lagged terms of climate variables were considered up to three lags before eliminating regression coefficients through significance. The final model was determined with significant coefficients.

For a more detailed study, the mean plus two standard deviation method was used to detect abnormal dengue transmission periods by modifying the recommendations of Badurdeen et al. [13,14]. Moreover, model-1 and model-2 were fitted again on the transformed dengue observations from abnormal transmission periods and with their respective climate variables. The R-squared values are used to compare the models.

3. Results and Discussion

Among climate variables, rainfall and average temperature contributed to dengue cases in the Matale region. Significantly correlated lags were identified through cross-correlation functions for rainfall and average temperature. The rainfall has a significant positive ($p<0.05$ at 95% confidence interval) association in 1-2-month lags while the temperature reached in 2-3-month lags.

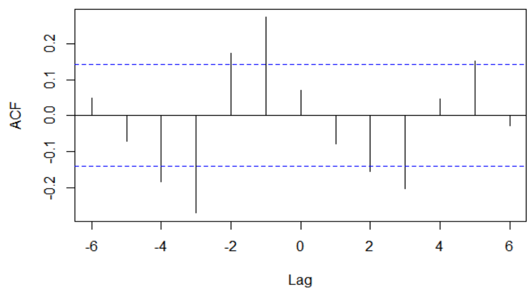

Figure 1: CCF- dengue cases and rainfall

Figures 1 and 2 show that lag 1 of rainfall and lag 2 of average temperature are the highest correlated lagged terms. Therefore, the GLM equation for model-1 was,

$$Y_t = \beta_0 + \beta_1(RF)_{t-1} + \beta_2(Temp)_{t-2}$$

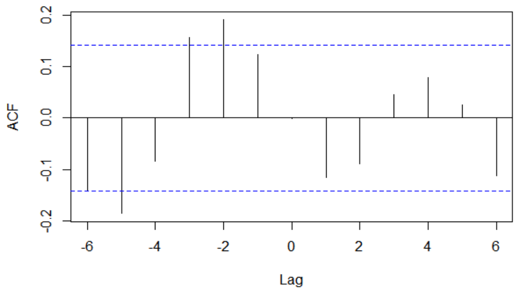

Figure 2: CCF- dengue cases and temperature

Where; Y_t is the predicted value of dengue observation at the time t and β_j is regression coefficient. RF_{t-j} is the $\log_{10}$ (Rainfall) at time lag j and $Temp_{t-j}$ is the $\log_{10}$(Temperature) at time lag j.

The results of model 1 are summarized in Figure 3. Figure 4 illustrates the results of model-2. After eliminating insignificant coefficients, the final model includes rainfall lags 1, 2, and temperature lag 2. The values of AIC, BIC, and RSS are summarized in Table 1.

```
Call:
glm(formula = Cases ~ RF_Lag1 + Temp_Lag2)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.7331  -0.9325   0.1496   0.9345   2.9668

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -18.7909     5.9717  -3.147  0.00192 **
RF_Lag1       0.8291     0.1792   4.626 6.93e-06 ***
Temp_Lag2    12.0175     4.1129   2.922  0.00391 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for gaussian family taken to be 1.4467)

    Null deviance: 307.70  on 190  degrees of freedom
Residual deviance: 271.98  on 188  degrees of freedom
  (2 observations deleted due to missingness)
AIC: 617.54

Number of Fisher Scoring iterations: 2
```

Figure 3: Output of model-1

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$$Y_t = 0.8291(RF)_{t-1} + 12.0175(Temp)_{t-2} - 18.7909$$

is the predicted regression equation of model-1. All the regression coefficients are significant at a 95% confidence interval with p<0.05.

