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Modelling Dengue Fever (DF) and Dengue Haemorrhagic Fever (DHF) Outbreak Using Poisson and Negative Binomial Model

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***Abstract*—**Dengue fever has become a major concern for health authorities all over the world particularly in the tropical countries. These countries, in particular are experiencing the most worrying outbreak of dengue fever (DF) and dengue haemorrhagic fever (DHF). The DF and DHF epidemics, thus, have become the main causes of hospital admissions and deaths in Malaysia. This paper, therefore, attempts to examine the environmental factors that may influence the recent dengue outbreak. The aim of this study is two-fold, firstly is to establish a statistical model to describe the relationship between the number of dengue cases and a range of explanatory variables and secondly, to identify the lag operator for explanatory variables which affect the dengue incidence the most. The explanatory variables involved include the level of cloud cover, percentage of relative humidity, amount of rainfall, maximum temperature, minimum temperature and wind speed. The Poisson and Negative Binomial regression analyses were used in this study. The results of the analyses on the 915 observations (daily data taken from July 2006 to Dec 2008), reveal that the climatic factors comprising of daily temperature and wind speed were found to significantly influence the incidence of dengue fever after 2 and 3 weeks of their occurrences. The effect of humidity, on the other hand, appears to be significant only after 2 weeks.

***Keywords*—**Dengue Fever, Dengue Hemorrhagic Fever, Negative Binomial Regression model, Poisson Regression model.

I. Introduction

DENGUE fever (DF) encompassing both the classical dengue fever and dengue hemorrhagic fever (DHF) are the main causes of morbidity and mortality in Malaysia and other tropical countries. The number of hospitalizations and reported deaths due to DF and DHF were alarming. The problem remains endemic despite enormous efforts and money being put into its control. 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. An important component of the dengue control program is the dengue surveillance which is practical, cost effective and serves as an early warning program so that corrective actions could be taken before an outbreak occurs. In Malaysia, various dengue control measures have been implemented involving the public and relevant authorities. Currently, the control program depends on the prompt notification once a patient is being admitted for suspected dengue case. Public health authorities will identify the target area based on the notification of cases and would then gear-up the vector control activities to minimize the spread. Part of the activities includes: house and premises inspections for Aedes surveillance, fogging in areas where a case is reported larviciding to destroy larval stages of Aedes mosquito, and enforcement of Destruction of Disease Bearing Insects Act in 1995 [1].

The dengue control programs are aimed to tackle the spread of the disease which are related to numerous complex and interrelated factors such as the environment, socio-economic and human behaviors. Although environmental factors have been reported to contribute to the increase in the breeding of mosquito vectors and hence the disease, no comprehensive scientific studies have been conducted to critically examine the role of these factors in enhancing dengue transmission [2]. Nor Azura et al. [3] who highlighted this issue argued that there is insufficient discussion about the suitable model to predict the future dengue outbreak.

Aedes mosquitoes, as a biological creature depend on temperature, water as well as few other climatic factors to complete their lifecycles. This may include also the virus transmission. 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 [4]. Thus, a comprehensive and up-to-date climatic information are the prerequisite in order to draw the action plans to alleviate the adverse impacts of any vector borne disease outbreak. Hence, this study aimed to identify the antecedent climatic factors that may influence the spread of dengue and also to identify the lag periods pertaining to the explanatory variable that have significant effect on the dengue incidence.

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II. Mosquito Lifecycle and Climate Change

The epidemiological cycle of dengue fever occurs when the female Aedes mosquitoes are infected during the blood meal from infectious individuals. The viruses are transmitted when the adult a female Aedes mosquitoes bites and sucks blood containing the dengue virus from infected person which then goes through a period known as ‘incubation’ period for the virus to replicate itself in the mosquito's body. This lasted about seven to twelve days after which it will be able to transmit the infection to another person. Usually, the symptoms of dengue fever will emerge after three days of infection. The infectious period lasted throughout its life-span of 2-3 weeks [5]-[8].

The life cycle of a mosquito consists of four stages: i) egg ii) larva iii) pupa, and iv) adult. Each of these stages can be easily recognized by their special appearance (Fig 1). On average, a female Aedes mosquito can lay about 300 eggs during her life span. Laid singly on the sides of water-holding containers such as bottles, can, tires, animal watering dishes, birdbaths, flowerpots and natural holes in vegetation. A period of about 48 hours is required for the eggs to hatch into larva. However, under optimal conditions, the egg of an Aedes mosquito can hatch into a larva in less than a day. The larva then takes about four days to develop into a pupa from which an adult mosquito will emerge after two days. Three days after the mosquito has bitten a person and taken in blood, it will lay eggs, and the cycle begins again [9].

