The role of socioeconomic status, environment, and temperature in the spatio-temporal distribution of the first Chikungunya epidemic in the city of Rio de Janeiro, Brazil

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Abstract

Chikungunya is an *Aedes*-borne disease therefore its dynamics are impacted by the vector’s ecology. We analysed the spatio-temporal distribution of the first chikungunya epidemic in Rio de Janeiro, estimating the effect of the socioeconomic and environmental factors as proxies of mosquitoes abundance. We fitted spatial models using notified cases counts by neighbourhood and week. To estimate the instantaneous and the memory effect of the temperature we used a transfer function. There were 13627 chikungunya cases in the study period. The sociodevelopment index, especially in the beginning of the epidemic, was inversely associated with the risk of cases, whereas the green area proportion effect was null for most weeks. The temperature increased the risk of chikungunya in most areas and this effect propagated for longer where the epidemic was concentrated. Factors related to the *Aedes* mosquitoes contribute to understanding the spatio-temporal dynamics of urban arboviral diseases.

Key-words: chikungunya, spatial model, epidemiology
Introduction

The first chikungunya virus (CHIKV) epidemic in Rio de Janeiro city, the second most populated city in Brazil and its main tourist destination, occurred in 2016 (de Souza et al., 2018). CHIKV is transmitted to humans by the same vectors as dengue viruses (DENV), the Aedes mosquitoes (WHO, 2017). Vector-control activities have not prevented Rio de Janeiro from being endemic for dengue for years, nor from having experienced large dengue epidemics, in general, every three to four years (Honório et al., 2009c; Nogueira et al., 1999; Santos et al., 2019).

For an arbovirus epidemic to occur three main elements are necessary, represented by the blue circle in Figure 1: mosquito population, susceptible human population, and the virus circulating (Kuno, 1995; Randolph and Rogers, 2010; Teixeira et al., 2009). The Ae. aegypti mosquito is present all over the city of Rio de Janeiro, facilitating a new arbovirus is established and spread quickly. Despite sharing the same vector, CHIKV and DENV belong to different families, which means that previous immunity to DENV does not cross-react with CHIKV and the population of Rio de Janeiro could be considered equally naïve to CHIKV before 2016. Therefore, the occurrence of local transmission was conditioned by the entry of the virus.

Figure 1. A theoretical model for a chikungunya epidemic in a given region. Direct associations are represented by black arrows and indirect associations by red arrows. The blue area includes the necessary elements for the epidemic to occur.
Reliable data on vector population, susceptible human population, and time of the entry of the virus, are not available at the intra-urban level in Rio de Janeiro city. Therefore, socioeconomic and environmental factors that have a direct effect (represented by black arrows in Figure 1) on the unmeasured elements can be considered to understand the spatio-temporal dynamics of the chikungunya epidemic by estimating their indirect association (represented by red arrows in Figure 1) with the number of cases. The mosquito population varies within the city and with time, as the mosquito ecology is affected by environmental factors such as the level of urbanization and temperature. Ae. aegypti mosquitoes are highly adapted to urban settings, and the proportion of green area is inversely correlated with the level of urbanization (Rosa-Freitas et al., 2010). The socioeconomic status impacts the mosquito population as disorderly urbanization and inadequate sanitary conditions favour the presence of the mosquito most common reproduction site: containers filled with water found inside or in the surroundings of domiciles (Carvalho et al., 2017; Honório et al., 2009a). The temperature affects the life cycle and the activity of the mosquito and the incubation period of the virus, with maximal transmission occurring around 26–29°C (Mordecai et al., 2017).