$$Y_t = 0.7324(RF)_{t-1} + 0.5577(RF)_{t-2} + 17.2274(Temp)_{t-2} - 27.1462$$

is the predicted regression equation of model 2. Rainfall at a time lag of 1 is the most critical climate variable with the smallest p-value and standard error.

```
Call:
glm(formula = Cases ~ RF_Lag1 + RF_Lag2 + Temp_Lag2)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.5077  -0.9368   0.1958   0.8827   2.8195

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -27.1462     6.5068  -4.172 4.63e-05 ***
RF_Lag1       0.7324     0.1797   4.076 6.79e-05 ***
RF_Lag2       0.5577     0.1924   2.898 0.004205 **
Temp_Lag2    17.2274     4.4057   3.910 0.000129 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for gaussian family taken to be 1.396095)

    Null deviance: 307.62  on 189  degrees of freedom
Residual deviance: 259.67  on 186  degrees of freedom
  (3 observations deleted due to missingness)
AIC: 608.55

Number of Fisher Scoring iterations: 2
```

Figure 4: Output of model-2

Table 1: Measures of model performance

Model	AIC	BIC	RSS
1	617.54	630.533	271.9796
2	608.5	624.778	259.6736

Considering the lowest AIC, BIC, and RSS values, model 2 was selected. Figure 5 shows the distribution $\log_{10}$ (differentiated cases) predicted by rainfall and temperature. We were able to capture the pattern of dengue cases from the predicted values. The graph indicates that the climate variables alone are insufficient to detail all the information on dengue cases. The corresponding R-squared value of the model equals 0.16. Although we obtained a lower R-squared value, the smaller p-values for the estimates indicate the significant association between climate variables and dengue transmission.

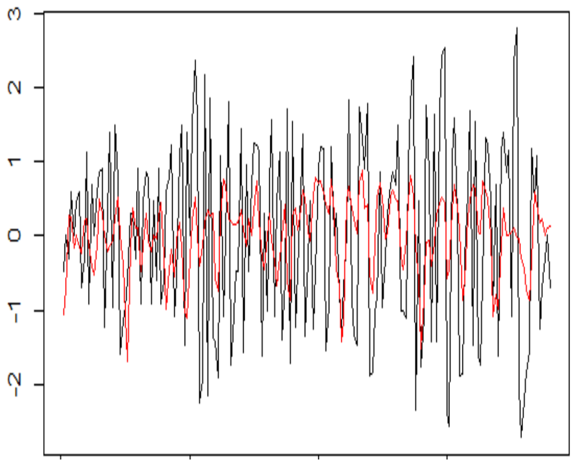

Figure 5: Actual dengue observations with fitted values. Red line represents fitted value and black line represents actual dengue observations.

The role of climate on the dengue outbreaks was evaluated after detecting epidemic periods. The highest correlated lags were obtained at rainfall lag1 and temperature lag2 on abnormal transmissions.

$$Y_t = 2.2805(RF)_{t-1} + 58.5671(Temp)_{t-2} - 88.3988$$

is the new predicted equation from model-1 considering extreme dengue cases alone. The respective R-squared value is 0.38. All the regression coefficients are significant here.

The refitted model-2 on abnormal transmission results in the following equation,

$$Y_t = 2.7733(RF)_{t-1} + 2.0224(RF)_{t-2} + 82.2899(Temp)_{t-2}$$

The R-squared value is 0.57, which explains 57% of information on dengue observation. As previously stated, it was only 16% when the entire series of dengue observations was included.

4. Conclusion

Dengue has been a critical public health problem in Matale and other parts of Sri Lanka. This study aimed to find a statistical method to ensure the role of climate variables on the occurrence of dengue while eliminating the weight from past lags. Generalized Linear Modeling is a powerful tool to explore the causal relationship between independent dengue observations and explanatory climate variables. The results of the models show that the number of dengue cases increases as rainfall and average temperature increases. The rainfall impacts dengue fever in 1-2 months and average temperature within 2-3 months. The degree of effect was minimal when we considered the entire dengue series from the study period. The impact was higher when it came to epidemic periods. Aside from predicting future dengue cases based on climate variables, we attempted to study the influence of climate alone on various dengue patterns, such as normal versus atypical transmissions. Adding more variables to the model to obtain more precise predictions would be useful.

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