Influence of temperature on the incidence of dengue in the city of Campinas, São Paulo state, Brazil (2013 – 2022)

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ABSTRACT

Global dengue cases rise, notably in Brazil. This study analyzes temperature’s role in its spread. By using monthly data and controlling for rainfall, linear regressions with ARIMA errors were estimated in order to measure the influence of temperature on the incidence of dengue in the city of Campinas, São Paulo state, Brazil. Findings reveal that a 1ºC increase in mean temperature leads to a cumulative increase of approximately 20% – 30% in dengue incidence within one to two months. Rainfall shows no discernible impact. Results highlight the importance of temperature on the spread of dengue and potentially other mosquito-borne diseases.

Keywords:

Dengue, time series modeling, temperature, rainfall, epidemiological forecasting.

Brief communication

Influence of temperature on the incidence of dengue in the city of Campinas, São Paulo state, Brazil (2013 – 2022)

The dengue global incidence has increased over the last years. A recent report by the World Health Organization (WHO) points to a ten-fold increase in reported cases between 2000 and 2019, with more than five million cases reported in 2019[1]. Brazil has been particularly affected and recorded more than 1.5 million cases in 2023, a surge of more than 65% comparing to two years prior[2].

Climate change is set to modify the landscape of infectious diseases, particularly mosquito-borne illnesses like dengue, yellow fever, Chikungunya and Zika[3]. Regarding dengue, different responses to climate shown by different *Aedes* species may lead to spatial shifts of the mosquito: *Aedes aegypti*, for example, has an optimal temperature for transmission of 29˚C, whereas *Aedes albopictus'* thermal optimum is estimated to be 26˚C[4]. As noted by Ryan et al[5], mosquito populations will probably undergo expansions in some regions and contractions in others in the context of climate change. Hence, the interconnections among mosquito vectors, the environment, and disease transmission pose a significant challenge for precise forecasting, crucial for public health preparedness.

Beyond concerns with potential changes in mosquito vector distributions, an increase in temperature may lead to increased population growth of *Aedes aegypti*[6]. Mathematical models also suggest this may be the case [4,5]. However, regarding Brazil, to the best of our knowledge this relationship has not been shown by means of econometric models.

In this brief report, this gap is addressed by means of time series techniques. Linear regressions with ARIMA (autoregressive integrated moving average) errors were estimated with data from the city of Campinas, State of São Paulo, Brazil. In this case, both rainfall and temperature were included as independent variables, while dengue incidence served as the dependent variable.

Stationarity is a crucial requirement when estimating time series models, since an underlying assumption of these models is that the time series data exhibits a stable statistical structure over time. Stationarity was verified using Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. Specification of the model was performed automatically with *forecast* package for *R*[7]. Complete modelling information including ARIMA coefficients and analysis of residuals is available from the supplementary material, as well as the *R* code used. Time dummies were introduced to account for months in which dengue incidence was higher than 100 per 100,000 population. This adjustment was implemented to better capture and accommodate the unique temporal patterns associated with these particular periods. Seasonality was automatically accounted for by the *forecast* package.

The monthly number of dengue cases was obtained from the State Health Department[8]. To smooth the series, a procedure similar to the one employed by Martinez et al. (2011)[9] was applied: a value of 1 was added to all observations in order to allow for logarithmic transformation of the series. The annual population count was obtained from the Brazilian Institute of Geography and Statistics (IBGE)[10] and interpolated linearly to provide monthly estimates. Temperature and rainfall data were obtained from the Center for Meteorological and Climatic Research Applied to Agriculture (CEPAGRI)[11]. The data covers the period from January 2013 to December 2022[12].

Figure 1 presents the monthly number of cases (per 100,000 population) in the municipality of Campinas. Peaks of infection draw attention. Some months record no dengue cases, while others, like in the year of 2014, record more than 2,000 cases per 100,000 population.

