# Weather Factors Associated with Reduced Risk of Dengue Transmission in an Urbanized Tropical City

**Hao Gui**
National University Singapore Saw Swee Hock School of Public Health

**Sylvia Gwee**
National University Singapore Saw Swee Hock School of Public Health https://orcid.org/0000-0003-0985-4750

**Jiayun Koh**
National University Singapore Saw Swee Hock School of Public Health

**Pang Junxiong** ( ephpjv@nus.edu.sg )
National University Singapore Saw Swee Hock School of Public Health https://orcid.org/0000-0002-9788-701X

---

**Research**

**Keywords:** Dengue, weather factors, temperature, rainfall, weather change

**Posted Date:** January 25th, 2021

**DOI:** https://doi.org/10.21203/rs.3.rs-152519/v1



---

# Weather Factors Associated with Reduced Risk of Dengue Transmission in an Urbanized Tropical City.

Gui Hao[a,b], Sylvia Gwee[a,b], Koh Jiayun[a,b], Pang Junxiong[a,b]

1. Saw Swee Hock School of Public Health, National University of Singapore and National University Health System, Singapore, 12 Science Drive 2, #10-01, Singapore 117549; ephgh@nus.edu.sg (G.H); ephsgxw@nus.edu.sg (G.S.X.W); ephkj@nus.edu.sg (K.J.Y); ephpjv@nus.edu.sg (P.J)

2. Centre for Infectious Disease Epidemiology and Research, National University of Singapore, Singapore, 12 Science Drive 2, #10-01, Singapore 117549

Corresponding author:

Pang Junxiong

Email: ephpjv@nus.edu.sg

Postal Address: 12 Science Drive 2, #10-01, Singapore 117549

# Abstract

*Background*

The association of weather factors on dengue transmission in an urbanized tropical environment remains inconclusive. This study aims to assess the impact of weather factors on dengue incidence in Singapore between 2012 and 2019.

*Methods*

Data on weather variables (daily temperature, air quality, rainfall & wind speed) and weekly dengue incidence rates were collected from 1 January 2012 to 25 August 2019. Statistically significant correlated variables identified from cross-correlation analysis using Pearson's correlation were examined in univariate ARIMA model. A distributed lag non-linear model (DLNM) with Quasi-Poisson model was established to assess any non-linear association between climatic factors and dengue incidence. The Quasi-Poisson model coefficients were evaluated using Quasi Akaike's Information Criterion (QAIC). To validate the model, the data was split into testing and validation sets, with QAIC, Mean Absolute Error (MAE) & Root Mean Square Error (RMSE) reported.

*Results*

Pollutant Standards Indices (PSI) greater than 100 was associated to lower weekly dengue incidence at a 5-week and a 7-week lag period. High wind speeds at 5-week lag time was also associated with reduced dengue transmission. Mean and minimum temperatures of 28°C and 25°C respectively were associated with reduced risk of weekly dengue transmission across all lags effect. Mean temperatures above 28°C at a 1-week lag and maximum temperatures above 32°C at an 11-week lag promoted dengue transmission. Rainfall was not correlated with dengue cases in Singapore.

Based on split-sample model validation, mean temperature was the best predictor of dengue (MAE: 43.15, RMSE: 51.39). Weather factors had varied influence on both pre-epidemic surge periods and non-epidemic periods, but had a stronger correlation with dengue transmission in non-epidemic periods.

*Conclusions*

Poor air quality and high wind speeds were associated with reduced risk of dengue transmission in an urbanized tropical environment. Only a limited temperature range promotes dengue transmission.

**Keywords:** Dengue, weather factors, temperature, rainfall, weather change

# 1. Introduction

Dengue is a mosquito-borne viral disease that is endemic in tropical and subtropical regions. Globalization and global warming, however, have facilitated its expansion to non-endemic countries over the years (1, 2). An estimated 50 to 200 million dengue infections occur annually, with more than half the world at risk of infection (3). The disease may escalate and cause dengue haemorrhagic fever (DHF) in a small minority, and the annual death toll from dengue lies between 20,000 and 25,000. Four antigenically distinct serotypes (DENV1/2/3/4) co-circulate globally, but DHF is more often associated with DENV2 and DENV3 infections (4-6).

The occurrence of dengue epidemics in endemic countries are multifactorial (7) and are reflective of the interplay between host, vector, virus & environment in disease transmission. Factors that drive epidemics include a change in predominant serotype (8, 9), or lowered herd immunity due to waning immunity and increased proportion of susceptible individuals accompanying population replacement (10, 11). Climatic factors are also integral to dengue transmission, as reflected by the seasonal nature of the disease (12, 13).

Recent studies have attributed *Aedes Aegypti* adaptation to outdoor environments as a major factor driving dengue transmission worldwide (14). In urban settings, outdoors breeding of Aedes aegypti in rainwater accumulating containers gives an indication of how climatic factors support environment factors that influence vector growth (15, 16). There is much evidence that meteorological factors including temperature, rainfall, humidity, and air quality influence vector growth and distribution both directly and indirectly. Studies have found that a temperature rise of up to 34°C increases all stages of *Aedes Aegypti* developmental rates, resulting in population growth (17). Increased dengue transmission under warmer temperatures can also arise from faster viral replication within the vector, shortened extrinsic incubation period, and increased feeding rate of *Aedes Aegypti* (17-19). Humidity also increases viral propagation and hatch percentage of *Aedes Aegypti* eggs (20, 21). Human practices coupled with climatic factors, such as water storage in dry climates, can also encourage mosquito productivity and dengue transmission (22).

In general, the significant effect of warmer temperatures on increased dengue rates is largely consistent across studies, while the role of humidity, air quality, rainfall and haze on dengue transmission is not clear and less often studied (8, 23, 24). A comprehensive understanding of how meteorological factors influence vectors and humans is crucial for disease forecasting

and control. Additionally, it has been recognised that predictive models for dengue transmission need to account for the interaction between climatic factors and be contextualised to specific population settings.

Singapore is a tropical country where dengue resurgence typically occurs in a 5-6 year cycle, but the last decade has seen dengue escalate to records numbers (9, 25). Despite aggressive vector control programs and public awareness campaigns, dengue cases surpassed the tens of thousands between 2013 and 2019 (9, 26, 27). Another strategy adopted by the Singapore government has been to publicise data on real-time distribution of cases and hotspots as part of timely alerts to the community (9, 25, 28). Nonetheless, evidence has shown that vector control is the most effective means to reduce dengue transmission (11), and it is envisaged that predictive surveillance and targeted response would be an efficient long-term strategy.

Hence, this study aims to assess the association between multiple weather factors and dengue incidence in Singapore between 2012 and 2019, as well as examine the role of less well-characterised weather variables including air quality and wind speeds. This would help inform dengue predictive models in the regional guide targeted disease control efforts.

# 2. Materials and Methods

## 2.1 Data collection

Weekly notified dengue cases in Singapore from 1 January 2012 to 25 August 2019 were collected from the Weekly Infectious Diseases Bulletin published by the Ministry of Health (28). Daily climatic data collected included mean, maximum & minimum temperature (°C), total rainfall (mm), wind speed (km/h) and pollutant standard index (PSI), all of which were obtained from the National Environment Agency (29). The data was collected across 63 meteorological stations evenly distributed over Singapore. City-wide data points were obtained by averaging across all stations while daily figures were averaged across each reporting week to obtain weekly-representative data. The total population data was based on the mid-year human population of the respective year from the Singapore Department of Statistics (30).

## 2.2 Statistical Analysis

### Autoregressive integrated moving average (ARIMA) Model

Autoregressive integrated moving average (ARIMA) is a class of models that 'explains' a given time series based on historical values. For initial analysis, the univariate ARIMA model was built to capture the time structure of dengue cases. Meteorological variables with appropriate lags were added as exogenous variables to improve the model.

The equation used for ARMA(p, q) model is as follows:

$$y_t = c + a_1 y_{t-1} + \cdots + a_p y_{t-p} + u_t + m_1 u_{t-1} + \cdots + m_q u_{t-q}$$ – Equation 1

Where $y_t$ is the target time series value at time t; c is constant; $u_t, u_{t-1}, \ldots, u_{t-q}$ are white noise error terms; $a_i$ (i = 1, 2, …, p) and $m_i$(i = 1, 2, …, q) are corresponding parameters. Since the time series graph (Figure 1) indicated a long-term trend and non-stationary trait clearly, first-differencing of the data was conducted to build the ARIMA model. Log-transformation of weekly dengue cases numbers was conducted to stabilize the variance.

In the selection of exogenous variables, pre-whitened cross correlation analysis was conducted to determine the appropriate lag time of weather factors in weeks to be incorporated in the model. The cross-correlation function (CCF) graphs showed all climatic factor correlations with weekly dengue incidence while accounting for lagged effects, at a significance level of 0.05. Due to autocorrelation of both time series, inference of coefficient's correlation may not be robust and pre-whitening technique was applied to circumvent this (31). Both Pearson and Spearman correlation were considered for linear and monotonic relationship respectively.