Like any other mosquito-borne diseases, the transmission of the dengue fever is sensitive to climatic change. For instance, the Aedes mosquitoes require standing water to breed, and a warm ambient temperature is critical to adult feeding behavior and mortality; the rate of larval development, and speed of virus replication. If the climate is too cold, viral development is slow and mosquitoes are unlikely to survive long enough to become infectious. In addition, the number of eggs laid by female adult Aedes depends on the optimal temperature [10].

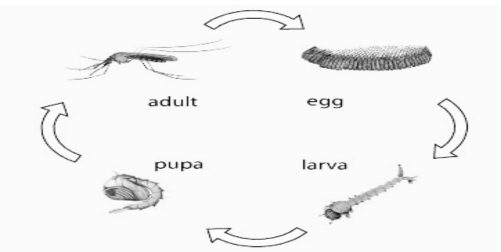

Fig. 1 Four Stages of Mosquito Lifecycle
(Source: http://www.mosquitoes.org)

The virus incubation period in Aedes mosquitoes is closely related to temperature which takes about 7 to 12 days to replicate. Furthermore, seasonal variations in temperature and rainfall have been observed to be correlated with levels of dengue infection, with a higher number of dengue cases associated with higher rainfall and temperature, resulting in the increases in mosquito breeding sites and the creation of water bodies for the developmental stages of egg, larva and pupa [4], [6],[8].

III. Data and Methodology

A. Data and Climatic Factors

This study was conducted in the new Federal capital of Putrajaya, Malaysia with a population of several thousands. Dengue cases data were extracted from the list of all admissions to the particular ward at the Hospital Putrajaya (HPJ), starting from July 2006 until December 2008. The data were recorded in designated module from the daily census in the Health Management Information System (HMIS) used at the hospital. It represents the number of DF/DHF patients admitted to Putrajaya Hospital in a day during the period of study (July 1st, 2006 to Dec 31st 2008). Being a specialist hospital and national referral centre for breast and endocrine specialities, the HPJ’s patients come from all over Malaysia. However, for dengue cases, almost all patients are from Putrajaya and surrounding areas such as Bangi, Kajang, Puchong, Dengkil and Sepang.

To model the dengue fever incidence, several climatic factors were used as explanatory variables. Data for daily climatic variables were collected from the Malaysian Metereologist Department provided by Petaling Jaya and Bangi weather station.

Cloud refers to mean cloud cover in a day. The values of cloud cover were estimated by trained observers from a meteorological station on the ground and measured in oktas (or eighths of the sky). These value estimates were given to the closest value only, scaled from 0 till 10. A value of 0 referred to clear sky, while 8 oktas or 10 on the decimal scale indicated overcast. Such estimates were representative of conditions within the range of visibility of the observer.

Humid refers to the mean relative humidity for a particular day. It is defined as the ratio of the partial pressure of water vapor in a gaseous mixture of air and water vapor to the saturated vapor pressure of water at a given temperature. Relative humidity is measured by a device called hygrometer and expressed as a percentage (%).

Rain refers to the daily rainfall amount (in millimeter) for a particular day. It was collected over the 24-hour period beginning from 08.00 a.m. till the next the day. Rain is the primary source of fresh water for most areas of the world, providing suitable conditions for diverse ecosystems.

Temp_max and Temp_Min refer to temperature, which is one of the principal parameters of thermodynamics which has been scientifically proven to have an impact towards ecological system. It was measured with thermometers and the values in a day might vary according to time and other climatic factors. In this study, the variable Temp_max and Temp_min refer to the maximum and minimum temperature recorded in a day respectively.

Wind refers to average wind speed of the day at the weather station. It measures the movement of air and other gases in an atmosphere at the surrounding area of measurement.

TABLE I
CLIMATE VARIABLES, VARIABLE LABEL AND UNITS OF MEASUREMENT

	Climate Variables	Variable Label	Units of Measurement
7.	Daily Cloudiness	Cloud	Oktas
8.	Daily Relative Humidity	Humid	%
9.	Daily Rainfall	Rain	mm
10.	Maximum Daily Temperatures	Temp_max	^{0}C
11.	Minimum Daily Temperatures	Temp_min	^{0}C
12.	Daily Windspeed	Wind	m/second

The list of the explanatory variables and their respective definition are shown in Table I.