Statistical models are traditional tools to study diseases. In the last decades, models that take into account the spatial dependency structure of the cases have been applied to better understand arboviral diseases epidemics (Carvalho et al., 2020; Lowe et al., 2011, 2018b), and the application of such models for intra-urban settings is growing more recently (Martínez-Bello et al., 2018, 2017; McHale et al., 2019; Teixeira and Cruz, 2011). Adjacent areas supposedly share similar characteristics. The inclusion of a (latent) spatial random effect, after adjusting for available covariates, accounts for both the spatial structure and unmeasurable factors (Morris et al., 2019). We applied spatial models, more specifically, intrinsic conditional autoregressive (ICAR) models (Besag, 1974), in which the the latent spatial effect in a given area depends on the spatial effects of
the neighbouring areas. We aimed to study the spatio-temporal dynamics of the first chikungunya epidemic in Rio de Janeiro city, exploring the effects of temperature, green area proportion and sociodevelopment index.

**Methods**

**Study site**

Rio de Janeiro is the second-largest city in Brazil with 6.3 million inhabitants (2010) and its primary tourist destination. Rio’s area is of 1204 km², with 160 neighbourhoods grouped into four large regions (Downtown, South, North and West). These regions are subdivided in 10 health districts called programmatic areas: area 1.0 (Downtown region); areas 2.1 and 2.2 (South region); areas 3.1, 3.2, 3.3 (North region); and areas 4.0, 5.1, 5.2 and 5.3 (West region) (Figure 2).

**Figure 2. Rio de Janeiro city by programmatic areas and neighbourhoods, 2010, Brazil.**

With three mountain massifs and 84 km of beaches, Rio has a diverse geography that is directly associated with the history of occupation and with socioeconomic disparities (Prefeitura do Rio de Janeiro, n.d.). The Downtown region is the historical, commercial and financial centre of the
city, with many cultural establishments. The South region is the most popular tourist destination, with famous beaches and wealthy neighbourhoods, while in the North region there are very large slums (“favelas”) and nearly 27% of the population, almost 2.4 million people, living in such communities (Cavallieri and Vial, 2012). The West region has more heterogeneous characteristics among its neighbourhoods, being the area 5.1 more densely populated, areas 5.2 and 5.3 less urbanized, and area 4.0 wealthier.

Data

Chikungunya cases

Data on chikungunya cases were obtained from the Notifiable Diseases Information System (SINAN) via the Rio de Janeiro Municipal Secretariat of Heath and are publicly available (Prefeitura do Rio de Janeiro and Secretaria Municipal de Saúde, 2016). Cases were geocoded to the neighbourhood of the patient’s residence by the Municipal Secretariat of Health.

We analysed notified cases of chikungunya (confirmed by laboratory or clinical-epidemiological criteria) occurring in Rio de Janeiro municipality between January and December 2016, by week and neighbourhood.

Case definitions follow Ministry of Health protocols. A suspected case of chikungunya is defined as a patient with sudden fever of over 38.5°C and severe arthralgia or arthritis not explained by other conditions, and who either lives in endemic areas or has visited one up to two weeks before the onset of symptoms or has an epidemiological link with a confirmed case. A confirmed case is a suspected case with at least one positive specific laboratory test for CHIKV or confirmed by clinical-epidemiological criteria (Ministério da Saúde, 2017).

Socioeconomic data

Population and sociodevelopment index data by neighbourhood were obtained from the Instituto Pereira Passos (Prefeitura do Rio de Janeiro, 2019a, 2019b). The sociodevelopment index
is based on eight indicators from the 2010 Demographic Census: 1) the percentage of domiciles with adequate water supply; 2) the percentage of domiciles with adequate sewage; 3) the percentage of domiciles with garbage collection; 4) the average number of toilets per resident; 5) the percentage of illiteracy among residents between 10 and 14 years old; 6) per capita income of the domiciles, expressed as minimum wages; 7) the percentage of domiciles with per capita income up to one minimum wage, and 8) the percentage of domiciles with per capita income greater than 5 minimum wage. The sociodevelopment index is calculated as the arithmetic average of the normalized indicators (each ranging from 0 to 1, being 0 the worst socioeconomic condition and 1, the best) (Prefeitura do Rio de Janeiro, 2019b).

Environment and temperature data

Land use data for the city of Rio de Janeiro were obtained from the Instituto Pereira Passos as a shapefile (Prefeitura do Rio de Janeiro, 2019c). We created the category “green area” by aggregating: agricultural areas, areas with swamps and shoals, areas with tree and shrub cover, and areas with woody-grass cover. Thereafter, we calculated the proportion of green area for each neighbourhood (Figure 4B).