### Distributed Lag Non-Linear Model

Recognising that not all relationships between weather and dengue cases are linear in practice, non-linear associations were also explored using a Distributed Lag Non-linear Model (DLNM) (32). The number of weekly dengue cases was assumed to follow an over-dispersed Poisson distribution (33). Instead of using simple Poisson regression, Quasi-Poisson regression with DLNM was considered to account for over-dispersion. The model equation for DLNM in this study is (20) as follows:

$$\log(E(y_t)) = \beta_0 + \beta_1 \log(y_{t-1}) + \beta_2 \log(y_{t-2}) + s_1(x_{t,j}, l_j, \delta_1, \delta_2, \Phi_j)$$

$$+ s_2(t, \delta, \Psi) + \log(N_t) \text{ – Equation 2}$$

$y_t$ is the number of dengue cases at week $t$, while $\beta_1$ and $\beta_2$ are the coefficients of the autoregression terms — Two autocorrelation terms were introduced into models as the ARIMA model and residual analysis indicated that dengue cases from the past two weeks would be significantly correlated with current number of cases. $s_1(x_{t,j}, l_j, \delta_1, \delta_2, \Phi_j)$ is the cross basis of distributed lag non-linear terms with $x_{t,j}$ representing a single weather factor at week t and $l_j$ representing the maximum lag number. A natural cubic spline (ns) smoothing method with $\delta_1, \delta_2$ degree of freedom (df) was used to describe the non-linear effect in both weather factor and lag time respectively, with $\Phi_j$ denoting corresponding coefficients. $s_2(t, \delta, \Psi)$ is another term processed with the ns function to describe the long-term trend of dengue cases, with $\delta, \Psi$ representing df of ns function and corresponding coefficients. Here, the df is assigned to be 1 per year, therefore the $\delta$ equals to duration of study period in years (approximately 8 years). $\log(N_t)$ is the offset term that considers the effect of differences in Singapore's mid-year population.

Quasi Akaike's Information Criterion (QAIC) was applied to judge the goodness of fit.

$$QAIC = -2\mathcal{L}(\widehat{\Theta}) + 2\widehat{\phi}k \text{ – Equation 3}$$

As shown in the equation above, $\mathcal{L}(\widehat{\Theta})$ is the log-likelihood of estimated parameters, $\widehat{\phi}$ is the estimated over-dispersion parameter and k is the number of parameters. Instead of using the same degree of freedom for all weather factors, we applied grid search method to derive the best degree of freedom for each factor, which satisfied both parsimony and fit accuracy based on QAIC. Thereafter, values between 1-5 was selected for $\delta_1$ term in equation 2, while values between 1-3 was selected for $\delta_2$. The selected values for maximum lag numbers $l_j$ in equation 2 was 0-16 weeks (i.e. roughly four months).

The exposure-response relationship estimated by DLNM was visualised with graphical representations, including 3D graphs, contour graphs, sliced graphs and overall effect graphs (32). The median of each climatic variables was used as the reference when building the DLNM model, in line with the aim of examining non-linear trends with possible threshold effects. Results of analysis could be described with relative risk (RR).

Preliminary multivariate analysis was carried out by including cross basis of each weather factor into DLNM. The procedure of variable selection was based on QAIC and forward

selection method was applied. In addition, sensitivity analysis was performed by changing degree freedom of natural cubic spline terms to check robustness of model.

**Prediction performance of the models**

In order to measure the predictive ability of the model, the data was split into two parts: The data from year 2012 till end of 2018 data was used as the training set, and the data from year 2019 was used as the validation set. Models were applied on training set to estimate the coefficients and make the prediction on validation set. The prediction power was measured by Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) — The smaller these values, the better the prediction is.

**Time series of epidemic surge periods and non-epidemic periods**

The study period was divided into two parts based on incline/decline patterns of the dengue time series, these comprise of epidemic surge periods (*Epi A-D*), and non-epidemic periods (Non-*Epi A-D*) that fall outside of surge periods. The specific time periods of epidemic surge periods identified are as follows: *Epi A* (2012-12-09 to 2013-06-16), *Epi B* (2014-02-23 to 2014-06-29), *Epi C* (2015-03-09 to 2016-01-07), *Epi D* (2018-10-28 to 2019-07-07). The determination of epidemics interval is according to the increasing trend shown between trough and peak in epidemic years (Like 2012, 2014, 2015, 2018). Data after 2019-07-07 (a non-epidemic period) was excluded in this comparison since this remainder period was about 1 month and not comparable with other epidemic/non-epidemic periods. Additionally, pre-whitened cross correlation was applied to understand the effect of climatic factors on dengue transmission during different epidemic surge periods.

All statistical analyses were performed on R software (version 3.6.1), and included the use of package ‘dlnm’, version 2.3.9 (34).

# 3. Results

## 3.1 Epidemiological characteristics of epidemics between 2012 and 2019 in Singapore

Between January 2012 and August 2019, there were a total of five major dengue epidemics with incidence above 100 per 100,000 in Singapore (35). The 2013 epidemic holds the current national record for the highest number of dengue cases recorded in a year, where the dengue incidence was 22,170 cases (404.9 cases per 100,000 population annually) and dengue 1 serotype was the predominant strain (Table S1). Thereafter high incidence levels continued to be seen in the 2014 epidemic, which became Singapore's second-largest outbreak within a year— the dengue incidence was 18,326 cases (325.6 cases per 100,000 population annually), with dengue 1 serotype as the predominant strain. The 2015 epidemic was comparatively mild with dengue incidence at 11, 294 cases (196.1 cases per 100,000 population annually) and was predominated by strain 2. Subsequently, the 2016 epidemic saw a dengue incidence of 13, 085 cases (229.1 cases per 100,000 population annually) and was predominated by dengue 2 serotype. After low dengue activity levels for a couple of years, the 2019 epidemic became the third-biggest dengue outbreak recorded nationally with a dengue incidence of 16,100 cases (282.3 cases per 100,000 population annually) and dengue 2 and 3 serotypes taking over as the co-predominant strains (30, 36, 37)

## 3.2 Linear relationship with weather factors in Cross-correlation & ARIMA modelling

The time series data shows the trend of dengue cases over the study period, with epidemics in 2013, 2014, 2015, 2016 and 2019 characterised by peaks (Figure 1).

Pearson's cross-correlation coefficients for each climatic factor after pre-whitening are shown in Table 1. In general, pollutant standards index (PSI) and wind speed have an inverse linear relationship associated with dengue incidence i.e. high PSI & wind speeds are correlated with lower dengue incidence, while mean, maximum and minimum temperature have a direct linear association with dengue incidence. No significant correlation was observed between rainfall and dengue incidence in Singapore. The maximum lag effect observed across all climatic correlations did not exceed 15 weeks. Both mean and minimum temperature exhibited a lag effect of 1-2 weeks. Additionally, an 11-week lag time for both mean and maximum temperature showed significant correlation with number of dengue cases. Other

significant cross-correlations with dengue incidence observed include 5 and 7 weeks lag for PSI, and 5 weeks for wind speed variable. (Table 1)

Moreover, a significant autocorrelation coefficient was found at lag time of 1 week as indicated by the autocorrelation graph (Figure S1). ARIMA (1, 1, 0) was selected as the best model to describe the trend and autoregressive parameters of the dengue time series. Residual diagnostics were conducted to assess model appropriateness, including the use of Ljung-Box tests, which accepted the null hypothesis given a p-value of 0.3686. (Figure S2-S3)

Using univariate ARIMA models with variables derived from significant cross-correlations, the following factors were found to be significantly associated with dengue incidence: PSI with a 5-week and 7-week lag time, mean temperature at 1-week & 11-week lag time, maximum temperature at an 11-week lag time and wind speed at a 5-week lag time (Table 1). Coefficients of the remaining variables did not show significant associations, despite showing a significant correlation in the cross-correlation analysis, which may indicate that the cross-correlation graphs produced wrong signals at significance level 0.05.

### 3.3 Non-linear relationship with weather factors in Cross-correlation & DLNM

Using Spearman cross-correlation analysis to explore possible non-linear trends (Figure 2), a positive correlation was found between temperature and dengue cases while PSI and wind speed showed negative correlation. Like the linear cross-correlation analysis, there was no apparent association between rainfall and dengue cases.

For the quasi-Poisson with DLNM association, estimated parameters with optimal fitting performance (the smallest QAIC) were chosen. Model fitness statistics of each weather factor were shown in Table 2. The best fitting model in univariate analysis included the effect of PSI on dengue cases lagged by a maximum of 16 weeks (lag 0-16), total rainfall (lag 0-15), mean temperature (lag 0-16), maximum temperature (lag 0-16) and wind speed (lag 0-5). The best-performing model was that of wind speed with the lowest QAIC of 4842.808, suggesting that wind speed explained dengue incidence the best amongst all climatic factors. Autocorrelation of residuals was tested to ensure absence of autocorrelation and assumption of overdispersion was checked (Figure S3), justifying the use of a Quasi-Poission regression in DLNM. The DLNM model output had a fitted number of dengue cases that mirrored the

observed trend of dengue cases closely as seen in Figure 3. The graphical output of dengue DLNM modelling for each climatic variable is described in the following sections.

**PSI**

With a median of 48.26 PSI defined as reference, visualisation of DLNM model output with the 3D graph (Figure 4) showed that the RR of dengue increased up to a PSI level of 100 approximately, beyond which the RR falls sharply. This pattern is also reflected in the contour plot.

The sliced graph for PSI (Figure 4) indicated that extreme PSI levels beyond around 100 reduced the RR of dengue at a lag of 5 and 7 weeks.

In the overall effects graph, which incorporates all lag times (Figure 4), it was observed that higher PSI corresponded to higher RR under PSI 100. Conversely, the relationship turned negative when PSI exceeded 100 and was statistically significant at extremely high PSI.

**Rainfall**

In the 3D graph (Figure 5), it can be observed that the RR of dengue spiked when total rainfall, with reference defined as 5.57mm, exceeds approximately 21mm. This is similarly reflected in the contour plot.

Although the RR of dengue was found to increase with total rainfall (lag time of 10 weeks) according to the sliced graph (Figure 5), the association was not statistically significant. This lack of association was also observed in the overall effects graph, which took into account all lag times.