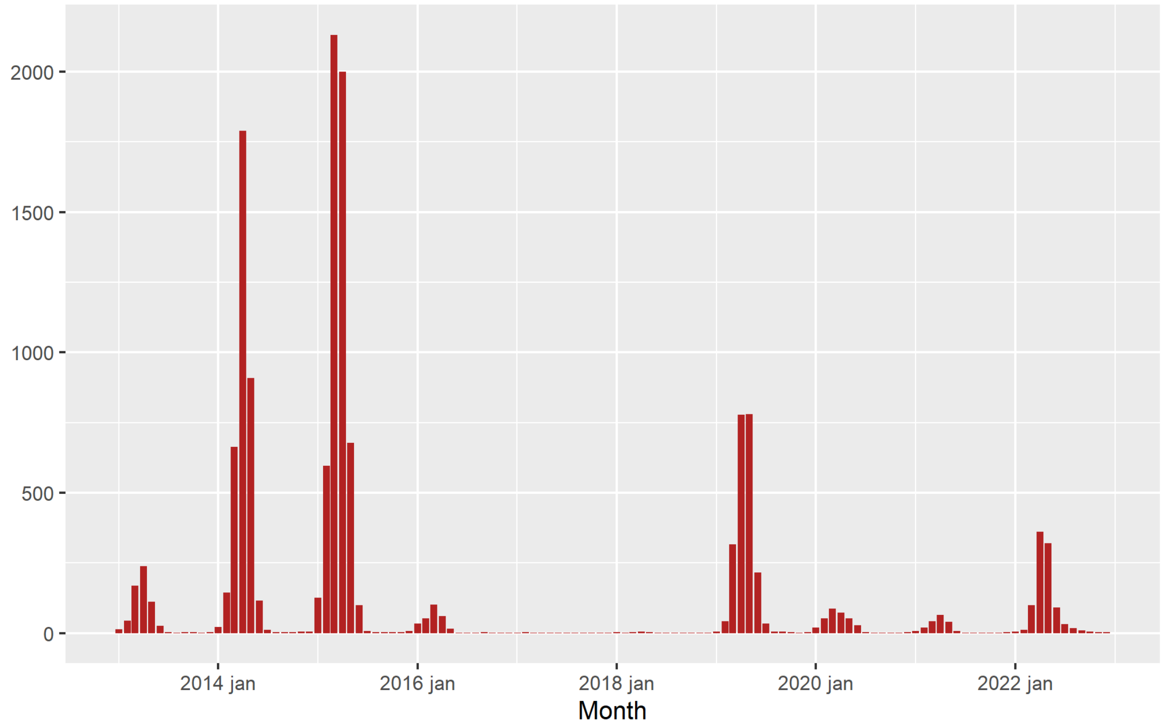

Figure 1: Monthly number of cases (per 100,000 population) in the city of Campinas (2013 – 2022).

The basic specification of the model is

$$y_i = \hat{\beta} x_{i-t} + \epsilon_i$$

where y_i is the logarithm of dengue incidence per 100,000 population at time i, $\hat{\beta}$ is the vector of estimated coefficients, x_{i-t} is a vector of the exogenous variables (rainfall and temperature) at time $i - t$ (where $0 \leq t \leq 2$), and the error term ϵ_i is modeled using $ARIMA\ (p, d, q)(P, D, Q)s$, that is, accounting for seasonality.

Two lag specifications were modelled: the first one allows for temperature and rain to have both a contemporaneous impact on the dengue incidence (*e.g.*, a change in temperature leads to a change in the incidence of the disease in the same month) and an impact lagged by one month. The second specification allows for an impact in up to two months. Additionally, two functional form modifications were employed: either temperature and rainfall are untransformed or logarithmized. Hence, four main models were estimated. Table 1 presents the results of the estimations, with coefficients for temperature in boldface and standard errors in parentheses.

Table 1: Regression results.