Temperature information was obtained from 38 meteorological weather stations in Rio de Janeiro from 5 different meteorological and environmental institutes for 2016. The institutes are the Brazilian National Institute of Meteorology (INMET, n.d.), the Brazilian Airspace Control Department (DECEA, n.d.), the Rio de Janeiro State Environmental Institute (INEA, n.d.), the Rio de Janeiro Municipal Environmental Secretariat (SMAC, n.d.) and the Alerta Rio System (Prefeitura do Rio de Janeiro, n.d.), and its measurements are made according to the recommendations of the World Meteorological Organization (World Meteorological Organization, 2007). All institutes make their meteorological data publicly available, being that the frequency of measurements of the first four organizations is hourly, while the Alerta Rio System realizes measurements every 15 minutes.
From the temperature measurements, we have computed the daily maximum, minimum and mean temperature, as well as we have evaluated the availability of the daily data in terms of missing measurements. The daily records that had more than 60% of missing measurements were excluded. We decided to use the minimum temperature as in tropical climates the minimum temperature acts as a limiting factor for the *Ae. aegypti* activity and population (Gomes et al., 2012; Lowe et al., 2017). We then obtained the minimum temperature for each week and station, and to obtain the minimum temperature by neighbourhood we applied universal kriging. Briefly, kriging is a method that uses a sample of data points to estimate the value of a given variable over a continuous space (Diggle and Ribeiro, 2007). First, we interpolated the minimum temperature to a grid with each unit measuring 500m x 500m. The grid with the meteorological weather stations is displayed in the Supplementary Material Figure 1. Then we obtained the minimum temperature of the neighbourhood by calculating the average of the minimum temperature of the grid units whose centroids were within the boundaries of the neighbourhood.

To process and organize the environmental data we used R version 3.6.1 (The R Foundation for Statistical Computing, 2020) and packages sf (Pebesma et al., 2019), geoR (Ripley et al., 2001) and tidyverse (Wickham and RStudio, 2017).

**Statistical analysis**

We used the Stan platform to fit spatial models, more specifically ICAR models, to a dataset consisting of neighbourhoods counts of chikungunya cases, exploring the effects of sociodevelopment index, green area proportion and minimum temperature. Let $Y_{i,t}$ be the counts of chikungunya cases at neighbourhood $i = 1, 2, \ldots, n = 160$, and week $t = 1, 2, \ldots, T$, where $Y_{i,t} \sim \text{Poisson} \left( \mu_{i,t} \right)$ and we explored the following structures for $\mu_{i,t}$:

- **Model 0**
  \[
  \log(\mu_{i,t}) = \log(e_i) + \beta_0 + \phi_i
  \]

- **Model 1**
  \[
  \log(\mu_{i,t}) = \log(e_i) + \beta_0 + X_i \beta_k, i
  \]
Model 2
\[ \log(\mu_{i,t}) = \log(e_i) + \beta_0 + X_i' \beta_{k,t} + \phi_i \]

Model 3
\[ \log(\mu_{i,t}) = \log(e_i) + \beta_0 + U_{i,t} + \phi_i \]
\[ U_{i,t} = \rho_i U_{i,t-1} + \zeta_i \text{Temperature}_{i,t} \]

Model 4
\[ \log(\mu_{i,t}) = \log(e_i) + \beta_0 + X_i' \beta_{k,t} + U_{i,t} + \phi_i \]
\[ U_{i,t} = \rho_i U_{i,t-1} + \zeta_i \text{Temperature}_{i,t} \]

The spatial effect is represented by \( \phi \), with each \( \phi_i \) being normally distributed with a mean equal to the average of its neighbours (the neighbour relationship is written as \( i \sim j \)), and its variance decreases according to the number of neighbours \( d_i \):

\[ p(\phi_i | \phi_{i \sim j}) = N \left( \frac{\sum_{j \sim i} \phi_j}{d_i}, \frac{\sigma}{d_i} \right) \]  

