COMPARISON OF INDICATOR KRIGING AND CONDITIONAL SIMULATION APPLIED TO SPATIAL DISTRIBUTION OF THE VECTOR *AEDES AEGYPTI*

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▪ ABSTRACT: This study was conducted to evaluate the spatial distribution of *Aedes aegypti* and to compare estimation methods of indicator kriging and conditional simulation. It was collected data from both dry and rainy periods through home visits and inspection of water contained in deposits in two areas (Train and New City) of the city of Macapá, Brazil. Among the main findings, it could be highlighted that the highest incidence of larvae was observed in the rainy season. It was also observed that, in both neighborhoods, the exponential model presented the best fit to the data. This model was used in the indicative kriging estimation method. It was applied descriptive measures such as mean, standard deviation and coefficient of variation for comparing observed and estimated values obtained by kriging and conditional simulation. The results showed that the conditional simulation was the best method for estimating the spatial distribution of *Aedes aegypti* in the two study areas.

▪ KEYWORDS: *Dengue*; epidemiology, geostatistics; interpolation.

1 Introduction

Epidemic is the spread of an infectious disease which quickly arises in a particular location or in large regions and that attacks, at the same time, a large number of persons.

Several ancient populations were destroyed by large-scale deaths from epidemics of leprosy, plague and cholera. Flu and dengue are quite frequent epidemics in Brazil today.

Dengue has become a major health problem in Brazil. 2016 began with an increase in the number of dengue cases compared to 2015. The studies show that in the first weeks of this year there was an increase of approximately 49% over the same period 2015. Lefevre *et al.* (2007) stated that between vectored diseases, dengue deserves greater attention since, even in the classic form, creates inconvenience to the population, in addition to spending resources in the control trial, this should be easier to control flu, but

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that's not what we see, on the contrary, it is seen larvae of dengue-causing mosquitoes to multiply more and more a result of rapid urbanization, pollution, environmental degradation, infrastructure deficiencies, sanitation and preventive education. Oliveira *et al.* (2003) also showed that the concentration of the species *A. aegypti* is mainly in urban areas with high concentrations of humans. Brassolatti and Andrade (2002) reported that, worldwide, the key step in combating the dengue program and the most difficult to succeed is about the community participation in the elimination phase and not allowing the vector breeding in breeding home.

Dengue is defined by Bridges and Netto (1994) as an arbovirus, whose etiologic agent is represented by a complex of four serotypes of the virus family Flaviviridae, genus flavivirus, composed of about 70 species, of which about 30 are pathogenic, all cause the same clinical syndrome. This can be transmitted mainly by two mosquito species: *A. aegypti* and *A. albopictus* (HONÓRIO *et al*., 2009).

There are reports in Brazil, epidemics since 1916, however the first epidemic documented clinical and laboratory findings was in 1982, in Boa Vista (Roraima), caused by the circulation of serotypes 1 (DEN-1) and 4 (DEN-4) considered the most dangerous (OSANAI et al 1983). The DEN-4 type was reintroduced in Brazil in 2010 in the municipalities of Boa Vista and Canta, located in the state of Roraima (TEMPORÃO *et al*., 2011). Specifically in the city of Macapá, the first cases of dengue recorded after laboratory confirmation, were cases imported mostly from the state of Pará. Frame this established until March 2001 when the first indigenous case of dengue surge in the municipality and consequently in the state.

The study and control of this epidemic proves extremely important. Therefore, tools that can provide quick and efficient responses are very important for decision-making of governments, health departments, etc. In this context, statistical methods arise as allies in the identification, measurement and provide subsidies for vector combat in certain urban and rural areas. Conventional statistical methods describe the distribution of a particular population as aggregate, uniform or random, thus ignoring the spatial distribution of sampling stations (FARIAS *et al.*, 2001). Geostatistical methods have been utilized to characterize the spatial distribution of insects by entomologists who study population dynamics (ELLSBURY *et al.*, 1998; DARNELL *et al.*, 1999; BARRIGOSSI *et al.*, 2001).