	Dependent variable: logarithm of number of dengue cases per 100,000 population			
	Model 1	Model 2	Model 3	Model 4
Mean temperature	**0.115 (0.039)***	-	**0.155 (0.043)***	-
Mean temperature (lag 1)	**0.097 (0.040)***	-	**0.114 (0.042)***	-
Mean temperature (lag 2)	-	-	**0.076 (0.044)***	-
log (Mean temperature)	-	**2.937 (0.848)***	-	**3.232 (0.901)***
log (Mean temperature) (lag 1)	-	**2.056 (0.847)***	-	**2.322 (0.863)***
log (Mean temperature) (lag 2)	-	-	-	**1.05 (0.889)**
Rainfall	0.000	-	0.000	-
Rainfall (lag 1)	0.000	-	0.000	-
Rainfall (lag 2)	-	-	0.000	-
log (Rainfall)	-	0.051 (0.054)	-	0.052 (0.062)
log (Rainfall) (lag 1)	-	0.019 (0.054)	-	0.031 (0.085)
log (Rainfall) (lag 2)	-	-	-	0.033 (0.062)
Dummies	0.697 (0.189)	0.726 (0.185)	0.633 (0.213)	0.716 (0.191)
Ljung-Box Q statistics (p-value at lags in parentheses)	Q(8) = 0.774 Q(16) = 0.287 Q(24) = 0.416	Q(8) = 0.660 Q(16) = 0.325 Q(24) = 0.451	Q(8) = 0.404 Q(16) = 0.218 Q(24) = 0.389	Q(8) = 0.682 Q(16) = 0.416 Q(24) = 0.518

Notes: *p<0.1; **p<0.05; ***p<0.01
Coefficients for temperature are in boldface and standard errors in parentheses.

In models 1 and 3, coefficients represent the semi-elasticity of dengue incidence to a 1ºC variation in temperature — *e.g.,* in model 1, a 1ºC rise in temperature implies an 11.5% elevation in the dengue incidence on the same month, and a 9.7% elevation after one month.

In models 2 and 4, since both the dengue incidence, temperature and rainfall are logarithmized, coefficients represent the elasticity of the incidence with respect to temperature and rainfall — *e.g.,* in model 2, a 1% elevation of temperature leads to a 2.9% elevation in the dengue incidence. Assuming a mean temperature of 25ºC would mean that a 1ºC rise in temperature (or 4% of the initial temperature) leads to an 11.6% elevation in the dengue incidence within the same month and to an 8% elevation in the next month.

Figure 2 presents the results as fan charts, assuming a mean temperature of 25ºC. Areas in red account for ± 1 standard error of the estimate. Models 1 and 2 suggest that a 1ºC elevation in temperature results in a combined elevation of the dengue incidence of approximately 20%. Models 3 and 4 suggest that this increase could reach 30% after two months, although it must be noted that the statistical significance is lower for the second lag coefficients (which is expected, since temperature effects tend to dissipate with time).

Rainfall has not been found to play a statistically significant role in predicting dengue incidence in Campinas. It is worth noting that the most prevalent breeding habitats in Campinas are containers such as plant pots, animal waterers, dismountable swimming pools, cans, bottles, and buckets, among others[13,14]. The abundance of these containers directly stems from human behavior and does not solely rely on rainwater for filling. Furthermore, the impact of precipitation can occur indirectly. For instance, during the 2014 epidemic in Campinas, which coincided with a severe drought[15], there was a trend of storing water in barrels at home, often without proper covering, thus facilitating the proliferation of breeding sites.