**Temperature**

With median values for mean temperatures at 28.02°C— the 3D & contour graphs (Figure 6) showed that RR of dengue was the highest at a mean temperature of 35°C, when a 1-week lag time was considered. In the sliced graph, although the RR of dengue appeared to increase with increasing mean temperature at a lag time of 1 week, the association was only marginally significant. However, in the overall effects graphs (Figure 6), there was a general

decrease in dengue incidence with increasing temperature when considering all lag times, except at an interval of around 27-28°C. However, all confidence intervals override zero line, which indicates the difference between relative risk of each temperature point and reference is not statistically significant.

For maximum temperatures at a reference value of 31.84°C, RR of dengue at an initial lag of 0 weeks increased with the elevation of temperature as seen in the 3D graph (Figure 6). The sliced graph at a lag time of 11 weeks also showed that extreme maximum temperatures were favourable for dengue transmission (Figure 6). On the other hand, the overall effects graph across all lag times showed that maximum temperatures below 32°C were significantly associated with increasing dengue incidence.

With minimum temperature at a reference value of 25.15°C, the sliced graph at six weeks lag time showed that RR of dengue increased (but RR remained <1.0) when minimum temperatures fell below 25°C and decreased at temperatures higher than 25°C—this relationship was statistically significant. Similarly, as shown in the overall effects graph minimum temperatures above and below reference point, had a protective effect on dengue transmission (Figure 6). This was also reflected in the contour plot.

Across all lag times, mean and minimum temperatures were relatively similar in their effects on dengue incidence; temperatures deviating from the median led to a reduction in dengue incidence. (Figure 6)

**Wind speed**

In terms of wind speed at a reference value of 7.52km/h, the 3D graph showed that dengue RR was the lowest at a wind speed of 15 km/h, when considering a lag time of 5 weeks (Figure 7).

Similarly, the sliced graph in Figure 6 showed that dengue RR at a lag period of 5 weeks fell sharply at extremely high wind speeds.

This was also reflected in the overall effects graph (Figure 7), where high wind speeds were associated with reduced dengue transmission (RR <1.0), and this was statistically significant.

**Multivariate analysis**

Utilising the forward selection methodology, wind speed was first selected for the model based on its smallest QAIC of 4842.808. The model was introduced with a second variable PSI, which had a QAIC of 4523.012, as wind speed was kept constant. Subsequent selection of remaining variables failed to reduce QAIC further, which implied that only cross basis of wind speed and PSI would be considered for the final model. To check the robustness of our model, overall effect graphs of both of PSI and wind speed were redrawn and similar performances in univariate model were found (Figure S4).

**Sensitivity analysis**

We conducted sensitivity analysis by changing the df of time trend ($\delta$) or df of lag time ($\delta_2$), and found the overall effect of each weather variable on dengue cases to be robust, albeit having slightly different performance with each change ($\delta_1$). Df of weather predictor was chosen from 1 to 5 (except for the optimal one with smallest QAIC which has been listed in Table 2). Graphs containing extremely wide confidence interval (CI) were excluded from results since the estimated RR will be not shown clearly in visualization. Although the trends of overall effect are similar to the best model, some minor points should be noted. For PSI (Figure S5), the peak of RR may not be exactly 100 (around 100), e The observation of a negative relationship between dengue cases and mean temperature below 27°C and a positive relationship at 27-28°C was not robust (Figure S6). When df = 1 or 3, the effect would be always positive under 28°C. Taken CI into consideration, the CI below 27 °C always included 0. For minimum temperature (Figure S8), the highest RR was noted at different minimum temperature instead of the reference median value, though the protective effect remains. For wind speed (Figure S9), different trends were observed for wind speed below 7 km/h when df was varied. This phenomenon can also be explained by the large CI including zero. Still, rainfall displays pattern indicating no correlation with dengue cases.

**3.4 Evaluation of Model Prediction Performance**

To exploit the predictive power of this model, data from 2012-2018 was used as the training set while data from 2019 was used for testing purposes. Among all models, mean temperature

was the best variable to forecast the future number of dengue cases, with a mean absolute error 43.15 and root mean square error 51.39 (Table S2).

### 3.5 Impact of Weather Factors on Epidemic surges and Non-epidemic periods

From the time series graph, four apparent peaks in 2013, 2014, 2016, 2019 can be observed (Figure 8). Significant correlation coefficients with corresponding lagged effects for individual epidemic/non-epidemic periods are shown in Table 3. Cases in the four pre-epidemic periods (*Epi A-D*) were correlated with a varied number of climatic factors with a lag period ranging from 0-17 weeks. The periods leading up to the epidemic in 2014 (*Epi B*, February 2014 – June 2016) and 2016 (*Epi C*, March 2015 – January 2016) were significantly correlated with all six climatic factors. On the other hand, the periods leading up to *Epi A* (December 2012– June 2013) and *Epi D* (October 2018- July 2019) were both found to be significantly correlated with only 3 climatic factors. Notably, *Epi A* was positively correlated with only temperature (mean, maximum and minimum) with a lag of 0-2 weeks. *Epi D* was the sole period negatively correlated with PSI, with a lag period of 0-6 weeks. (Table 3) In addition, *Epi D* was also significantly correlated with maximum temperature when lagged by 6-14 weeks and a 15-17 weeks lag in wind speed. Overall, significant associations were found between temperature and *Epi A-C*, but maximum temperature was the only consistent risk factor for all four epidemic periods.On the other hand, non-epidemic periods (Non-*Epi A-D*) were consistently correlated with temperature (maximum, minimum and mean), wind speed and PSI, except for Non-*Epi C*, which was only correlated with temperature and wind speed. (Table 3) Minimum temperature and wind speed were statistically significant risk factors that influenced dengue transmission for the most periods. Wind speed was also the only climatic factor that showed mostly negative correlation throughout all epidemic and non-epidemic periods. Cross-correlation graphs of the climatic factors and dengue incidence across individual epidemic/non-epidemic periods can be found in the supplementary file (Figure S10-17).

# 4. Discussion

This study explored the association between dengue incidence and several weather factors in Singapore between 2012 and 2019, furthering the analysis by Xu and co-authors, who explored weather factors' impact on dengue in Singapore between 2001 and 2009 (20). Relationship between weather factors and dengue cases may vary across different periods, especially with increasing global warming and urbanisation. Therefore, an independent research on these relationships is critical to guide environmental-related policy. Apart from weather variables included in Xu et al., this study considered PSI as a new indicator that could influence dengue trend. During the process of model fitting, degree of freedom parameters and the largest number of weeks were estimated independently in each weather-related model instead of using the same setting of parameters in all models.

In this study, mean and minimum temperature deviating from a median of around 28°C and 25°C respectively were found to decrease the risk of dengue transmission when considering all lags effect. This is reflective of the relatively uniform temperatures that Singapore experiences year-round, and suggests that any perturbation reduces dengue incidence - increasing temperatures in the future will hinder transmission. On the other hand, a systematic review of temperature's effect on dengue risk found that higher mean, maximum and minimum temperature were individually associated with increased dengue transmission. (38) However, the same review also concluded that the odds of dengue increases steeply up to 29 °C, and that dengue risk begins to decrease if temperatures are higher than 29 °C. Hence, our study's results seem to support the idea of an optimum temperature range that promotes dengue transmission, rather than a general increase in dengue incidence accompanying increasing temperatures.

Another study looking at dengue patterns in Singapore from 1974 until 2011 found that higher minimum and mean temperature were related to higher dengue transmission, while maximum temperature was not statistically significant. (39) On the other hand, Xu et al. reported that dengue incidence in Singapore was amplified by mean temperatures above 27.8°C (reference value) in 2001-2009, while mean temperatures deviating from 27.8°C in 2004-2006 and 2007-2009 were associated with reduced dengue transmission (20). Concurrently, molecular studies show that Aedes Aegypti survival and development thrives beyond the 30°C range (40, 41). Others concluded that the ideal range of survival (88-93%) through all phases of development occurs between 20-30 °C (40), including Yang, et al.

(2009) who reported 29.2 °C as the best temperature to produce the most offspring [24]. One possible explanation for these discrepancies could be the differing effects of temperature on various development stages of mosquitos and the dengue virus, accompanied by the dominant strategy of vector control employed at any specific period. The National Environment Agency in Singapore provides guidance to pest control operators on ideal times for outdoor fogging to kill adult mosquitos, while recognising that citizen efforts with indoor insecticides and elimination of stagnant water habitats (for mosquito larva) are more effective in non-cluster areas within Singapore. (42) Hence, it is important to note the context in which the role of temperature in dengue transmission is being investigated – this is because the predominance of indoor or outdoor breeding, fogging or source control methods employed in specific geographies and periods may differ.

However, when considering only one specific lag effect, this study found that mean temperatures above around 28°C at a 1-week lag and maximum temperatures above around 32°C at an 11-week lag promoted dengue transmission. The 11- week lag effect of maximum temperature could be induced by ecological factors pertaining to the Aedes vector such as the length of gonotrophic cycle, larval development and growth rate of *Aedes* mosquitoes. On the other hand, the 1- week lag effect of mean temperature may be a result of behavioral tendencies of *Aedes* mosquitoes and human that have repercussion in the shorter term such as time to bloodmeal or health-seeking behavior after presentation of symptoms. These associations at specific lag should be emphasized to facilitate warning measures.

