

Modelling by simulations Monte Carlo of First Historical Zika Outbreak in Salta, Argentina, occurred in 2017.



Abstract

Scopes and Objectives: We analyzed some aspects of the first historical outbreak of Zika that occurred in Salta, Argentina, in the year 2017. We obtained elementary estimates, such as the prevalence ratio and describe the probabilistic behavior of the outbreak by simulation of type Monte Carlo.

Study design: Retrospective-descriptive studies and stochastic computational experiment analysis.

Place and Duration of Study: Department of Mathematic, Faculty of Exact Sciences. National University of Salta, Argentina, from December 2020 to September 2021.

Methodology: Descriptive and computational experiment analysis. Estimates of parameters and Simulation of type Monte Carlo.

Results: We describe the probabilistic behavior through Monte Carlo simulation of the first historical outbreak of Zika in Salta Argentina, 2017. Based on the data of registered Zika cases, we estimate a probabilistic model for it. We also spatially describe the outbreak by estimating the prevalence ratio. Finally, by computational experiment we generate epidemic outbreaks with 10, 20 and 30 runs, determining the intrinsic growth rate and estimating the basic reproductive number R_0 for a generation time that takes into account both man and mosquito. We find that the estimates are significantly affected for the simulation type factor of 10 runs. The computational experiment shows that the descriptions of the outbreak and the estimates of R_0 obtained, if the number of repetitions of the experiment corresponds to 20 and 30 runs, are qualitatively acceptable.

Keywords: Models Theoretical; Basic Reproduction Number; Simulation; Monte Carlo; Zika virus;

2010 Mathematics Subject Classification: 62P10; 62J05; 62-07; 65C20; 65C05

1 Introduction

There is uncertainty surrounding about the time of introduction of the virus to the region, although epidemiological and genetic findings estimate that the Zika virus (ZIKV) arrived in Brazil between May and December 2013 [Faria2016]. However some authors point out that after spreading through the Pacific islands, the ZIKV begins its incursion into Brazil in 2015 led to a widespread epidemic in Latin America [Duffy2009],[German2016],[PAHO2016].

From there it begins to spread in a north-south direction through Brazil, Zika reaches Argentina [PAHO2016],[Wong2016]. In the particular case of the province of Salta, in Argentina, the first historical outbreaks occurred in the years 2017 and 2018, respectively, affecting mainly inhabitants of localities in the departments of San Martín, Orán and Rivadavia [BIV2018], with an estimated force of infection between $\alpha_{2017} \approx 0.32 \text{ week}^{-1}$ (SD 0.02) and $\alpha_{2017} \approx 0.42 \text{ week}^{-1}$ (SD 0.05) [Rosales2020].

The ZIKV is an arbovirus (arthropod-borne virus) of the *Flaviviridae* family. Transmission is mainly vector, from infected mosquitoes, mainly of the genus *Aedes*. The first outbreak of ZIKV occurred on islands of the Federated States of Micronesia in 2007. Then the virus spread in the Pacific region and to the Caribbean and South and Central America [Faria2016],[Duffy2009].

After entering South America in May 2015 through the Northeast of Brazil, the ZIKV enters Argentina between April and June 2016, and in 2017 in its continuous expansion, it has arrived in the province of Salta [Wong2016]. In the case of Salta province, the situation of cases Zika is new, the first cases were reported in 2017, and provide research opportunities of vital importance in different epidemiological aspects [BIV2018]. For example, the theoretical concept the basic reproduction number, R_0 , of infectious diseases, could be related to the initial growth of an epidemic outbreak [PAHO2016]. Growth rate estimates for exponential and logistic models play a fundamental role and its estimates for a historical outbreak can be used for retrospective, modeling, and simulation studies.

Currently, there are no medicines or vaccines against ZIKV or specific antiviral treatment for clinical ZIKV infection. To address this medical need, novel ZIKV interventions suitable for prevention and therapeutic purposes are urgent [Nguyenetal2021]. All this, added to the poor sanitary infrastructures and the high rates of poverty in these regions of the country, mean that all diseases with similar potentialities, should not be neglected by the governmental entities of the province of Salta and the country.

ZIKV has the potential to be transmitted in Argentina throughout the current geographic range of the mosquito vector. Although the transmission would be mainly seasonal [Wong2016]. Estimates of parameters related to the ZIKV will allow to make better decisions and optimize the design of plans for the provision and supply of treatments, prevention and control measures, by the Public Health authorities for the affected regions.

1.1 Scope and objectives

In this work we continue the analysis of the first historical outbreak of Zika that occurred in Salta, Argentina. In this sense, we estimate the prevalence rate and construct a prevalence map with the estimated values in order to delimit, with this spatial model, with more precision the area of occurrence of the disease for the first time in the province of Salta. This estimation allows us to have an idea of the magnitude of infection in the different departments of the Province.