For all models \( e_i \) is the expected number of chikungunya cases at neighbourhood \( i \), representing the number of cases that would have been observed if there were no differences in the incidence of cases across time and space:

\[ e_i = \left( \frac{\sum_{i=1}^{n} \sum_{t=1}^{T} Y_{i,t} \text{population}_i}{\sum_{i=1}^{n} \text{population}_i} \right) / T \]

Model 0 includes only the intercept (\( \beta_0 \)) and the spatial effect (\( \phi \)). Model 1 represents the model with covariates without the spatial component, where \( X' \) represents a vector of \( k \) covariates and \( \beta_{k,t} \) is the coefficient of covariate \( k \) in week \( t \). We decided to consider time-varying coefficients for the covariates to explore if their effects in the number of cases vary as the epidemic progresses.

The covariates included in the \( X' \) vector were sociodevelopment index and proportion of green area. The proportion of green area showed a skewed distribution, therefore this variable was transformed to the cubic root. We also fitted models including the population density, but the 90% credible interval of its coefficient included 0 for most weeks and the inclusion of this variable...
reduced the model fitting, hence, it was not considered in the final model. Model 2 includes both the
covariates and the spatial component.

The temperature influences the number of cases over different times, therefore we estimate
its effect using a transfer function \( U_{i,t} \) that considers that the temperature has an immediate effect
\( \zeta_i \) and that a proportion \( \rho_i \) of this effect propagates through future times. This proportion \( \rho_i \) is
called memory effect and can be any value between 0 and 1. The main advantage of using a transfer
function is that there is no need to specify the lag of the effect, the lag estimation is data-driven
(Alves et al., 2010). To combine and visualize both effects of the temperature, we obtained the
impulse response function of the temperature for each neighbourhood. This function expresses the
effect of a 1 unit increase in the temperature of one week propagating in time (Alves et al., 2010).
Model 3 is model 0 adding the transfer function \( U_{i,t} \). The temperature was standardized. Finally,
model 4 is model 3 adding the covariates.

The models were fitted under the Bayesian framework using the Stan platform (Carpenter et
al., 2017) to run 4 chains of 10000 iterations each where the first 5000 were the warmup. We used
visual inspection of the chains and R-hat statistic to check convergence (Gelman and Rubin, 1992;
Stan Development Team, n.d.). Model selection was based on the Watanabe-Akaike information
criterion (WAIC) (Watanabe, 2010). It is worth mentioning that we also fitted models that
considered the reparametrization of the Besag-York-Mollié (BYM2) as proposed by Riebler et al.,
2016, but the random component was over 90% spatial, and the unstructured effect was not
statistically important in none of the neighbourhoods.

For the statistical analysis we used R version 3.6.1 (The R Foundation for Statistical
Computing, 2020) and packages rstan (Guo et al., 2019) and loo (Vehtari et al., 2017). Maps and
graphs were created using QGIS version 3.12 (QGIS Development Team, 2020) and ggplot2
version 3.2.0 (Wickham, 2016).
**Results**

Between January and December 2016, 13,627 cases of chikungunya were notified in the city of Rio de Janeiro, corresponding to an incidence of 21.6 cases per 10,000 inhabitants. The number of cases peaked at week 17/2016, with 1118 chikungunya cases (Figure 3A). The cumulative number of cases by neighbourhood ranged from 0 (Grumari, area 4.0) to 721 (Realengo, area 5.1). The highest incidence was found in Catumbi (area 1.0), of 211.0 cases per 10,000 inhabitants (Figure 3B).