The decreased risk of dengue transmission with high wind speeds found in this study was consistent with the results of another study in subtropical city in Guangzhou, China, which reported that wind velocity was inversely associated with dengue incidence in the same month (43). One potential mechanism that could account for the influence of wind speed is the suppression of mosquitoes' host-seeking flight activity (44), which translates to reduced oviposition and contact with hosts. As suggested by Hoffman et al. (2002), wind may deter plume following in mosquitoes due to their inability to progress upwind or dilute chemical attractants emitted by the host (45). Alternatively, wind also directly affects the evaporation rate of both outdoor and indoor vector breeding sites (46), reducing availability of breeding sites and larval productivity.

From this analysis, we concluded that extremely high PSI values (>150) reduced the number dengue cases in Singapore between 2012-2019. This is supported by a study from Malaysia,

wherein a moderate negative correlation was detected between trapped larvae counts and Air Pollution Index (API) with a one-week lag (47). Another found particulate matter 10 microns or less (PM10) to have a statistically significant negative correlation with dengue cases (48). On the other hand, a lack of association between dengue activity and haze was concluded by another study from Singapore, investigating dengue activity between 2001-2008 (49). It should be noted that the study only utilized the ARIMA model, which explored linear association, whereas this analysis was supplemented with the use of a non-linear quasi-poison model. Smoke, a component of haze, is anecdotally claimed to repel insects from biting (50, 51). The toxicity of haze was believed to reduce mosquito density, as deleterious effect from direct and indirect exposure to haze was found on the development and survival of butterflies (52). Nonetheless, research pertaining to haze remains sparse. More evidence is required on the mechanisms by which air quality may affect mosquito development or biting habits.

Although the volume of rainfall has long been viewed as a plausible factor affecting dengue in domain of public health, there have been conflicting evidence – including this analysis and another previous study looking at dengue incidence in Singapore from 2000 to 2007 (53) – demonstrating an absence of relationship between rainfall and dengue incidence [28, 29]. One possible explanation could be the role of indoor breeding in urban settings, which is sheltered from outdoor elements. The importance of stagnant water as breeding sites is emphasized by anti-dengue campaigns in Singapore compelling citizens to routinely empty water from flowerpots/trays, containers and closed perimeter drains. According to MOH's report on vector surveillance in 2018 (35), the top breeding habitats for Aedes Aegypti included domestic containers (32%), flowerpots/trays (11.1%), ornamental containers (9.3%) and closed perimeter drains (3.7%). On the other hand, a study looking at dengue incidence in Malaysia from 2008-2010 showed that increased bi-weekly accumulated rainfall had a positively strong effect on dengue cases (44). Yet, experimental and observational studies have shown that excessive rainfall can 'flush out' breeding sites and destroy developing larvae. At least two studies in Singapore have demonstrated that dengue incidence between 2000 & 2016 was significantly reduced following months where flushing events from wet weather were most frequent (54, 55). These collectively indicate that more detailed analysis, including the use of spatial data to clarify areas prone to flooding and contribution of indoor breeding on mosquito breeding, may be required to understand the complex role of rainfall patterns on dengue transmission.

*Limitations*

The generalisability of the predictive value may not be guaranteed since the model included autoregression parts as covariates. Only short-term predictions can be performed with these results, since long- term prediction would cause larger prediction errors and be inaccurate. With climatic variables derived from our quasi-poisson model, dengue predictions made a week in advance would have moderate performance, as assessed by split-sample model validation.

Additionally, this analysis did not include relative humidity and absolute humidity, though they have proved to be crucial meteorological factors influencing dengue incidence in previous studies. In particular, Xu et al. (2014)'s Singapore study concluded that absolute humidity was the most useful weather factor in dengue forecasting.

Moreover, our model did not consider other major factors including circulating dengue serotypes and geospatial differences. In Singapore, the variations of urban housing across its geography, from landed estates to high-rise buildings have been found to influence differences in dengue distribution (14). Additionally, weekly meteorological indicators in this analysis were calculated by averaging data across all 63 stations nationwide, and ignores potential geographical differences in weather (though this is minimised given the small size of Singapore). Nevertheless, the occurrence of dengue clusters is recognised as another important reason to adopt a geospatial perspective in dengue predictive modelling. Further studies should obtain these data with greater granularity, to describe patterns of dengue incidence more precisely. Lastly, the study assumes the effectiveness of vector control is only up to a constant limit, regardless of its intensity level, across this period.

# 5. Conclusion

Only a limited temperature range promotes dengue transmission in an urbanised tropical city. On the other hand, poor air quality and high wind speeds were associated with lower dengue transmission levels. Rainfall had no influence on dengue weekly incidence, though correlated factors like flooding were not further examined. Future studies incorporating these information along with geospatial data would allow further assessment of the relationships

between these weather factors and dengue risk. This may guide public health and environmental policy in similar tropical urban environments for dengue control.

## 6. References


1. Lee SH, Nam KW, Jeong JY, Yoo SJ, Koh YS, Lee S, et al. The effects of climate change and globalization on mosquito vectors: evidence from Jeju Island, South Korea on the potential for Asian tiger mosquito (Aedes albopictus) influxes and survival from Vietnam rather than Japan. PLoS One. 2013;8(7):e68512.
2. Simo FBN, Bigna JJ, Kenmoe S, Ndangang MS, Temfack E, Moundipa PF, et al. Dengue virus infection in people residing in Africa: a systematic review and meta-analysis of prevalence studies. Scientific Reports. 2019;9(1):13626.
3. Murray NE, Quam MB, Wilder-Smith A. Epidemiology of dengue: past, present and future prospects. Clin Epidemiol. 2013;5:299-309.
4. Fried JR, Gibbons RV, Kalayanarooj S, Thomas SJ, Srikiatkhachorn A, Yoon IK, et al. Serotype-specific differences in the risk of dengue hemorrhagic fever: an analysis of data collected in Bangkok, Thailand from 1994 to 2006. PLoS Negl Trop Dis. 2010;4(3):e617.
5. Khan MI, Anwar E, Agha A, Hassanien NS, Ullah E, Syed IA, et al. Factors predicting severe dengue in patients with dengue Fever. Mediterr J Hematol Infect Dis. 2013;5(1):e2013014.
6. Vicente CR, Herbinger KH, Fr[illegible]schl G, Malta Romano C, de Souza Areias Cabidelle A, Cerutti Junior C. Serotype influences on dengue severity: a cross-sectional study on 485 confirmed dengue cases in Vit[illegible]ria, Brazil. BMC Infect Dis. 2016;16:320.
7. Junxiong P, Yee-Sin L. Clustering, climate and dengue transmission. Expert review of anti-infective therapy. 2015;13(6):731-40.
8. Hii YL, Zaki RA, Aghamohammadi N, Rockl[illegible]v J. Research on Climate and Dengue in Malaysia: A Systematic Review. Curr Environ Health Rep. 2016;3(1):81-90.
9. Rajarethinam J, Ang L-W, Ong J, Ycasas J, Hapuarachchi HC, Yap G, et al. Dengue in Singapore from 2004 to 2016: Cyclical Epidemic Patterns Dominated by Serotypes 1 and 2. Am J Trop Med Hyg. 2018;99(1):204-10.
10. Koh BK, Ng LC, Kita Y, Tang CS, Ang LW, Wong KY, et al. The 2005 dengue epidemic in Singapore: epidemiology, prevention and control. Ann Acad Med Singap. 2008;37(7):538-45.
11. Ooi E-E, Goh K-T, Gubler DJ. Dengue prevention and 35 years of vector control in Singapore. Emerg Infect Dis. 2006;12(6):887-93.
12. Fan J-C, Liu Q-Y. Potential impacts of climate change on dengue fever distribution using RCP scenarios in China. Advances in Climate Change Research. 2019;10(1):1-8.
13. Hii YL, Rockl[illegible]v J, Ng N, Tang CS, Pang FY, Sauerborn R. Climate variability and increase in intensity and magnitude of dengue incidence in Singapore. Glob Health Action. 2009;2:10.3402/gha.v2i0.2036.
14. Seidahmed OME, Lu D, Chong CS, Ng LC, Eltahir EAB. Patterns of Urban Housing Shape Dengue Distribution in Singapore at Neighborhood and Country Scales. GeoHealth. 2018;2(1):54-67.
15. Ngugi HN, Mutuku FM, Ndenga BA, Musunzaji PS, Mbakaya JO, Aswani P, et al. Characterization and productivity profiles of Aedes aegypti (L.) breeding habitats across rural and urban landscapes in western and coastal Kenya. Parasites & Vectors. 2017;10(1):331.
16. S. Wongkoon, M. Jaroensutasinee, K. Jaroensutasinee, Preechaporn W. Development sites of Aedes aegypti and Ae. albopictus in Nakhon Si Thammarat, Thailand. WHO Dengue Bulletin. 2007;31:141-52.
17. Morin CW, Comrie AC, Ernst K. Climate and dengue transmission: evidence and implications. Environ Health Perspect. 2013;121(11-12):1264-72.
18. Lai Y-H. The climatic factors affecting dengue fever outbreaks in southern Taiwan: an application of symbolic data analysis. BioMedical Engineering OnLine. 2018;17(2):148.
19. Ebi KL, Nealon J. Dengue in a changing climate. Environ Res. 2016;151:115-23.
20. Xu H-Y, Fu X, Lee LKH, Ma S, Goh KT, Wong J, et al. Statistical Modeling Reveals the Effect of Absolute Humidity on Dengue in Singapore. PLOS Neglected Tropical Diseases. 2014;8(5):e2805.