On the other hand, we designed a basic block to model by Monte Carlo simulation this first historical outbreak of ZIKV. The design of the probabilistic model such as the one presented in this work could be incorporated into basic modeling blocks to generate intrinsic growth rates that could be introduced in epidemiological models such as SIR, SEIRS, etc., to generate various scenarios for the analysis of other diseases.

We perform a statistical analysis of the outputs provided by the computational implementations and present examples of them.

In addition, we relate the intrinsic growth rates of the simulated epidemics with the estimates of the basic reproductive number that they provide and compare them with the estimates of the basic reproductive number of the real historical outbreak that occurred in Salta, Argentina in 2017. We also study how the estimates of the basic reproductive number R_0 could be influenced if the simulation of the historical outbreak of Zika is carried out with 10, 20 and 30 runs.

All these estimates could be used in other retrospective studies, for simulation of scenarios with theoretical models and for analysis in decision-making in prevention and control measures.

2 Materials and Methods

In the subsections that follow, we briefly comment on different aspects of the methods applied in this work.

Characterizing an outbreak in space implies describing the geographical or spatial distribution of the cases, based on the respective attack rates. The spatial distribution of cases can be described based on various characteristics that are considered relevant to document the geographical extension of the outbreak, as well as to clarify its etiology, exposure and spread. Outbreak spatial study in particular can benefit from the use of maps [Mopec32002].

On the other hand, the basic instrument to characterize an outbreak in time is the epidemic curve. Characterizing an outbreak in time implies establishing the duration of the outbreak, defining its nature and estimating the probable period of exposure [Mopec32002].

2.1 Parameters

Two of the classic measures of frequency of a disease are incidence and prevalence. Prevalence is not a dynamic measure, so a more appropriate name is prevalence ratio. The prevalence is directly defined as the proportion of the population suffering from the disease at a specific time [Mopec32002],[ScS2000]. It is the measure of the total number of existing cases, called cases prevalent, of a disease at a point or period of time and in a given population, without distinguishing whether or not they are new cases. Prevalence is an indicator of the magnitude of the presence of a disease or other health event in the population, [Mopec32002] [ScS2000].

We estimate the prevalence by departments in the province of Salta with the data of human cases registered in the first outbreak in 2017 and using the projection of the populations obtained from Citypopulation [citypopulation2021], we estimated the prevalence ratio. With these values we design maps using shape files from Instituto Geográfico Nacional Argentino (IGN) [IGN2020] and QGIS Software Development Team [Qgis2020], in this way we present a spatial model that approximately shows the region affected by Zika in Salta.

2.2 Definitions

In this subsection we present some definitions that were used in the present study, in order to highlight their application to the situation under analysis.

Taking into account the concept of endemic corridor and the epidemic curve of registered cases, we are going to define the silence phase, endemic phase and epidemic phase based on the following Definition 2.1 and we will describe the situation that presented the first historical outbreak of Zika in Salta.

A times series is a set of observations x_t , each one being recorded at a specific time t . In this case the observations are made at fixed time intervals. To allow for the possibly unpredictable nature of future observations it is natural to suppose that each observation x_t is a realized value of a certain random variable aleatoria X_t [Brockwell2002]. Let x_t be the number of Zika cases registered at time t , to analyze the impact of the outbreak and in order to estimate the limits for the silent, endemic and

epidemic phases respectively, we consider the data recorded as a discrete time series. For this we introduce the following definition.

Definition 2.1. Let $\{X_t\}$ a sequence of random variables IID of which $\{x_t\}$ is postulated to be a realization, then the silence phase, endemic phase and epidemic phase are the intervals $[0, Q_1)$, $[Q_1, Q_3)$ and $[Q_3, +\infty)$, respectively, where Q_1 , Q_2 and Q_3 correspond to the first, second and third quartile of the observed data $\{x_t\}$. x_t correspond to number weekly news cases of Zika occurred in the localities of Department San Martín, Orán and Rivadavia in the province of Salta and $t = 1, 2, \dots$ indicate each epidemiological week from 4 of 2017 to 23 of 2017.

For the modelling by simulations of the epidemic curve, we will define the random variable in a certain probability space.

Despite of we do not discuss in detail a probabilistic space (Ω, \mathcal{A}, P) associated to the random experiment ε , we precise the sample space and the random variable corresponding in the following Definition 2.2.

Consider an experiment ε where the number of observations of a particular time interval, i -epidemiological week, in which cases of Zika have occurred, is of interest.