B. Statistical Model

To model the dengue cases series, the Generalized Linear modeling incorporated GENSTAT [11] software was used in this study. The Poisson regression analysis was used since the distribution of dengue cases data is in a form of Poisson distribution function. Poisson distribution appears to be appropriate when the response variable consists of nonnegative integers and is not normally distributed [12]-[14]. Furthermore, the occurrence must be random and independent of each other. Poisson regression is a regression technique available for modeling variables that describe count or discrete data of the occurrences of some event over a specified interval. This is a common process in clinical and epidemiological research [15], [16].

The dependent variable used is the number of dengue cases per day, DENGUE, while the explanatory variables were CLOUD, HUMID, RAIN, TEMP_MAX, TEMP_MIN and WIND. The Poisson regression analysis assumes that the underlying distribution of the response variable Y under consideration is Poisson. The Poisson probability distribution with parameter μ is given by the formula:

$$pr(Y:\mu)=\frac{e^{-\mu_i}\mu_i^{Y_i}}{Y_i!},\quad Y_i=0,1,2,...,\infty \tag{1}$$

where Y_i is a random variable representing the number of dengue cases at day i for a given period, μ_i is both mean and variance of Y_i. In order to develop a dengue fever model, μ_i is expressed as a function of some explanatory variable through log link function in the following form:

$$\ln\mu_i=\beta' x_i \quad \text{or} \quad \mu_i=exp\left(\beta' x_i\right) \tag{2}$$

The logarithm of the response variable is linked to a linear function of explanatory variables such that:

$$log_e\left(Y\right)=\beta_o+\beta_1 X_1+\beta_2 X_2+\ldots+\beta_i X_i \tag{3}$$

and $$Y=\left(e^{\beta_o}\right)\left(e^{\beta_1 X_1}\right)\left(e^{\beta_2 X_2}\right)\ldots\left(e^{\beta_i X_i}\right) \tag{4}$$

In other words, the typical Poisson regression model expressed the log outcome rate as a linear function of a set of predictors. However, in multivariate time series analysis, the impact of the explanatory variables X on Y is seldom instantaneous. In most cases, for instance the dengue cases, Y responds to climatic factors of X after a lapse of time or commonly known as "lag". Thus, the daily dengue cases are regressed with the respective lagged climates variable datasets on the basis on the Finite Distributed Lagged (FDL) Model. In FDL, a change in independent variable does not necessarily lead to an immediate change in the dependent variable [14],[17]. Thus, the lag climate data used in this study consist of 7, 14, 21 and 28 days lag operator. The Poisson regression analysis with FDL for each of the datasets will consider the following model;

$$\begin{aligned}Log_e\left(dengue\,cases\right)&=\beta_o+\beta_1\left(Cloud\right)_{t-i}+\beta_2\left(Humid\right)_{t-i}+\\&\beta_3\left(Rain\right)_{t-i}+\beta_4\left(Temp\_Max\right)_{t-i}+\\&\beta_5\left(Temp\_Min\right)_{t-i}+\beta_6\left(Wind\right)_{t-i}\end{aligned} \tag{5}$$

where β_o is constant, $\beta_1,\ldots,\beta_6$ are the unknown parameter values to be estimated and i is a finite distributed lag operator.

In Modeling Poisson regression model, one of the major assumptions is the equality of the mean and variance. If this assumption is violated, an overdispersion problem can arise. In order to overcome the overdispersion, this study considered the generalization of Poisson model that is the Negative Binomial regression model as suggested by Breslow [18]. The negative binomial distribution is a form of the Poisson distribution in which the distribution's parameter is itself considered a random variable. The variation of this parameter can account for a variance of the data that is higher or lower than the mean. This condition whereby the variance is higher than the mean is known as 'overdispersion'. When overdispersion exists, the variance function in negative binomial is introduced. Negative binomial regression can be considered as a generalization of Poisson regression and assumes that the conditional mean μ_i of Y_i is not only determined by X_i but also a heterogeneity component e_i unrelated to X_i. The formulation can be expressed as:

$$\mu_i=exp\left(X_i\beta_i+e_i\right)=exp\left(X_i\beta_i\right)exp\left(e_i\right)$$

where $exp\left(e_i\right)\sim Gamma\left(\alpha^{-1},\alpha^{-1}\right)$ (6)