21. Thu HM, Aye KM, Thein S. The effect of temperature and humidity on dengue virus propagation in Aedes aegypti mosquitos. Southeast Asian J Trop Med Public Health. 1998;29(2):280-4.
22. Aziz AT, Dieng H, Ahmad AH, Mahyoub JA, Turkistani AM, Mesed H, et al. Household survey of container-breeding mosquitoes and climatic factors influencing the prevalence of Aedes aegypti (Diptera: Culicidae) in Makkah City, Saudi Arabia. Asian Pac J Trop Biomed. 2012;2(11):849-57.
23. Naish S, Dale P, Mackenzie JS, McBride J, Mengersen K, Tong S. Climate change and dengue: a critical and systematic review of quantitative modelling approaches. BMC Infectious Diseases. 2014;14(1):167.
24. Wilder-Smith A, Earnest A, Tan SB, Ooi EE, Gubler DJ. Lack of association of dengue activity with haze. Epidemiol Infect. 2010;138(7):962-7.
25. Hapuarachchi HC, Koo C, Rajarethinam J, Chong C-S, Lin C, Yap G, et al. Epidemic resurgence of dengue fever in Singapore in 2013-2014: A virological and entomological perspective. BMC Infectious Diseases. 2016;16(1):300.
26. S. NJ. Dengue cases at four-year high TODAY Online2020 [Available from: https://www.todayonline.com/singapore/dengue-cases-four-year-high.
27. Chew MF. Forum: Dengue control measures have significantly reduced transmissions The Straits Times2020 [Available from: https://www.straitstimes.com/forum/dengue-control-measures-have-significantly-reduced-transmissions.
28. Health Mo. Weekly Infectious Diseases Bulletin: Ministry of Health; [Available from: https://www.moh.gov.sg/resources-statistics/infectious-disease-statistics/2020/weekly-infectious-diseases-bulletin.
29. Agency NE. Historical Daily Records: National Environment Agency; 2020 [Available from: http://www.weather.gov.sg/climate-historical-daily.
30. Department of Statistics S. Population and Population Structure: Department of Statistics, Singapore; 2020 [Available from: https://www.singstat.gov.sg/find-data/search-by-theme/population/population-and-population-structure/latest-data.
31. Bayazit M, ˆnˆ?z B. To prewhiten or not to prewhiten in trend analysis? Hydrological Sciences Journal. 2007;52(4):611-24.
32. Gasparrini A, Armstrong B, Kenward MG. Distributed lag non-linear models. Stat Med. 2010;29(21):2224-34.
33. Berk R, MacDonald J. Overdispersion and Poisson Regression. Journal of Quantitative Criminology. 2008;24:269-84.
34. Gasparrini A. Distributed Lag Linear and Non-Linear Models in R: The Package dlnm. J Stat Softw. 2011;43(8):1-20.
35. Health Mo. Communicable Diseases Surveillance in Singapore [Available from: https://www.moh.gov.sg/resources-statistics.
36. Times TS. Dengue cases up again after five weeks of decline: The Straits Times; 2020 [Available from: https://www.straitstimes.com/singapore/dengue-cases-up-again-after-five-weeks-of-decline.
37. Asia CN. Dengue cases expected to exceed 16,000 cases unless immediate action taken: NEA: Channel News Asia; 2020 [Available from: https://www.channelnewsasia.com/news/singapore/dengue-cases-expected-exceed-16000-nea-12659668.
38. Fan J, Wei W, Bai Z, Fan C, Li S, Liu Q, et al. A systematic review and meta-analysis of dengue risk with temperature change. International journal of environmental research and public health. 2015;12(1):1-15.
39. Struchiner CJ, Rocklöv J, Wilder-Smith A, Massad E. Increasing dengue incidence in Singapore over the past 40 years: population growth, climate and mobility. PloS one. 2015;10(8):e0136286.

40. Rueda LM, Patel KJ, Axtell RC, Stinner RE. Temperature-dependent development and survival rates of Culex quinquefasciatus and Aedes aegypti (Diptera: Culicidae). J Med Entomol. 1990;27(5):892-8.
41. Marinho RA, Beserra EB, Bezerra-Gusmão MA, Porto Vde S, Olinda RA, Dos Santos CA. Effects of temperature on the life cycle, expansion, and dispersion of Aedes aegypti (Diptera: Culicidae) in three cities in Paraiba, Brazil. J Vector Ecol. 2016;41(1):1-10.
42. Teo T. Pest control operators advised on best times for fogging. The Straits Times. 2016.
43. Lu L, Lin H, Tian L, Yang W, Sun J, Liu Q. Time series analysis of dengue fever and weather in Guangzhou, China. BMC Public Health. 2009;9(1):395.
44. Cheong YL, Burkart K, Leitão PJ, Lakes T. Assessing weather effects on dengue disease in Malaysia. Int J Environ Res Public Health. 2013;10(12):6319-34.
45. Hoffmann EJ, Miller JR. Reduction of Mosquito (Diptera: Culicidae) Attacks on a Human Subject by Combination of Wind and Vapor-Phase DEET Repellent. Journal of Medical Entomology. 2002;39(6):935-8.
46. Ehelepola NDB, Ariyaratne K, Buddhadasa WMNP, Ratnayake S, Wickramasinghe M. A study of the correlation between dengue and weather in Kandy City, Sri Lanka (2003 -2012) and lessons learned. Infectious Diseases of Poverty. 2015;4(1):42.
47. Ahmad R, Suzilah I, Wan Najdah WMA, Topek O, Mustafakamal I, Lee HL. Factors determining dengue outbreak in Malaysia. PLOS ONE. 2018;13(2):e0193326.
48. Carneiro MAF, Alves B, Gehrke FS, Domingues JN, Sá N, Paixão S, et al. Environmental factors can influence dengue reported cases. Rev Assoc Med Bras (1992). 2017;63(11):957-61.
49. Wilder-Smith A, Earnest A, Tan SB, Ooi EE, Gubler DJ. Lack of association of dengue activity with haze. Epidemiology and infection. 2010;138(7):962-7.
50. Vernède R, van Meer MM, Alpers MP. Smoke as a form of personal protection against mosquitos, a field study in Papua New Guinea. Southeast Asian J Trop Med Public Health. 1994;25(4):771-5.
51. Biran A, Smith L, Lines J, Ensink J, Cameron M. Smoke and malaria: are interventions to reduce exposure to indoor air pollution likely to increase exposure to mosquitoes? Trans R Soc Trop Med Hyg. 2007;101(11):1065-71.
52. Tan YQ, Dion E, Monteiro An. Haze smoke impacts survival and development of butterflies. Scientific Reports. 2018;8(1):15667.
53. Pinto E, Coelho M, Oliver L, Massad E. The influence of climate variables on dengue in Singapore. International journal of environmental health research. 2011;21:415-26.
54. Seidahmed OME, Eltahir EAB. A Sequence of Flushing and Drying of Breeding Habitats of Aedes aegypti (L.) Prior to the Low Dengue Season in Singapore. PLOS Neglected Tropical Diseases. 2016;10(7):e0004842.
55. Benedum CM, Seidahmed OME, Eltahir EAB, Markuzon N. Statistical modeling of the effect of rainfall flushing on dengue transmission in Singapore. PLOS Neglected Tropical Diseases. 2018;12(12):e0006935.

**Figures:**

Figure 1. Weekly number of dengue fever cases with smoothed line

Figure 2: Time-lagged Spearman correlation between climate factors and dengue incidence

Figure 3: The estimated number of dengue cases (DLNM) juxtaposed against original dengue time series

Figure 4: DNLM dengue modelling with PSI (A) 3D graph (B) Contour Plot (C) Sliced Graphs at lag time of 5 & 7 weeks (D) Overall effects graph

Figure 5: DNLM dengue modelling with Total Rainfall (A) 3D graph (B) Contour Plot (C) Sliced Graph at lag time of 10 weeks (D) Overall effects graph

Figure 6: DNLM dengue modelling with Mean temperature, Maximum temperature and Minimum temperature (Left to right respectively) (A) 3D graphs (B) Contour Plots (C) Sliced Graphs at lag times of 1 week, 11 weeks and 6 weeks for mean, maximum and minimum temperature respectively (D) Overall effects graph

Figure 7: DNLM dengue modelling with Wind speed (A) 3D graph (B) Contour Plot (C) Sliced Graph at lag time of 5 weeks (D) Overall effects graph

Figure 8: Epidemiological periods over the whole dengue time series

**Data Files**

**Additional File 1:** Supplementary material (word document) including additional tables and figures.

**Declarations**

**Ethics approval and consent to participate:** Not applicable

**Consent for publication:** All authors have read and agreed to the final manuscript for publication.

**Availability of data and materials:** All data generated or analysed during this study are included in this published article and the supplementary file.

**Funding:** This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

**Competing interests:** The authors declare that they have no competing interests.

**Authors' Contributions:** GH, KJY and NL carried out the extraction of data. GH analysed the data and wrote the first manuscript draft. GH, GSXW and KJY edited subsequent versions of the draft. PJ conceived of the study.