The triplet (Ω, \mathcal{A}, P) consisting of the sample space Ω , the σ -algebra \mathcal{A} of subsets of Ω , and a probability measure P defined on \mathcal{A} is called a probability space [Allen2007]. We try to define succinctly the probability space for the analyzed situation in a brief and expressed as follows

Definition 2.2. Let (Ω, \mathcal{A}, P) a probabilistic space associated to random experiment ε , with $\Omega = \{\omega_i \mid i = 1, 2, \dots, m; \omega_i = i\text{-th epidemiological week, in which the cases registered that occurred in localities of Department San Martín, Orán and Rivadavia in the first historical outbreak of Zika in Salta}\}$. Let X a discrete random variable defined by $X : \Omega \rightarrow \mathbf{R}, X(\omega_i) = n_i$, number of times a case of Zika has occurred in the i -th epidemiological week, ω_i . Let $\mathcal{A} = \{\emptyset, \{\omega_1\}, \{\omega_2\}, \dots, \{\omega_m\}, \Omega\}$, be the σ -algebra of events generated by assuming that $\{\omega_i\} \in \mathcal{A}$ for $i = 0, 1, 2, \dots, m$. and $P(\omega_i) = P_{n_i}(\omega_i) \approx f_r(\omega_i) = \frac{n_i}{N}$ be the probability of n_i cases results in the interval i -th epidemiological week, ω_i , where f_r is the corresponding relative frequency provided by the data and N is the total number of cases of the outbreak.

2.3 Statistical Analysis

The simplest boxplot is based on the following five-number summary: smallest x_i , lower fourth, median, upper fourth, largest x_i . We perform the analysis of the five-number through the construction of the box plot, to determine the of the smallest observation, the largest, the first quartile, the median and the third quartile in order to describe the set of data and the epidemic curve smoothed by moving averages with respect to the epidemic corridor and determine the limits of the epidemic phases.

The statistical program used was Statgraphics Centurion (version 16.1.03) [Statg2010] and the statistical analysis was performed in this software. For the simulations, we generate the cases in each run, perform several series of 10, 20, and 30 runs, and calculate the average to make comparisons with the real epidemic curve. The results thus obtained were analyzed using the Chi-Square goodness-of-fit test.

Regarding the type of simulations we carry out, to generate the epidemic curves of 10, 20 and 30 runs, in each of which 252 cases of Zika were randomly generated, we classify them in simulations of type A, B and C respectively. We denote this type of simulation simulations type A, STA for 10 runs. Similarly for 20 runs and 30 runs, Type B and Type C simulations, denoted STB and STC respectively.

To analyze whether the estimates of R_0 , calculated using the expression of the Begon&Harper model [Begon2006] are influenced or not by the number of runs, we performed a multi-factor analysis of variance to determine which of the factors STA, STB, STC have a statistically significant effect on the values of R_0 . We also use the plot of Means and 95% Fisher LSD to graphically interpret the significant effects.

2.4 Simulations

With the data of Zika number cases of the historical outbreak first occurred in Salta, we have estimated the relative and cumulative frequencies of cases submitted in each epidemiology week, so that, they can be described qualitative by making simulations of the Monte-Carlo type. In order to perform simulation experiments, an estimation for the empirical cumulative distribution function (c.d.f.), denoted by $F_X(\cdot)$, corresponding to each epidemiological week of the outbreak is necessary; i.e., that is, every epidemiological week where Zika cases have occurred. Where X be a discrete random variable with $P(X = x_i) = p_i$ con $i = 1, 2, \dots, n$ with $\sum_{i=1}^n p_i = 1$ and $x_1 < x_2 < \dots < x_n$, and the c.d.f., $F_X(\cdot)$ is given by $F_X(x) = \sum_{i: x_i \leq x} p_i$, [Meyer1998].

Implementations of algorithms for the simulations, Monte Carlo type, were similar to those developed by Rosales *et al.* [Rosales2017][Rosales2019], in order to get estimates of the Zika weekly case number and obtain the approximate values of the number cases registered in the localities of province de Salta. We simulate various runs with random generations of weekly cases considering the period of duration of the epidemic outbreak and the total number of case registered in this historical irruption of ZIKV in Salta. Finally, we calculate the corresponding weekly averages for the epidemic curve approximation and make comparisons of the obtained scenarios.

2.5 Influence on the estimation of R_0 for different types of simulation

We could learn a great deal about an infection if an expression for its basic reproduction number R_0 . For microparasites R_0 is defined as average number of secondary infections produced when one infected individual is introduced into a host population in which every host is susceptible [ScS2000].

As Zika is a vector-borne disease, we estimate R_0 from the data using the Begon&Harper's expression [Begon2006], with modifications for the Generation Time (T_g) [Walli2007], so that it takes into account both the human being and the mosquito. This T_g time is generated stochastically similar to what was done in work [Rosales2020].