As a result, the density function of Y_i can be derived as:

$$f\left(Y_i\,|\,X_i\right)=\frac{\Gamma\left(Y_i+\alpha^{-1}\right)}{\Gamma\left(Y_i+1\right)\Gamma\left(\alpha^{-1}\right)}\left(\frac{\alpha^{-1}}{\alpha^{-1}+\mu_i}\right)+\left(\frac{\mu_i}{\alpha^{-1}+\mu_i}\right)^{Y_i} \tag{7}$$

where Γ denotes the gamma integral which specializes to a factorial integer argument [19].

The estimation of the parameters is done by maximizing the log likelihood function of;

$$\ln L(\beta)=\sum_{i=1}^{n}\left(y_i x_i'\beta-\exp(x_i'\beta)-\ln y_i!\right) \tag{8}$$

The solution to the set of Maximum Likelihood Estimator is done using numerical method generated using the computer-based iteration procedure in GenStat [18].

IV. SIGNIFICANCE TESTING

This study used the maximum likelihood ratio statistics or commonly known as Deviance (D) statistics to test for the goodness of fitted model for both Poisson and Negative Binomial model.

Deviance D in the normal linear regression is similar to R^2 or coefficient of determination which is used to provide the descriptive information about the model fit and is calculated by:

$$R^2 = \frac{\sum(\hat{y}-\bar{y})^2}{\sum(y-\bar{y})^2} \tag{9}$$

where y is the observed value of y, $\hat{y}$ is the value of y predicted from the model, and $\bar{y}$ is the mean value of y.

In Poisson regression, the residuals are neither normally distributed, nor do they have constant variance. Due to non linear characteristic of the conditional mean, some measures alternatives to R^2 have been suggested [14], [19]. The log-likelihood Ratio Statistic (Deviance) is introduced to check the appropriateness of a chosen response distribution when explanatory variables are added or excluded from the model. The Deviance value is defined as:

$$Deviance\,(D) = 2\left\{\sum_i \left[y_i \ln(y_i / \hat{\mu}_i) - (y_i - \hat{\mu}_i)\right]\right. \tag{10}$$

For a well fitted model with appropriate link function, error distribution and functional form, the expected value of residual deviance should approximately be equal to the number of degree of freedom, regardless of the value of μ.

V. Results

A. Descriptive Epidemiology

Based on the information obtained from the 915 dengue cases, the average number of dengue cases under study was about 2 cases per day with the highest case recorded of 10 cases per day. For most of the days under study, the average cloud cover in the skies per day was about 7.04 Oktas ranging from 6.5 Oktas to 8 Oktas. In addition, it was also found that the differences between minimum and maximum relative humidity were wide. Relative humidity for a particular day was distributed with mean and standard deviation values of 76.46% and 6.93% respectively. The humidity pattern was quite similar with dengue case series pattern. The average daily rainfall amount was 7.89 mm with frequent peaks in April and through October to December. The average maximum and minimum temperature during the period of study were 32.75ºC and 23.77 ºC respectively. For maximum and minimum temperature, the range was between 25ºC to 35ºC and 21ºC to 26ºC respectively. Wind speed across the period of study had large variations at coefficient of variation of 26.4%. The wind speed ranged from smallest value of 0.3 m/s to 4 m/s across the period. However, the difference across the average monthly value did not vary much as it only ranged between 1 m/s to 2 m/s.

B. Regression Analysis on Lagged Dataset

In modelling the dengue cases, 16 different models (2 procedures × 2 methods × 4 lagged datasets) were estimated using Finite Distributed Lag (FDL) regression model. Starting with a saturated model that involved all possible explanatory variables, a procedure for eliminating insignificant variables using backward and stepwise was undertaken and the most parsimonious model was obtained on the basis of the Deviance value.

The level of statistical significance was indicated by the ratio of the parameter to the standard error of the estimate. The resulting models using Finite Distributed Lag (FDL) regression model were shown in Table II. Models were estimated using four different lagged values of explanatory variables based on 7, 14, 21 and 28 days. The analysis on the effect of climatic variables for 7 days lagged towards dengue incidence is shown in Model A. In its reduced form, for the Poisson Model, PA, only Humid, Temp_max and Temp_min were significant at 5% confidence level. Though the terms were significant, the constant values were still insignificant. To allow for overdispersion, the full model of Negative Binomial NBA was estimated resulting in only one significant variable of minimum temperature. The reduced model of NBA indicates that the constant term and minimum temperature were significant, however this model was unsatisfactory.