**Acknowledgements:** We would like to thank Nicholas Lau for helping to extract publicly available data for this study.

# Figures

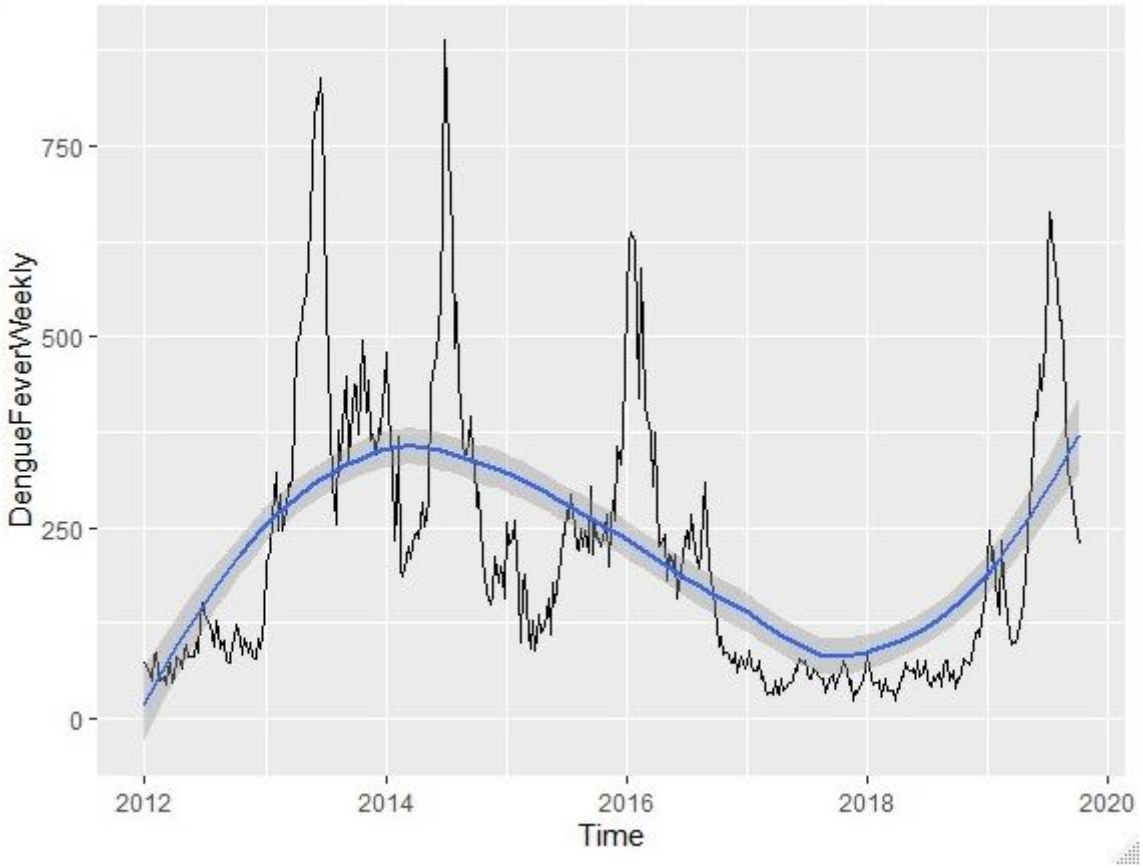



**Figure 1**

Weekly number of dengue fever cases with smoothed line

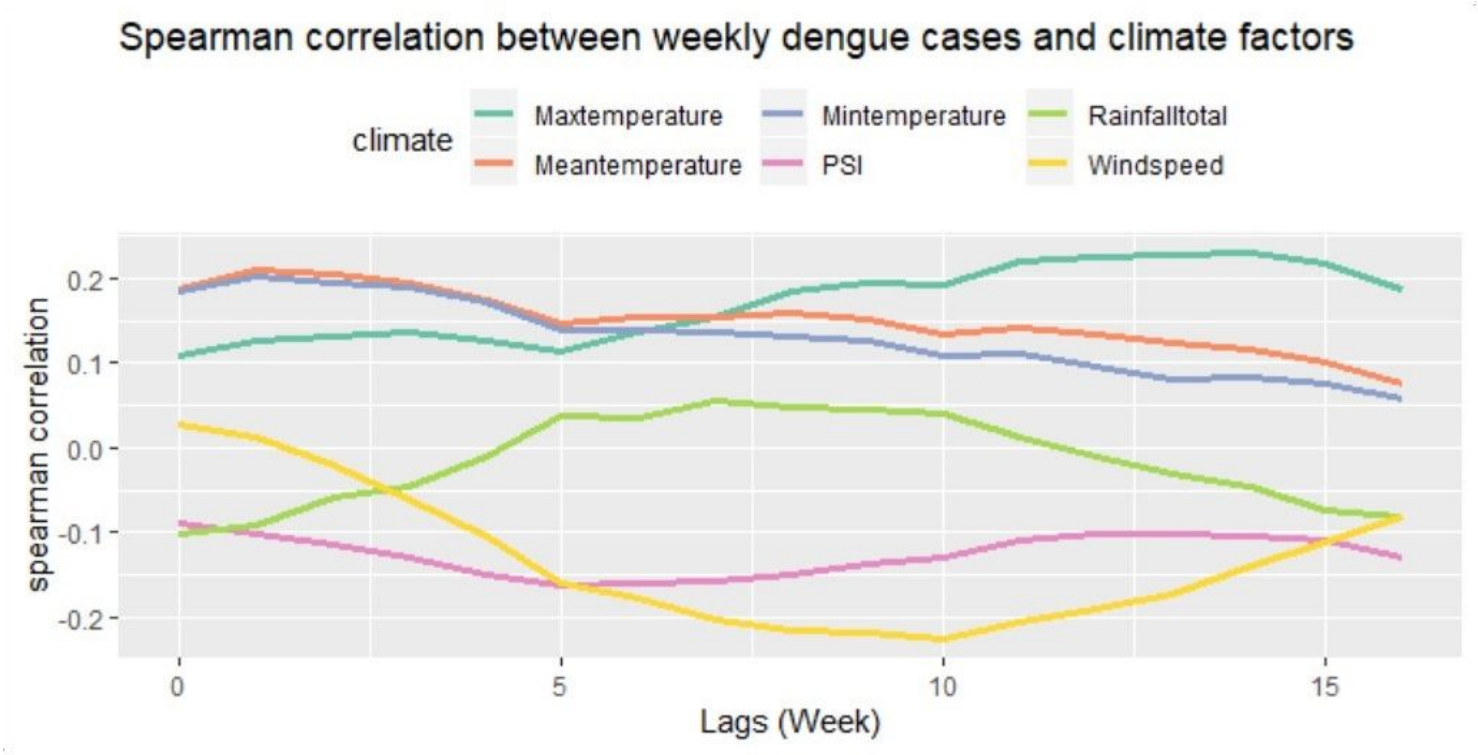
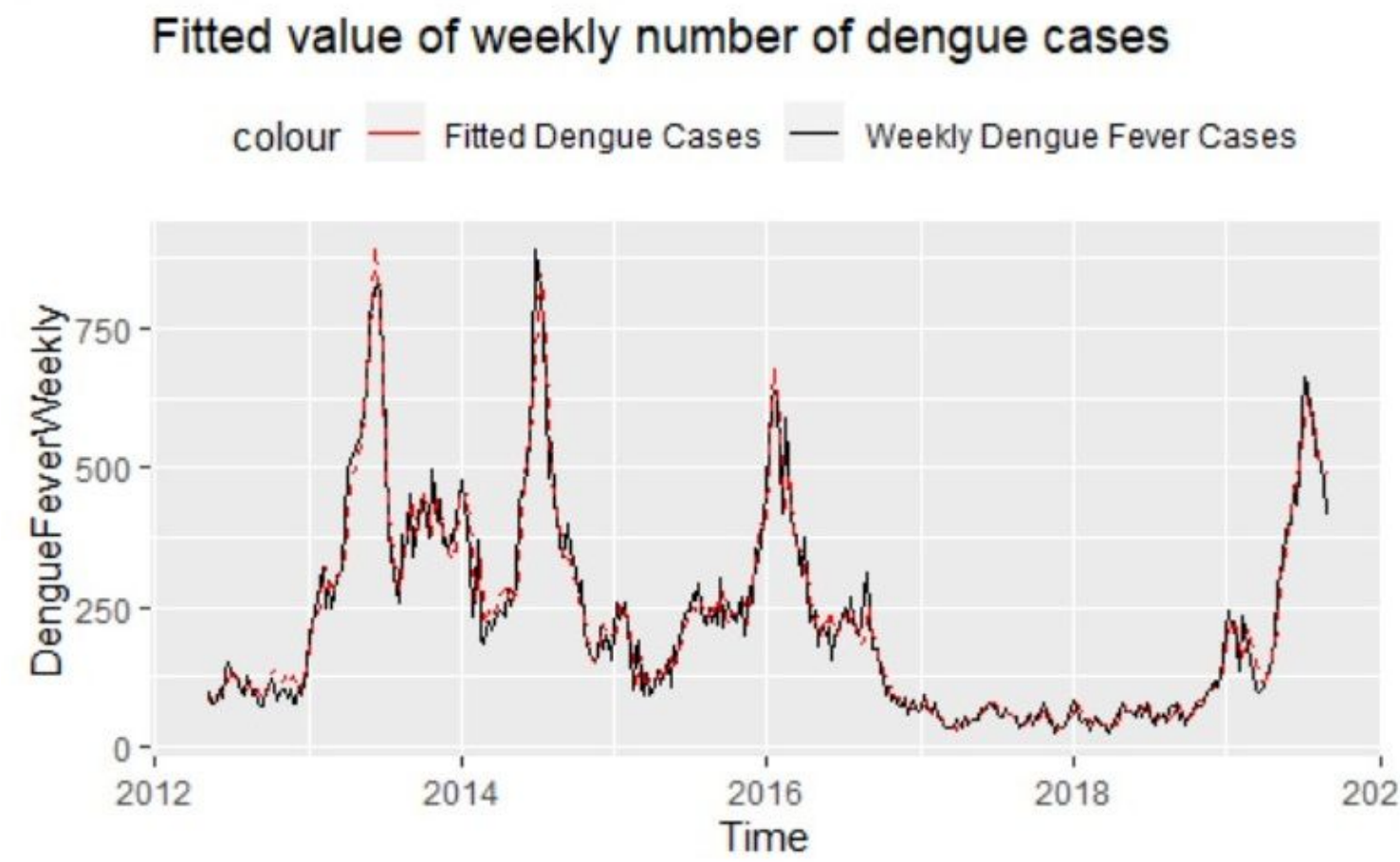