2 Materials and methods

The area under study refers to two neighborhoods of Macapá. These neighborhoods are: Train and New City. Macapá is the most populous city of the Amapá state, being the only Brazilian capital bathed by the waters of the Amazon. It is cut by the Equator and its altitude is approximately 16 m above sea level, covering an area of 27795 km2. The number of inhabitants has a non-homogeneous occupation of physical space in which it identifies disability in infrastructure, such as substandard housing, population density, sanitation limitations, especially regarding the distribution of piped water and sewage collection networks, inadequate information systems and public education

The collection of larvae was carried out through "home visit" considering the inspection technique recommended by the Technical Operational Policy Manual of the National Program of Dengue Control (BRAZIL, 2001). The inspection was initiated from outside (patio, yard or garden), always following the right. The inspection of the property continues with an internal visit and must be initiated from the funds, so going from room to room until all deposits containing water were carefully examined.

The collection is based on the verification of the presence or absence of larvae in 186 sampled and georeferenced points, as can be seen in the base map of ‘New City’ and ‘Train’ (Figures 1 and 2). To obtain the samples, selected at the most four housing block by block to include one residence on each side thereof (the wastelands and wetlands were excluded due to difficult access).

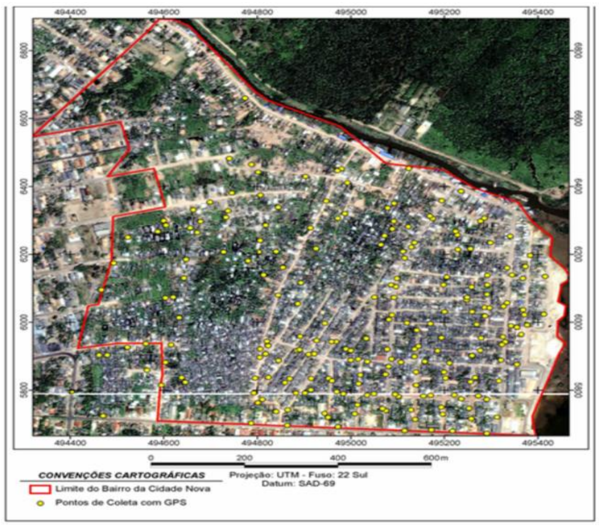

Figura 1 - Spatial sampling map of the properties of the neighborhood New City, showing the 186 properties sampled.

Figura 2- Spatial sampling map of the properties of the neighborhood Train, showing the 186 properties sampled.

2.1 Geostatistical Analysis

The spatial dependence between neighboring samples can be measured with the semivariogram. The semivariogram can be estimated by

$$\gamma\ (h) = \frac{1}{2n}\sum_{i=1}^{n}\left(Z(x_i) - Z(x_j)\right)^2, \forall d\left(x_i, x_j\right) < h \qquad (1)$$

where n is the total number of pairs of mosquitoes counts that are separated by a distance h. The graph of versus the corresponding values of h, called a semivariogram, is a function of the distance h, and, therefore, depends on distance magnitude and direction (FARIAS *et al*., 2008).

The equation (1) expresses the spatial dependence among samples and to allow estimation of values for unsampled locations. For properties that are spatially dependent, the increment is expected to increase with distance, up to some distance beyond which it stabilizes at a sill value (symbolized as C1) and is numerically almost equal to the variance of the data. This distance is called the range (a) and represents the radius of a circle within which the observations are correlated. The semivariance value at the intercept to the axis is called nugget effect (C0), and represents the variability at distances smaller than the minimum sampling distance. Dominy *et al*. (2002) comment that the randomness introduced makes predictions of unsampled locations difficult. As a result, understanding and reducing the nugget effect has significant importance because a high nugget effect can be related to poor sampling practice.

A comparison of semivariogram parameters, for different situations, can provide important information on the corresponding spatial distribution.