For lagged 14 days data, the climatic variables that had significant effect on dengue incidence were the Humid, Temp_max and Temp_min and Wind. However, based on the reduced Poisson model, the constant parameter of the model remains insignificant. The Negative Binomial model indicates that variable Humid, Temp_min and Wind speed have significant influence on the dengue fever incidence with significant constant term. The mean deviance of the reduced model NBB was the second smallest from the 16 models examined. This model appears to be satisfactory for indicator of dengue incidence based on 14 days lagged climate data.

The analyses on the effect of climatic variables for 21 days lagged towards dengue incidence were presented by Model C. From the overall Poisson model of PC, it can be seen that only Temp min and Wind are the significant terms at the 5% confidence level. The reduced Poisson model PC shows that the overall terms are significant. However, the value of mean deviance in Model PC indicates the existence of overdispersion. Allowing for this factor the reduce Negative Binomial model gave the best reduction of scaled deviance per degree of freedom in model NBC and all terms included were highly significant. Reduced variables selection procedures result in all predictors and constant being significant. The mean deviance value for this model is the lowest among 20 models examined. This model is also satisfactory as an indicator for the incidence of dengue fever using 21 days lagged climate data.

The analysis on the effect of climatic variables using 28 days lagged towards dengue incidence were shown in the last model of Model D. The reduced Poisson model of PD shows that Temp min and Wind are significant at the 5% confidence level. After being corrected for overdispersion, the constant term is still insignificant. Therefore, after comparing the 16 different models, it can be concluded that the regression equation for the suggested model to explain dengue incidence

TABLE II
POISSON AND NEGATIVE BINOMIAL REGRESSION MODEL WITH LAGGED OPERATOR

	Dependent Variable: Dengue Cases							
	MODEL A LAG 7 DAYS		MODEL B LAG 14 DAYS		MODEL C LAG 21 DAYS		MODEL D LAG 28 DAYS	
	Poisson PA	NegBin NBA	Poisson PB	NegBin NBB	Poisson PC	NegBin NBC	Poisson PD	NegBin NBD
Constant	0.888	-2.78*	-0.85	**-2.42***	-2.188*	**-2.27***	-0.972	-1.12
	(0.993)	(1.07)	(1.03)	**(1.14)**	(0.768)	**(1.07)**	(0.769)	(1.07)
Cloud								
Humid	-0.01323*		-0.02042*	**-0.01583***				
	(0.00386)		(0.00426)	**(0.00539)**				
Rain								
Temp_Max	-0.0351*		-0.046*					
	(0.0178)		(0.0179)					
Temp_Min	0.1524*	0.1413*	0.205*	**0.1914***	0.1306*	**0.1333***	0.0884*	0.0933*
	(0.032)	(0.0447)	(0.0322)	**(0.0443)**	(0.0321)	**(0.0449)**	(0.0322)	(0.0448)
Wind			0.2227*	**-0.2072***	-0.1973*	**-0.1868***	-0.3209*	-0.2999*
			(0.0621)	**(0.0847)**	(0.0567)	**(0.0594)**	(0.0579)	(0.0793)
Degree of Freedom	911	913	910	**911**	912	**912**	912	912
Deviance	1634	1016	1605	**1017**	1638	**1016**	1628	1018
Mean Deviance	1.793	1.113	1.763	**1.117**	1.796	**1.114**	1.785	1.116

in Putrajaya is best explained by climate data with lag operator of 14 and 21 days. Based on lag of 14 days climate data, the dengue fever incidence are significantly being influenced by humidity, minimum temperature and wind speed factor. However, if we use the climate data with of lag 21 days, the dengue incidence is likely to be influenced only by the minimum temperature and the wind factor.

VI. CONCLUSION

This study focused on how the climate variable and the effect of lagged operator can influence the occurrence of dengue fever (DF/DHF) in Putrajaya. By applying the Poisson and Negative Binomial regression analysis, the best model to describe the dengue outbreak was found to be significant in the analysis using lagged operator of 14 and 21 days climate data. Both models gave the best reduction of scaled deviance per degree of freedom and all terms included were highly significant and consistent whilst holding the principal of parsimony intact.