**Figure 3.** Notified chikungunya cases by week (A) and chikungunya cases cumulative incidence per 10,000 inhabitants by neighbourhood (B), January to December 2016, Rio de Janeiro city, Brazil.
The mean sociodevelopment index was 0.6080, ranging from 0.282 in Grumari (area 4.0) to 0.819 in Lagoa (area 2.1). Higher sociodevelopment indexes were observed in the areas 2.1 and 4.0 (Figure 4A). Fifteen neighbourhoods did not have any green area, mostly located in areas 1.0, 3.1, 3.2 and 3.3 (Figure 4B). Alto da Boa Vista (area 2.2) presented the highest percentage of green area, of 90.4%. The average minimum temperature was 19.9 °C, ranging from 10.7 °C in Campo dos Afonsos (area 5.1) to 26.1 °C in Cidade Nova (area 1.0). Neighbourhoods located in the east coastal region of Rio had higher temperatures on average (Figure 4C). Around week 17 the temperature decreased in the city, starting to increase again around week 35 (Figure 4D).

Figure 4. Sociodevelopment index in 2010 (A), percentage of green area coverage in 2015 (B), and minimum temperature (°C) in 2016 average by neighbourhood (C) and boxplot by neighbourhood and week (D), Rio de Janeiro city, Brazil.

Due to the small numbers of chikungunya cases at the beginning of 2016, we decided to model the cases starting at week 9, when the number of cases in the city exceeded 50 for the first
time. Model 4 had the best fit (WAIC = 17934.8) followed by Model 2 (WAIC = 19656.6), Model 3 (WAIC = 21262.1), Model 1 (WAIC = 26418.3) and finally Model 0 (WAIC = 34114.6).

The posterior summary of the time-varying coefficients for sociodevelopment index and proportion of green area for each model are presented in Figure 5. The sociodevelopment index consistently presented a protective effect, inversely associated with the epidemic curve. As the number of cases increased, the protective effect of the sociodevelopment index decreased, remaining almost constant during the peak of the epidemic, and increased again once the number of cases started decreasing. Actually, for Model 4 the effect of this variable was null during the peak of the epidemic (around week 17). The proportion of green area presented a protective effect in Model 1. However, once we included the spatial component in the model, its effect moved towards the null.

**Figure 5. Time-varying coefficients (in the log scale) for sociodevelopment index (SDI) and green area proportion for spatial models for chikungunya cases from weeks 9 to 52 2016, Rio de Janeiro city, Brazil.**
The inclusion of the covariates and the transfer function in Model 4 decreased the spatial effects compared to Model 0 in 102 of the 160 neighbourhoods (Supplementary Material Figure 2). Overall, all models presented similar spatial effects structure, with a clear trend of positive spatial effects in areas where the epidemic was concentrated (areas 1.0, 2.2, the mainland part of 3.1, 3.2, 3.3 and 5.1) and negative spatial effects in less affected areas (Figure 6).

Figure 6. Chikungunya cases spatial effects (in the log scale) for Model 4, weeks 9 to 52 2016, Rio de Janeiro city, Brazil.

The posterior distributions of the instantaneous and memory effects of the minimum temperature are displayed in Figure 7. For most neighbourhoods (113/160, or 70.6%) the instantaneous effect of the temperature increased the risk of chikungunya cases (Figure 7A). The temperature instantaneous effect, however, was in general small, reaching its maximum in Catumbi (area 1.0), where the temperature relative risk was 2.28 (90%CI 2.07-2.53). The memory effect represents the proportion of the instantaneous effect that propagates in time. Therefore, for neighbourhoods where the temperature effect was null, the memory effect is irrelevant.
When we combine the instantaneous and the memory effects in the impulse response function, we observed three patterns, exemplified with 9 selected neighbourhoods in Figure 8: null effect (Figure 8 first row), rapid decay of the effect (second row), and slow decay of the effect (third row). The impulse response functions for all neighbourhoods are available in the Supplementary Material Figure 3.

The impulse response function is represented in time and space in Video 1. The first frame represents the mean temperature instantaneous relative risk, the impulse, and the following frames represent the propagation of this impulse on subsequent weeks. When the temperature relative risk is null (90% credible interval includes the 1), the neighbourhood is depicted blank. The strong
memory effect in some neighbourhoods (Figure 7B) is observed in Video 1 by the persistence of the
temperature effect for several weeks after the impulse, although such effect declines to values very
close to 1. These neighbourhoods were concentrated in areas 1.0, 2.2, mainland 3.1, 3.2, 3.3 and
5.1.