As we expressed before we carry out different simulations with different number of runs, for example, simulations with 10, 20 and 30 runs in which Zika cases are stochastically generated per weeks and the average of the cases generated in each week is taken and a probabilistic model is obtained for the first historical epidemic outbreak, occurred in Salta in 2017.

Simulated outbreaks can provide an intrinsic growth rates, and through the relationship between these rates and the expression of R_0 found by Begon&Harper [Begon2006] it is possible to obtain estimates of the basic reproductive number R_0 . The quality of the estimates could depend on the type of simulations. To analyze the possible statistically significant effect of the type factors of runs in R_0 , we carried out simulations, several tests and graphs that we exemplified.

3 Results

The spatial model that we estimate by the approximate calculation of the prevalence ratio is presented in Figure 1. The prevalence map accurately shows the departments of the province of Salta that were actually affected by the first historical outbreak in Salta. The localities where the cases were registered belong to the departments of San Martín, Orán and Rivadavia. The estimated prevalence ratios were 90.07×10^{-5} , 17.69×10^{-5} and 13.42×10^{-5} , respectively.

Figure 2 shows the the number cases of this first historical outbreak of Zika, after entering South America in May 2015 through Northeast Brazil, this outbreak developed with a total of 252 cases distributed in localities of the Departments of the northern and northeastern of the Province of Salta, specifically in the Departments of Orán, General San Martín and Rivadavia, which were indicated with their respective prevalence ratios in Figure 1.

Also, Figure 2 represents the smoothed curve of human cases infected by ZikV, during the first epidemiological outbreak registered in the province of Salta, Argentina, during the epidemiological weeks between EW 4 - EW 23, year 2017. The weeks were renumbered according to the origin of coordinates. It was obtained using the 4 EW moving average window technique. The yellow, red

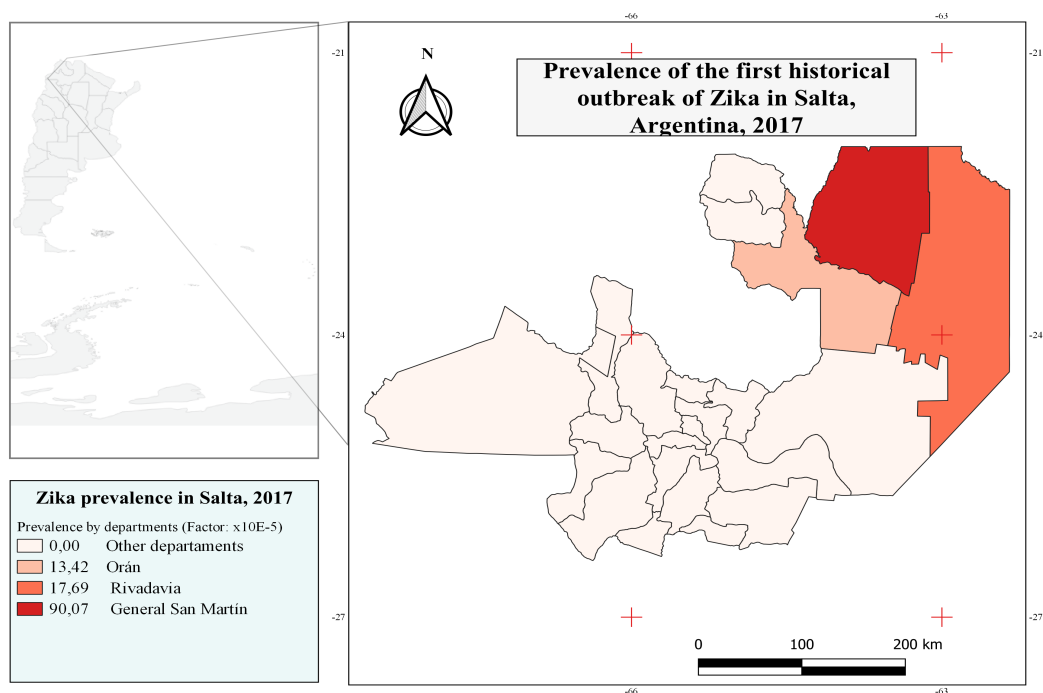


Figure 1: Indication of the region of study, located in the Province of Salta, Argentina. The study area is composed of the departments of Orán, General San Martín and Rivadavia. The map show the prevalence ratio of Zika by Departments mentioned in the first historical outbreak and was designed by the authors with shape files from Instituto Geográfico Nacional Argentino [IGN2020] using QGIS Software Development Team (3.12) [Qgis2020].

and black horizontal lines allow the delimitation of what could be considered as references of the phases of silence, endemic and epidemic, for others events of occurrences of Zika that could occur in the future in the region. The boxplot provides the following five-number summary: smallest 0, lower fourth 2.75, median 12, upper fourth 24.25, largest 29.