Based on the above arguments, it can be concluded that the best model to explain the dengue outbreak per day using lagged of 14 days climate data is:

$$Dengue_t = 0.08892\left[e^{-0.01583Humid_{t-14}}\right]\left[e^{0.1914Temp\_Min_{t-14}}\right]\left[e^{-0.2072Wind_{t-14}}\right] \quad (11)$$

The following conclusions can be made based on the model (11) developed:

1) Daily Humidity is an important variable to explain the dengue incidence outbreak. The past 14 days of humidity value is estimated to negatively influence the incidence of dengue cases by 1.57 %..
2) Daily minimum temperature is also an important variable which affects the dengue incidence. The past 14 days minimum temperature value is estimated to positively influence the incidence of dengue cases by 21.09%.
3) Daily wind speed is another important variable to reflect on the dengue incidence. The past 14 days wind speed value is estimated to negatively influence dengue cases by 18.71%.

Another significant predictor to explain dengue outbreak per day is the climatic data of lag 21 days. The best model using lagged 21 days climate data is:

$$Dengue_t = 0.1033\left[e^{0.1333Temp\_Min_{t-21}}\right]\left[e^{-0.186Wind_{t-21}}\right] \quad (12)$$

The following conclusion can be made based on model (12) above:

1) Daily minimum temperature is an important variable to be considered in this model. The past 21 days minimum temperature value is estimated to positively influence the dengue cases by 14.25%.
2) While the daily wind speed is also an important variable. The past 21 days wind speed value is estimated to negatively influence dengue cases by 16.97%.

In general, for dengue virus to spread, the vector and pathogen of the virus must accommodate certain climate conditions. Aedes life cycle and their metabolic rates are dependent on various environmental conditions such as temperature and hydrology in order to survive. Temperature has a direct relationship with the metabolic of Aedes mosquitoes. It promotes mosquito larva development, expands the geographic range of the vector, increases the biting rate, and shortens the pathogen incubation period in their bodies. All previous studies on climatic effect towards dengue incidence have established that temperature, wind speed and humidity are the significant predictors [4], [10], [20]. In conclusion, based on the evidence presented, this study, therefore, supports the results from findings of several studies made earlier.

VII. RECOMMENDATIONS

A. Recommendation for Public Health Authority

In this study, minimum temperature and wind speed at lag 21 days have been identified as significant predictors towards dengue incidence in Putrajaya. Thus, for a particular day, an observation towards the minimum temperature in a day and wind speed can be estimated to have some impact in the number of dengue cases within the next 21 days (3 weeks). If the minimum temperature recorded increases from the previous day, the number of dengue cases is expected to increase in the next 21 days. The negative association of wind speed with the number of dengue cases means that if the average wind speed in a day is increasing from the previous day, in the next 21 days the number of dengue cases is expected to decrease and vice versa. Therefore, to the health authorities in Putrajaya are advised to give special attention to these two climates data as the value recorded in particular day can lead to the next 21 days estimation of dengue cases. If the minimum temperature for several days in a week keeps on increasing or showing the values above the normal range, health authorities can speed up the dengue control program in the potential infected area.

B. Recommendation for Further Study

In this study, climatic data from Petaling Jaya and Bangi were used to measure their effect on dengue cases variability in Putrajaya area. The weather and climate in Petaling Jaya and Bangi were assumed similar to those in Putrajaya. However, some might argue that in Malaysia the climates are different between localities. Therefore, in order to resolve this issue, in the future study the researcher can adopt the Principal Component Analysis (PCA) procedure to find the estimated weather in Putrajaya. Climates measure recorded from several weather stations located in the area surrounding Putrajaya can be used in the analysis. For instance, the previous study across 8 provinces in Indonesia [22] had performed a PCA on 63 weather stations to produce 5 different rainfalls region on a study of dengue incidence. Therefore, further study can apply the PCA on the climates data from Petaling Jaya, Sepang and Bangi since these three weather stations are located in areas surrounding Putrajaya.

Dengue cases are subjected to various factors as briefly specified in the limitation of this study. Any further study may incorporate all factors into the analysis to produce an integrated analysis of the predictors. Number of population and number of construction project are among the socio-economic indicators that can be analyzed in the model. Further study can also be made towards dengue cases in other areas. Previous study has found a strong association between dengue cases and climates that varies between its regions [23]. Therefore, further research is recommended to see whether regional differences are also applicable in Malaysia.

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