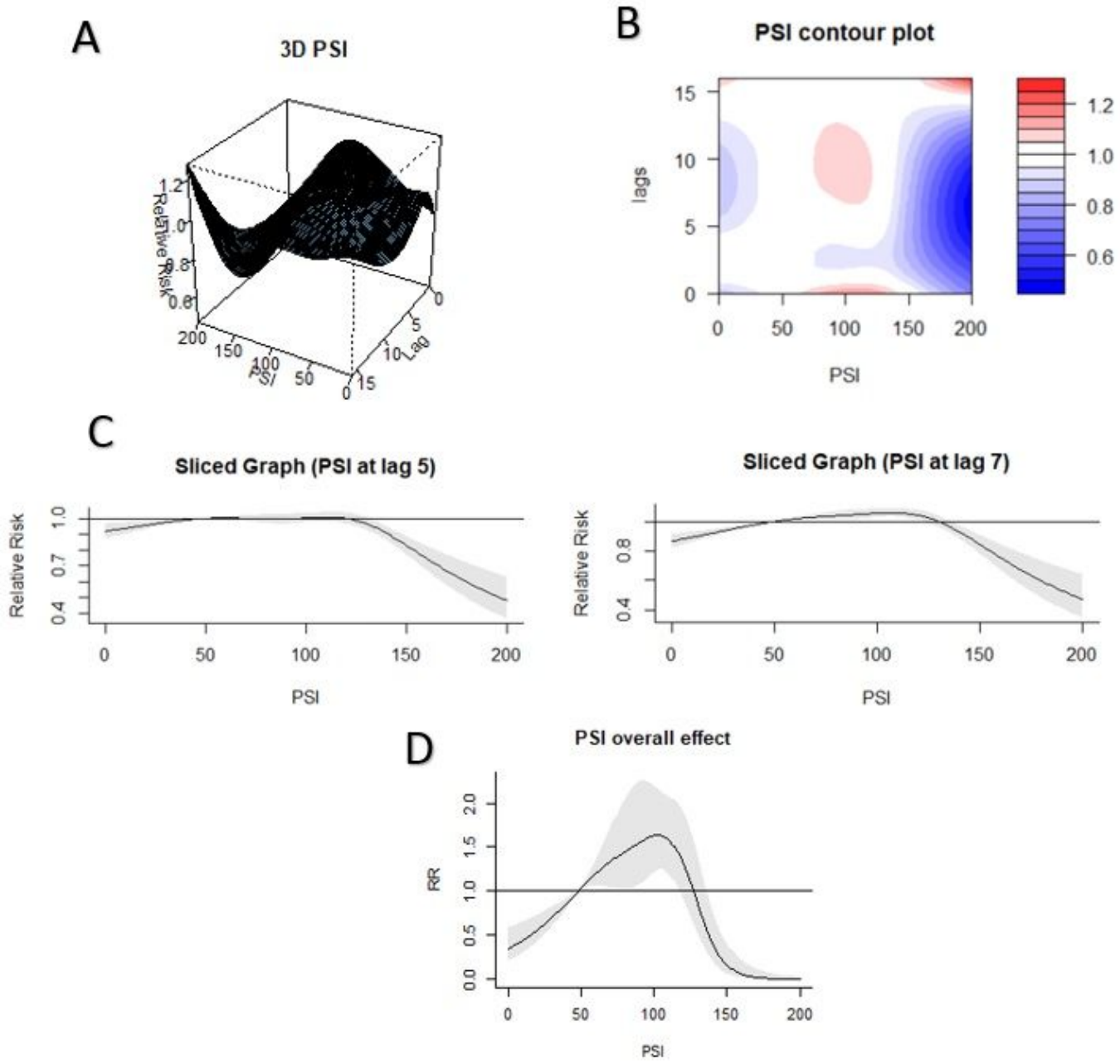

**Figure 2**

Time-lagged Spearman correlation between climate factors and dengue incidence



## Figure 3

The estimated number of dengue cases (DLNM) juxtaposed against original dengue time series




## Figure 4

DNLM dengue modelling with PSI (A) 3D graph (B) Contour Plot (C) Sliced Graphs at lag time of 5 & 7 weeks (D) Overall effects graph

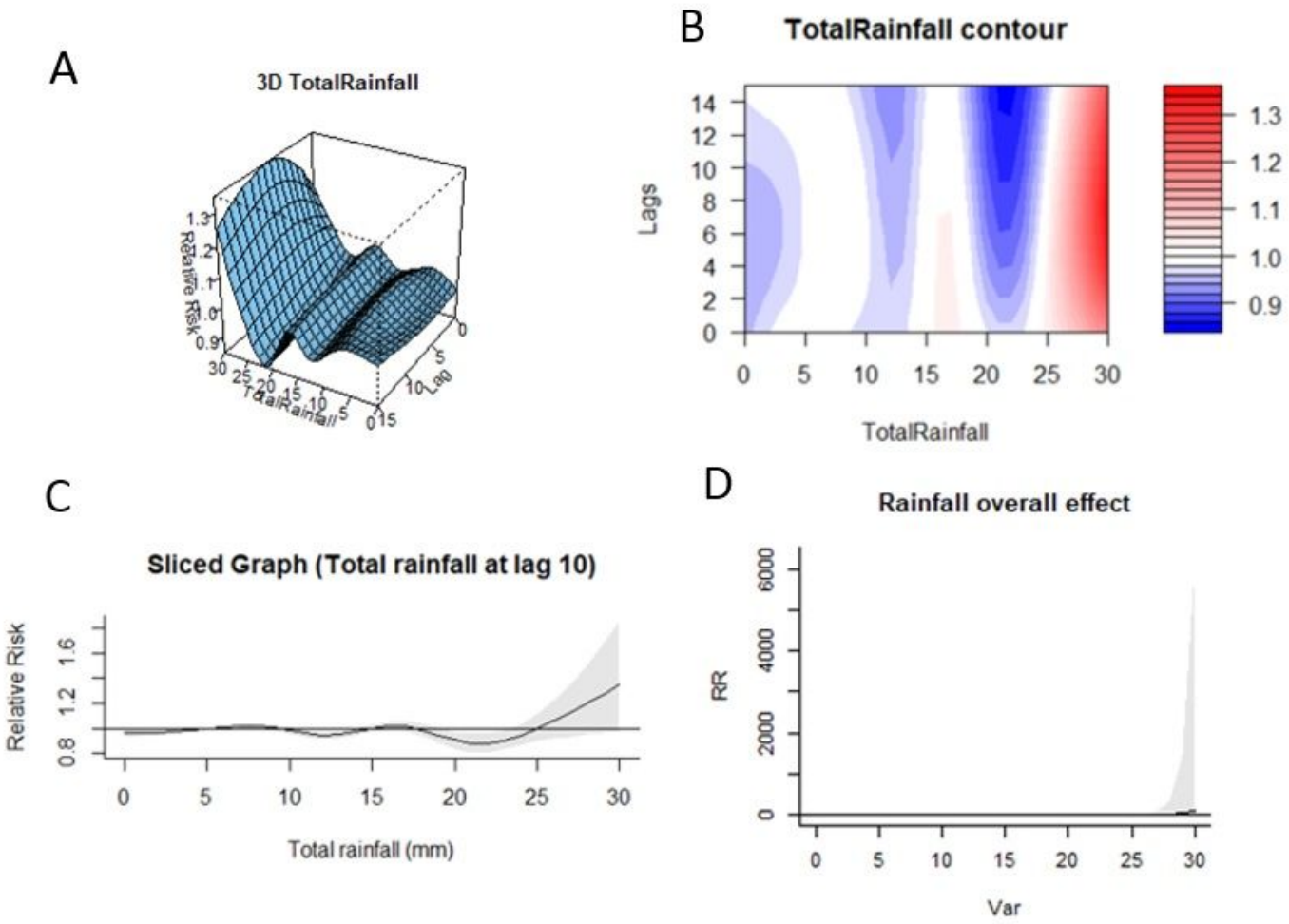
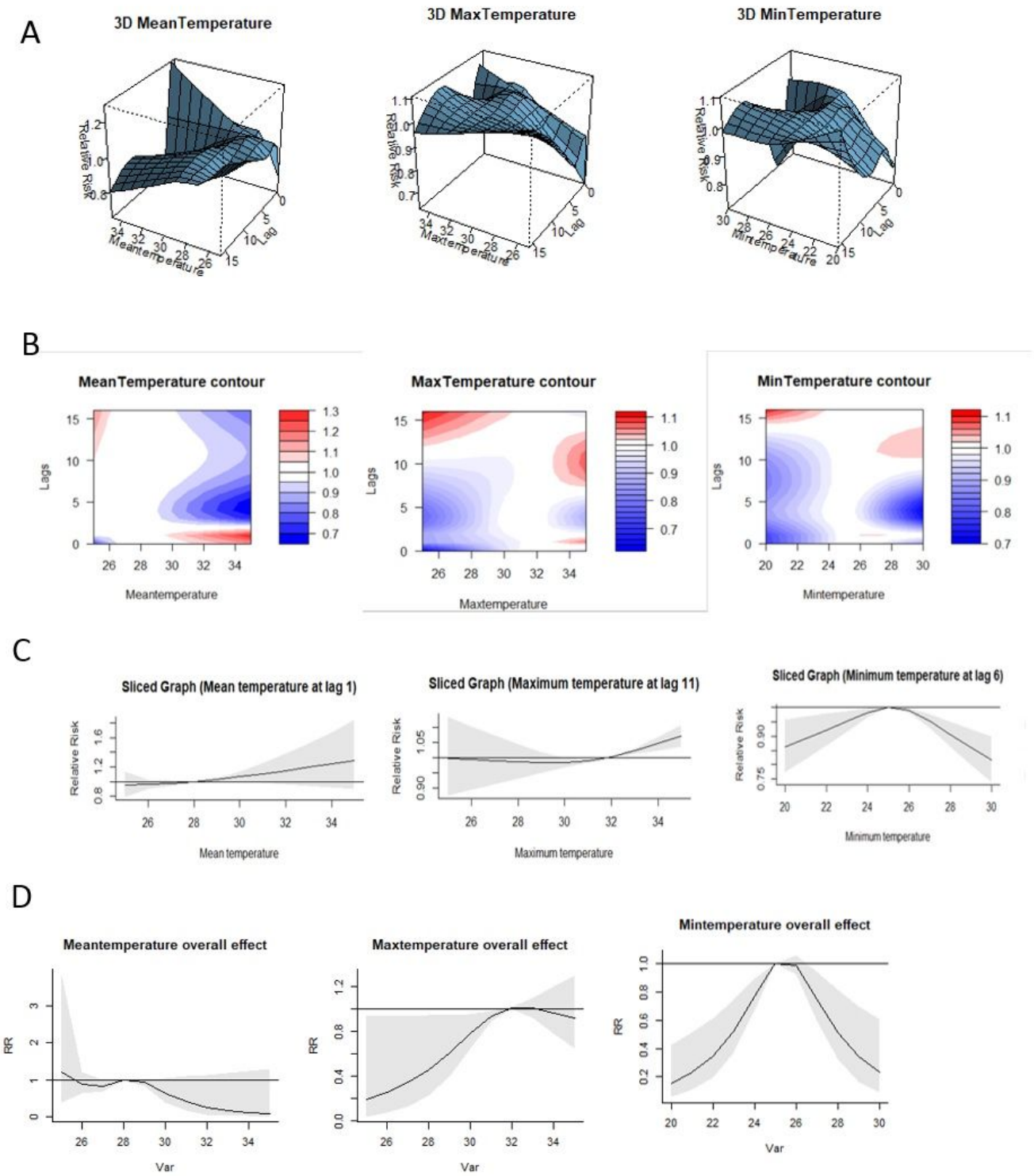