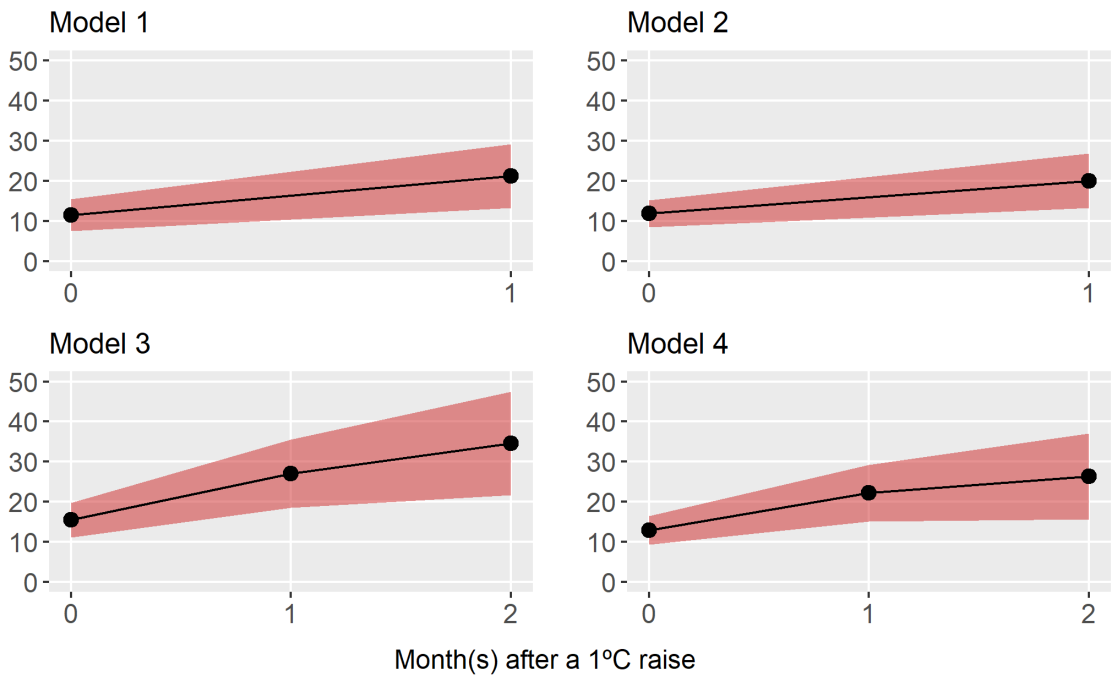

Figure 2: Projected percentage increase in the cumulative number of cases due to a hypothetical temperature rise from 25°C to 26°C.

This study has some limitations. Dengue is a complex disease influenced by multiple factors, necessitating a comprehensive understanding of the various elements that collectively contribute to triggering or preventing epidemics. While our focus was not to encompass all conditioning factors associated with dengue, we aimed to employ a promising methodology to underscore its importance and potential for predicting this disease, as well as other vector-borne illnesses, particularly within the context of a changing climate. Econometric models can serve as valuable tools for assisting stakeholders in comprehending the evolving patterns of disease occurrence and formulating proactive public policies to mitigate new outbreaks.

Another limitation is that the accuracy of dengue case reporting has improved over time, yet remains reliant on secondary data provided by the Campinas Health Secretariat through the reporting system. This reliance on secondary data is a constraint inherent to long-term studies on dengue in Brazil. Nevertheless, given that we selected a recent study period, the data available were the most appropriate and comprehensive for our investigation.

This paper extends beyond a previous study published in this Journal[9], which predicted dengue cases by means of a SARIMA model. We were able to complement the analysis by incorporating two additional climate variables — temperature and precipitation — using a similar methodology. The discovery that rising temperatures can forecast an increase in dengue incidence is alarming, particularly given Campinas' location in a tropical climate zone. If temperature increases can exacerbate dengue incidence in areas already characterized by hot and humid tropical climates, this finding suggests that dengue fever may not only expand into cooler regions, which are expected to warm with climate change, but also intensify outbreaks in already high-risk areas. Similar trends are anticipated for diseases such as Zika[16] and Chikungunya[17] in Brazil.

Authors' contribution statement

Bernardo Geraldini: conceptualization, methodology, software, data curation, formal analysis, visualization, writing – original draft.

Igor Cavallini Johansen: writing – original draft, writing – review & editing.

Marcelo Justus: methodology, supervision, writing – review and editing.

Conflict of interest statement

The authors declare that there is no conflict of interest.

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Research data availability statement

The entire dataset supporting the results of this study was made available in GitHub and can be accessed in https://github.com/bfsg839/dengue_data.

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