Table 1 shows the relative frequencies and the accumulated frequencies determined by the first historical outbreak of Zika, this allows us to estimate a probabilistic model for the situation presented in the North-Northeast region of the Salta Province.

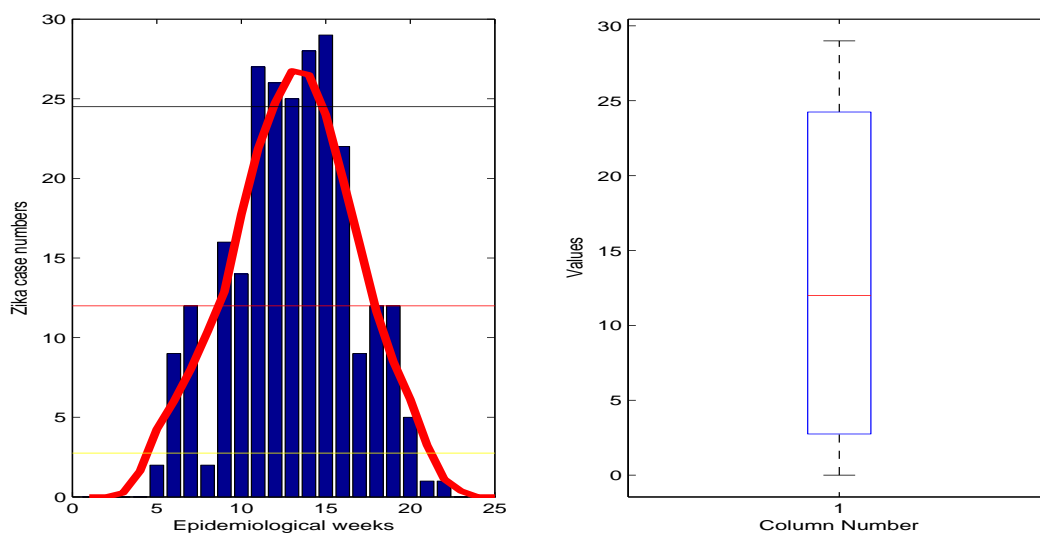


Figure 2: Left: First historical outbreak of Zika in Salta, Argentina 2017. Developed between the epidemiological weeks *EW 4 - EW 23*, of year 2017, with a total of 252 cases distributed in localities in the northern and northeastern Departments of the Province of Salta, specifically in the Departments of Orán, General San Martín and Rivadavia. Right: Box plot for the outbreak. Source: BIV [BIV2018].

Table 1 Relative frequencies of weekly Zika cases number and its cumulative frequencies for the historical peak first of Zika occurred from *EW 4 to EW 23*, Salta, Argentina, 2017.*

EW	Relative frequency	Cumulative frequency
1	0.0000	0.0000
2	0.0079	0.0079
3	0.0357	0.0436
4	0.0476	0.0912
5	0.0079	0.0991
6	0.0635	0.1626
7	0.0556	0.2182
8	0.1071	0.3253
9	0.1032	0.4285
10	0.0992	0.5277
11	0.1111	0.6388
12	0.1151	0.7539
13	0.0873	0.8412
14	0.0357	0.8769
15	0.0476	0.9245
16	0.0476	0.9721
17	0.0198	0.9919
18	0.0040	0.9959
19	0.0040	0.9999
20	0.0001	1.0000

*: Total number of Zika cases in the first historical outbreak in Salta, $N = 252$.

The values in Table 1, based on the data from the first Zika outbreak in Salta, allow us to propose a probabilistic model, as specified in the following Proposition 3.1.

Proposition 3.1. *The estimation for the c.d.f., $F_X(x)$ based on the data corresponding to the historical outbreak first of ZIKV occurred in Salta, Argentina, 2017, in the Departments of San Martín, Orán and Rivadavia, provide the following probabilistic model, $F_X : \mathbf{R} \rightarrow [0, 1]$*

$$x \mapsto F_X(x) = \begin{cases} 0.0000 & x \in (-\infty, 0] \\ 0.0079 & x \in (0, 1] \\ 0.0436 & x \in (1, 2] \\ 0.0912 & x \in (3, 4] \\ 0.0991 & x \in (4, 5] \\ 0.1626 & x \in (5, 6] \\ 0.2182 & x \in (6, 7] \\ 0.3253 & x \in (7, 8] \\ 0.4285 & x \in (8, 9] \\ 0.5277 & x \in (9, 10] \\ 0.6388 & x \in (10, 11] \\ 0.7539 & x \in (11, 12] \\ 0.8412 & x \in (12, 13] \\ 0.8769 & x \in (13, 14] \\ 0.9245 & x \in (14, 15] \\ 0.9721 & x \in (15, 16] \\ 0.9919 & x \in (16, 17] \\ 0.9959 & x \in (17, 18] \\ 0.9999 & x \in (18, 19] \\ 1.0000 & x \in (19, \infty] \end{cases} \quad (3.1)$$

By simulation we generate rough estimates for the first historical outbreak of Zika in Salta. Several runs were performed each with 252 stochastically obtained Zika cases. The first historical outbreak that marked the arrival of Zika in Salta, in 2017, registered 252 human cases. Some examples of these results are presented in the figures. Figures 3, 4 shows three examples of these runs, of type A and B, also to the right, the respective evaluations of the averages values of the number cases obtained for each run is compared to the actual outbreak that occurred in Salta.