**Figure 5**

DNLM dengue modelling with Total Rainfall (A) 3D graph (B) Contour Plot (C) Sliced Graph at lag time of 10 weeks (D) Overall effects graph




## Figure 6

DNLM dengue modelling with Mean temperature, Maximum temperature and Minimum temperature (Left to right respectively) (A) 3D graphs (B) Contour Plots (C) Sliced Graphs at lag times of 1 week, 11 weeks and 6 weeks for mean, maximum and minimum temperature respectively (D) Overall effects graph

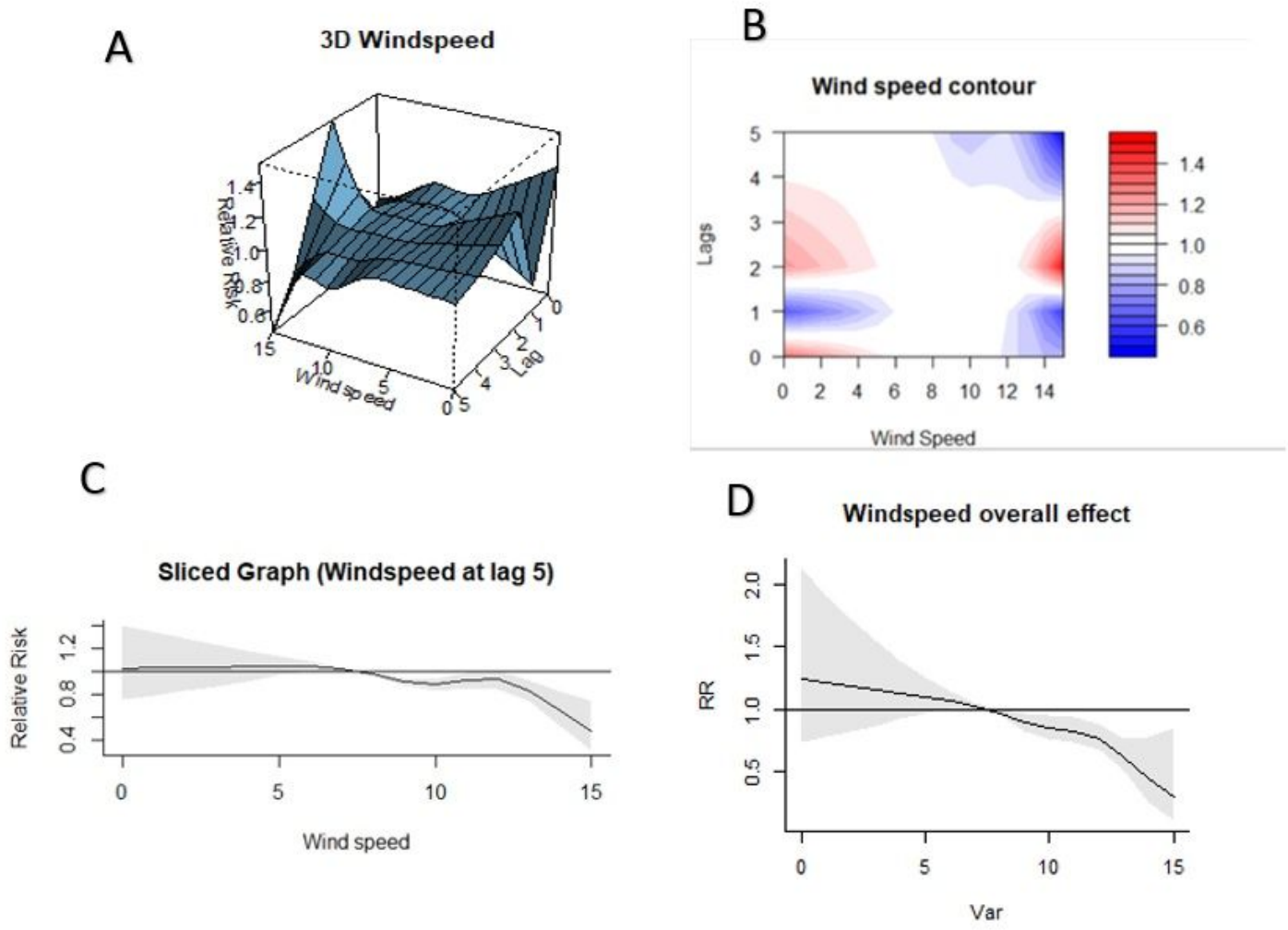



**Figure 7**

DNLM dengue modelling with Wind speed (A) 3D graph (B) Contour Plot (C) Sliced Graph at lag time of 5 weeks (D) Overall effects graph

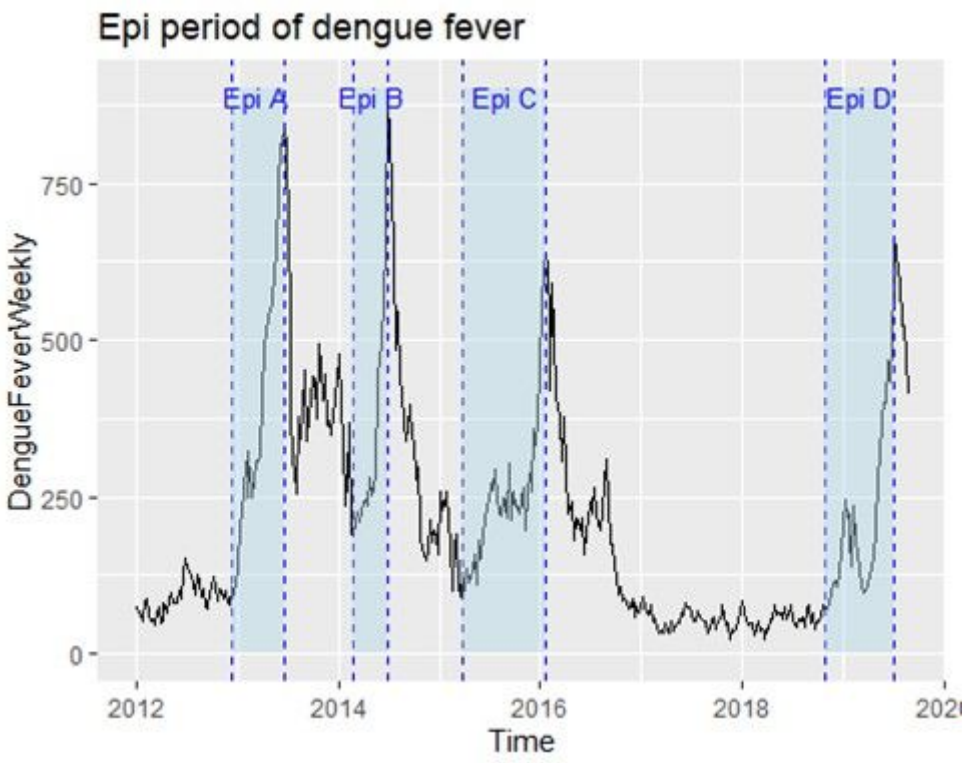



**Figure 8**

Epidemiological periods over the whole dengue time series

# Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- AdditionalFile1.docx
- Table1.CrosscorrelationanalysisandARIMAmodelling.docx
- Table2.Distributedlagnonlinearmodel.docx
- Table3.Variablesassociatedwithdifferentperiods.docx