Figure 8. Impulse response function of the minimum temperature effect on chikungunya cases
over time, posterior mean and 90% credible interval, in selected neighbourhoods, Rio de
Janeiro city, Brazil.

Video 1. Minimum temperature instantaneous effect on chikungunya cases and its
propagation in time by neighbourhood, Rio de Janeiro city, Brazil.
The estimated relative risk increased rapidly in the first weeks, peaking at week 17 and then decaying progressively (Video 2 and Figure 9). The decrease in the relative risk coincided with the decrease in the minimum temperature in the city (Figure 4D). High relative risks for chikungunya were mostly observed in areas 1.0, 2.2, 3.1, 3.2, 3.3 and 5.1. The neighbourhoods of the remaining areas presented relative risks below 1 for almost the entire study period. The relative risks with the credible interval are available in the Supplementary Material Figure 4.

**Figure 9.** Posterior chikungunya relative risk by neighbourhood in selected weeks, Rio de Janeiro city, Brazil.

**Video 2.** Posterior chikungunya relative risk by neighbourhood, weeks 9 to 52 2016, Rio de Janeiro city, Brazil.
Discussion

In this study, we present spatio-temporal models fitted to estimate the distribution of the first chikungunya epidemic in Rio de Janeiro city using as covariates factors that are indirectly related to the main necessary elements of an arboviral epidemic (Figure 1). The sociodevelopment index and the proportion of green area were included in the model with time-varying coefficients, which allowed us to explore how the effects of these factors changed with the progression of the epidemic. The temperature was included in the model using a transfer function, allowing for a memory effect that propagates in time, in addition to the instantaneous effect. To our knowledge, this is the first time a transfer function is applied for temperature when modelling arboviral diseases.

We consistently found the sociodevelopment index inversely associated with the risk of chikungunya in all models (Figure 5A). This index is composed of sanitary conditions indicators, among others, and poor sanitary conditions are known to favour the reproduction of the *Ae. aegypti* mosquitoes. The association of low socioeconomic locations with increased risk of chikungunya was also found in a study in French Guiana (Bonifay et al., 2017) and in a study in Barraquilla, a Colombian city (McHale et al., 2019). Our results indicate that poor neighbourhoods were the first ones to be affected by the chikungunya epidemic. In the event that another new arbovirus enters the city, this could also be the case, highlighting the importance of vector control activities in these locations.

When the spatial dependency was not considered (Model 1), the green area proportion had a negative association with the number of chikungunya cases (Figure 5). Such association was observed for dengue in São Paulo, where low vegetation cover areas presented higher dengue incidence rates (Teixeira and Cruz, 2011). However, with the inclusion of the spatial component (Models 2 and 4) the effect of the green area proportion moved towards null. This is possible due to spatial confounding, which happens when covariates that are spatially smooth are collinear with spatial random effects (Clayton et al., 1993).
The temperature was important for most neighbourhoods, increasing the risk of chikungunya. In our models, we assumed that the temperature has an instantaneous effect and that a proportion of this effect propagates in time (the memory effect). The instantaneous one represents the effect of the temperature on the activity of the mosquito and human behaviour. The biting rate of the *Ae. aegypti* increases with the temperature until around 35 °C (Mordecai et al., 2017), while people become more exposed to mosquitoes in warm temperatures. The temperature also accelerates the extrinsic incubation period of the virus in the mosquito, and transmission was estimated to peak around 28.5 °C (Mordecai et al., 2017). On the other hand, the temperature effect on the population of mosquitoes by increasing fecundity, egg-to-adult-survival, development rate and lifespan, is not only on the same week but also accumulates in time, which is captured by the memory effect. It is important to note that for each of these elements of the mosquito ecology the temperature effect is not linear, but reaches a peak and then starts decreasing. For example, the biting rate decreases in temperatures above 35 °C (Mordecai et al., 2017).