The ANOVA table decomposes the variability of Value of R_0 into contributions due to different numbers of runs in the simulations, simulation type A, B and C; denoted STA, STB and STC respectively. The contribution of each type of simulation is measured by eliminating the effects of the other types. The P-values test the statistical significance of each of the STA, STB, and STC types. Since a P-value is less than 0.05, this factor has a statistically significant effect on R_0 with a 95.0% confidence level.

Table 2 ANOVA table, the F-tests allow to identify the significant factor Type A for the estimates of reproduction number, R_0 of first historical outbreak of Zika occurred in Salta, Argentina, 2017.*

Analysis of Variance for R_0	Sum of Squares	gl	Mean Square	F-Ratio	P-Value
Main Effects					
Type A (STA)	0.02002	2	0.01001	5.76	0.0083
Waste	0.04694	27			
Total(Corrected)	0.06696	29			

*: Based on simulations for generation times T stochastically obtained. All F-ratios are based on the mean square of the residual error.

The Figure 5 shows the graph of means and of 95% Fisher LSD (Least Significant Difference) intervals corresponding to the types of runs in each simulation, STA, STB and STC. It is observed that the estimated values of the basic reproduction number, R_0 , for the exponential model of Begon&Harper [Begon2006], differ significantly for the STA simulations factor, those where 10 runs are performed to obtain the probabilistic models of the epidemic curves for ZIKV.

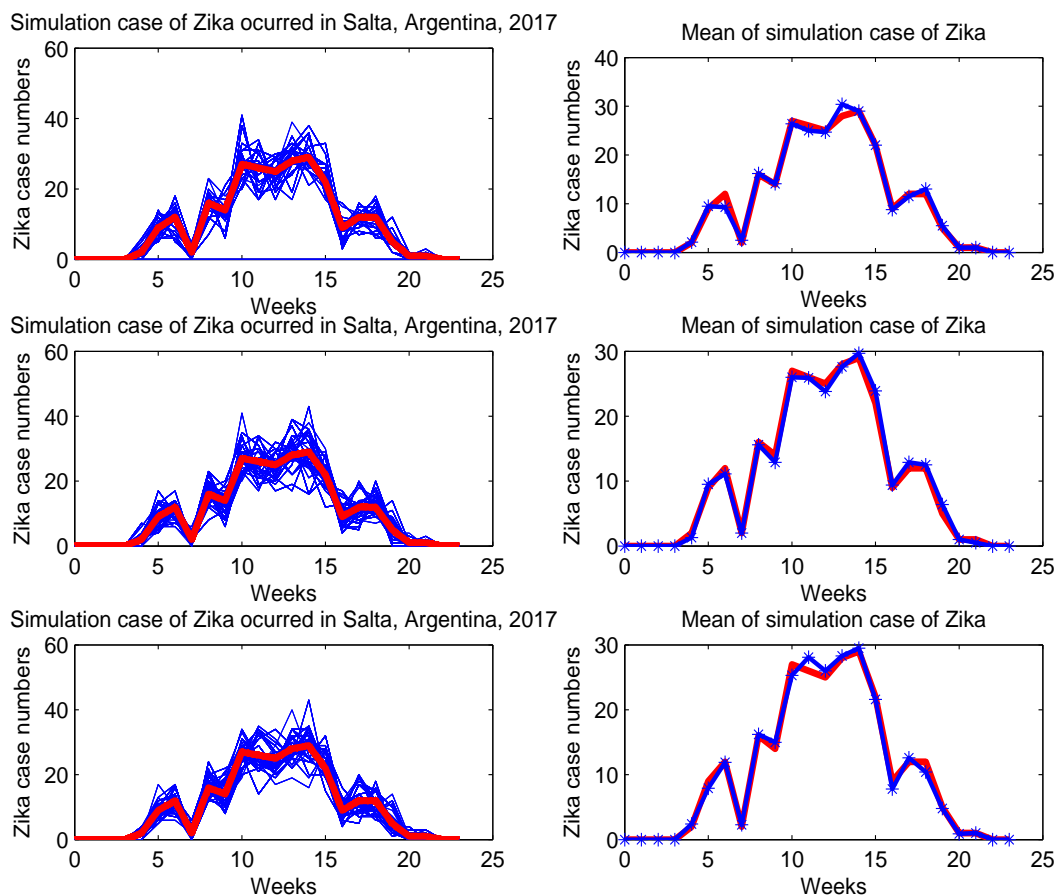


Figure 3: Left An example showing three simulations of 10 runs and right, the corresponding average values of number cases of Zika stochastically obtained (*- blue lines).

4 Discussion

As Fajardo points out [Fajardo2017], the prevalence measures the proportion of people who are ill at the time of evaluating the condition in the population, therefore, there is no follow-up time. In this case, we measure the prevalence that occurred during the outbreak of the first historical outbreak of Zika in Salta. The estimates showed that the San Martín department, 90.07×10^{-5} , was affected approximately 5 times more than the Orán department, 17.69×10^{-5} , while the prevalence in the Orán department was approximately 1.3 times more than in the Rivadavia department, 13.42×10^{-5} . The prevalence map, Figure 1, shows the commented situation and the region affected by Zika and also the rest of the departments of the Province, in which no cases were registered can be observed with the spatial model.

The Table 3 shows the relative frequencies of weekly Zika cases number and its cumulative frequencies for the historical peak first of Zika occurred from EW 4 to EW 23, Salta, Argentina, 2017. On the other hand, the function given by (3.1) provides, the estimation for the c.d.f., $F_X(x)$ based on the data corresponding to the historical outbreak first of ZIKV occurred in Salta, Argentina, 2017, in the Departments of San Martín, Orán and Rivadavia, resulting like this the probabilistic model obtained.

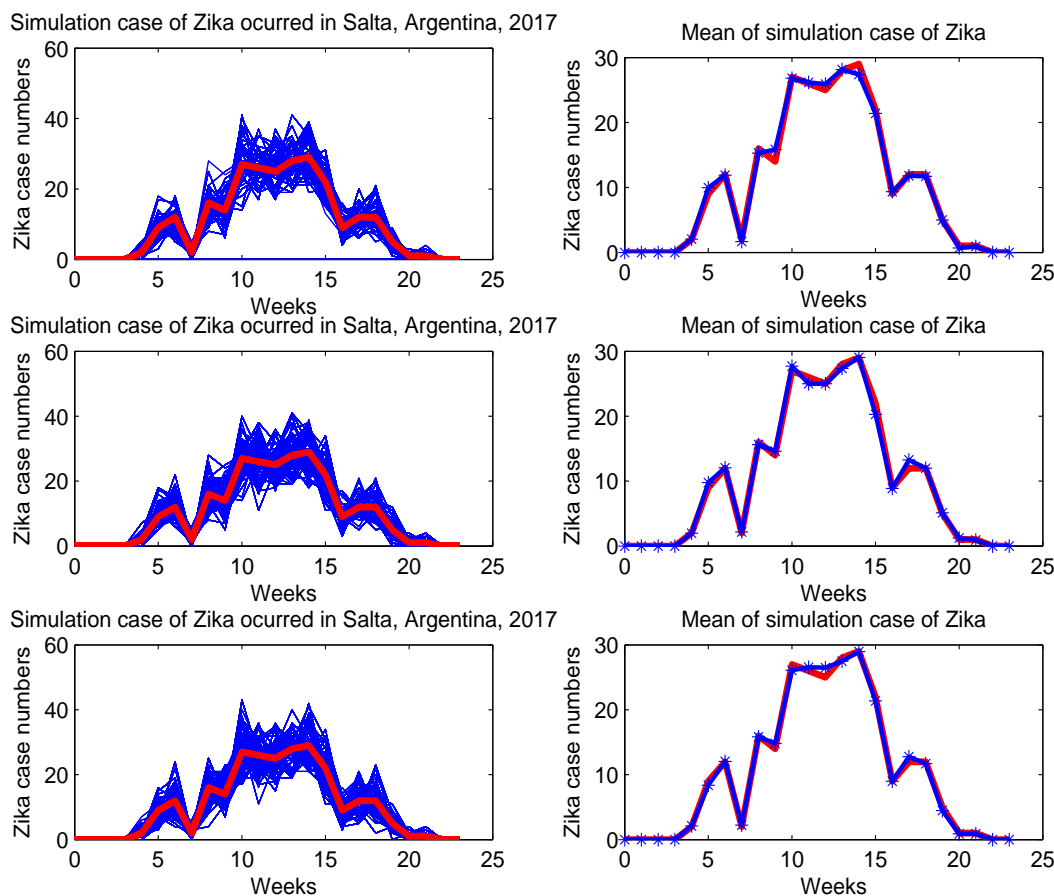


Figure 4: Left An example showing three runs of 20 runs and right, the corresponding average values of number cases of Zika stochastically obtained (*- blue lines).