Interestingly, the CHIKV epidemic in Rio de Janeiro in 2016 did not reach the whole city, with high-risk areas mostly concentrated in the North and Downtown regions. The decrease in the number of cases coincided with the decrease in the minimum temperature, around week 17 (Figures 3A and 4D). These two observations combined suggest that the epidemic was interrupted not because of the depletion of the susceptible human population, but because the decrease in the temperature caused a reduction in the transmission in such a way that the epidemic was not sustained. It is important to note that although the number of cases diminished substantially, there were still chikungunya cases being reported until the end of the year. Rio de Janeiro is a tropical city and the minimum temperature rarely is below the minimum temperature needed for transmission to occur, of 13.5 °C (Mordecai et al., 2017). A previous study conducted in the city showed that the *Ae. aegypti* population varies seasonally, but the mosquito is present all over the
This could explain the long persistence of the temperature effect in time in some neighbourhoods (Video 1).

Spatial models are important and useful to identify high-risk areas for diseases. The application of such models considering intra-urban scenarios is still growing for arboviral diseases. Our study identified high-risk neighbourhoods for chikungunya first epidemic in Rio de Janeiro city, which concentrated mostly in the North and Downtown regions (Figure 9 and Video 2). Such regions were already identified as high-risk locations for dengue (Xavier et al., 2017). In our previous study, neighbourhoods from these regions were more likely to constitute simultaneous clusters for dengue, Zika and chikungunya (Freitas et al., 2019). These regions have a combination of factors that favours the *Ae. aegypti* ecology and the transmission of arboviral diseases: low vegetation, low socioeconomic status and increased temperature (Figure 4). Vector control activities should be prioritized and intensified in the identified high-risk areas, as they appear to be the first ones affected by the epidemic. Also, the long-term persistence of the temperature effect (Video 1) and of a small number of cases even after the decline of the epidemic indicate that the mosquito continues to circulate and transmit the disease throughout the year, meaning interventions should be continuous in these locations.

Our study has some limitations. As for any study using secondary data on arboviral diseases, there is an uncertainty on the diagnosis of the reported cases as well as underreporting. It is important to consider that in the same year the city was also experiencing dengue and Zika epidemics (Freitas et al., 2019). Because of the association between Zika and severe congenital manifestations, the disease awareness around Zika may have improved the reporting rates (Lowe et al., 2018a). However, the simultaneous occurrence of three arbovirus epidemics may have impaired the differential diagnosis, as they cause similar symptoms. We analysed the data aggregated at the neighbourhood level as the data are more reliable at this spatial unit, but smaller areas inside the same neighbourhood can present different socioeconomic and environmental characteristics. Finer
scales such as census tracts should be considered in future studies. Finally, an important limitation is the assumption that the chikungunya risk is related to the neighbourhood of residence, while some people may get infected in other locations.

The model here presented has the potential to be applied to other cities and other urban arboviral diseases. However, this may depend on the climate of the city. If the temperature presents a wide range of variation and reaches values that can either boost or impair transmission, a time-varying instantaneous effect for the temperature should be explored (Alves et al., 2010). Mosquito population information is expensive to collect and often unreliable. Therefore not depending on such data is a strength of our model. By using temperature, socioeconomic and green area data as proxies of the key elements of arboviruses transmission, our model contributed to better understand the spatio-temporal dynamics of the first chikungunya epidemic in a tropical metropolitan city.

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Competing interests

We declare we have no competing interests.

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Supplementary Material

Figure 1. Meteorological weather stations (red dots) in the 500m X 500m grid and neighbourhoods, Rio de Janeiro city, Brazil.
Figure 2. Correlation between the spatial effects (in the log scale) of Model 0 versus Model 4, by neighbourhood, weeks 9 to 52 2016, Rio de Janeiro city, Brazil.
Figure 3. Impulse response of the minimum temperature, posterior mean and 90% credible interval, by neighbourhood, Rio de Janeiro city, Brazil.
Figure 4. Classification of the chikungunya relative risk by neighbourhood based on the 90% credible interval, selected weeks, Rio de Janeiro city, Brazil.