Wiratsudakul et. al. points out that the compartmental model is still commonly used for the timely assessment of epidemics. However, much more complex modeling frameworks (metapopulation, network, and individual-based models) have been of increasing interest [Wirat2018], here we present a simple method to obtain probabilistic qualitative descriptions to model epidemic outbreaks, which provide a different point of view from that of deterministic models, in this case applied to Zika, however the methodology could be applied to other diseases.

Estimates of the basic reproductive number R_0 were made, according to the expression of Begón, et. al. [Begon2006] These estimates were obtained by varying the number of runs in 10, 20 and 30. Since a P-value (0.0083) is less than 0.05, this factor has a statistically significant effect on R_0 with 95.0% of confidence level. This value corresponds to the simulations of type A, STA, 10 runs to obtain the epidemic curve and compare it with the real epidemic, see Table 3 graphs of means and of Fisher LSD in Figure 5. These descriptions were better when the number of experimental runs were 20 and 30, see Figure 3, 4, right. Previous estimates of the basic reproduction number for the region, $R_0 \approx 1.10595\%CI[1.104-1.106]$ and $R_0 \approx 1.111\ 95\%CI[1.110-1.112]$ [Rosales2020], small values, induce us to agree with what is expressed by Zhang et.al. that the ZIKV epidemic is characterized by slow growth [Zhang2017].

Taking into account of means and of 95% Fisher LSD (Least Significant Difference) intervals corresponding to the types of runs in each simulation, STA, STB and STC, Figure 5. It is observed that

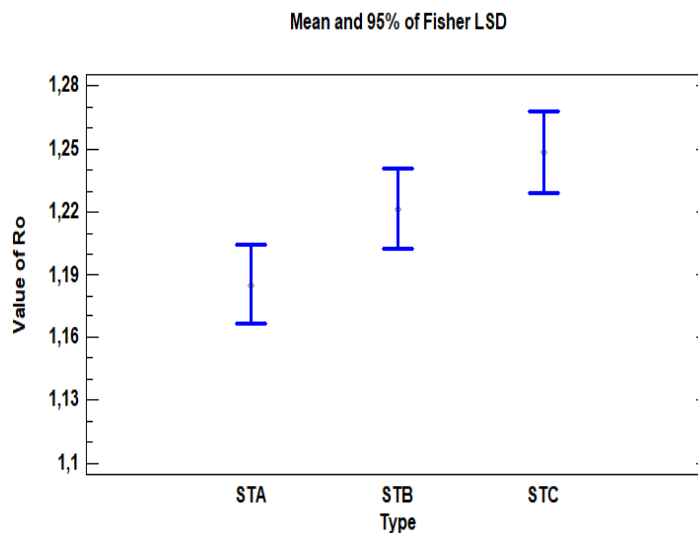


Figure 5: Graph of means and of 95% Fisher LSD (Least Significant Difference) intervals corresponding to the types of runs in each simulation, STA, STB and STC. The estimated values of the basic reproduction number, R_0 , differ significantly for the STA simulations factor.

the estimated values of the basic reproduction number, R_0 , differ significantly for the STA simulations factor, those where 10 runs are performed to obtain the probabilistic models of the epidemic curves for ZIKV. This suggests that our simulator would provide good descriptions of the epidemic curve when performing 20 or 30 runs. This detail would be important if, for example, it is necessary to obtain several intrinsic growth rates of the epidemic outbreak to be used in deterministic models.

5 CONCLUSIONS

In this work we have qualitatively described the first historical outbreak of Zika that occurred in Salta, in 2017, using Monte-Carlo simulations. The methodology proposed here is simple and we think that it can easily be applied to the description of epidemic outbreaks of other diseases. The model found to describe the probabilistic behavior for the first historical outbreak of Zika in Salta in its expansion through South America has been presented in Proposition 3.1. At present, after the outbreaks of 2017 and 2018, Zika has remained in a phase of silence in this region of Argentina.

On the other hand, a classic measure of the frequency of a disease, the prevalence ratio, was estimated. In this case, a map was constructed with the estimated prevalence values in the departments that were affected by ZIKV infection.

Our simulator provides probabilistic models of the epidemic outbreak that fit reasonably well if the number of randomized experiments is 20 and 30 replicates. Thus, the epidemic curves generated allows us to estimate their respective intrinsic growth rates. Therefore, using the Begon&Harper expression [Begon2006], it is possible to estimate R_0 using a generation time that includes both the human being and the mosquito. These R_0 estimates are affected by the simulation type factor STA,

which correspond to 10 runs. However, if 20 or 30 runs are carried out, the scenarios obtained are quite acceptable and could generate rates to apply to deterministic models SIR and SEIR types.

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