Many times, one may be interested in going beyond modeling the spatial structure, such as when values for unsampled locations must be estimated to build a detailed, precise map of the variable under study. In this case, it is necessary to interpolate between the sampled points. If an estimation, is to be made for any location, as linear combination of the neighboring measured values (x_0), then as

$$z\ \left(x_0\right) = \sum_{i=1}^{N} \lambda_i z(x_i\ ), \qquad (2)$$

where N is the number of measured values involved in the estimation, and are the weights associated with each measured value. If the spatial correlation expressed through the semivariogram is used to define the weights, then the estimation process is called ordinary kriging. This estimation is unbiased and has minimum variance (DEUTSCH and JOURNEL 1992).

2.2 Conditional simulation

The stochastic simulation generates several independent sequences of the studied phenomenon, wherein each draw generates a new different series but with the same statistical properties and equally probable, characterized by the ability to reproduce the variation of the input data in the case of geostatistics, from the variogram. This objective differs from that estimation is to minimize the variance of the estimation error. For this reason, the estimation tends to produce spatial variation patterns more smoothed than actual.

This condition is especially characteristic of kriging. In general, the goals of the simulation and the estimation are incompatible. The estimated values $Z^*(x)$ tend to fit itself by means of the actual values of $Z(x)$, even if the simulated values $Z_S(x)$ best reproduce the aspect of fluctuation of the real phenomenon (CALVETE and RAMIREZ 1990).

$$Z_{SC}(x) = Z^*(x) + \left(Z_S(x) - Z_S^*(x)\right), \tag{3}$$

where $Z^*(x)$ is the estimated value in x obtained by kriging, $Z_S(x)$ is the simulated value (without conditional processing) and $Z_S^*(x)$ is the kriging estimated value taking into account the simulated values in the sampling points. The expression above can be written as

$$Z_{SC}(x) = Z^*(x) + e_{SC}(x), \tag{4}$$

where $e_{SC}(x)$ represents the kriging inaccuracy of the simulated values Z_S without conditional processing. Taking into account the original data $Z^*(x)$, the kriging values are obtained by

$$Z(x) = Z^*(x) + e_k(x). \tag{5}$$

Because kriging value is estimated, it can be assumed that $E[e_{SC}(x)] = E[e_k(x)] = 0$. The $Z_{SC}(x)$ covariance has the same value of $Z(x)$ covariance because kriging inaccuracies $e(x) = [Z(x) - Z^*(x)]$ and $e_{SC}(x) = [Z(x) - Z_{S*}^*(x)]$ have the same covariance, and, $e(x)$ and $Z^*(x)$ are orthogonal.

In kriging it is assumed that

$$Z_S(x_i) = Z_S^*(x_i) \text{ and } Z(x_i) = Z^*(x_i), \tag{6}$$

with $Z_{SC}(x_i) = Z(x_i)$ for all *i*. Therefore, a simulation process that keeps the covariance structure of Z and coincides with the observations is chosen and, consequently, $Z_{SC}(x_i)$ is accepted as the conditionally simulated process of *Z*.

To evaluate the methods of estimation of this study is used to display geostatistical maps and from the images are measurements obtained as the mean $(\overline{X})$ the deviation (S) and the coefficient of variation (CV) of observed values (OV) and the estimated (VE) by indicative kriging (KRIG) and conditional simulation (SC) to assess and verify which method is most suitable for the study

3 Results

Initially, it was observed in the inspected buildings in the city of Macapá that the highest incidence numbers of larvae were recorded for the rainy season, and the New City neighborhood with the highest amount of collected larvae.

Table 1 - Number and percent of inspected homes in the city of Macapá to the vector larvae incidence verification of *Aedes aegypti*, in the neighborhoods of Train and New City for both the dry (Oct / 05) and rainy (Feb / 06) seasons

Neighborhood	Variables	Dry period		Rainy period	
		Quantity	Percentage	Quantity	Percentage
Train	Absence	164	88,17	148	79,57
	Presence	22	11,83	38	20,43
	Total	186	100,00	186	100,00
New City	Absence	181	83,03	156	71,56
	Presence	37	16,97	62	28,44
	Total	218	100,00	218	100,00

First of all, it was necessary to measure the degree of spatial dependence among samples, which can be assessed by semivariogram for examination and interpretation of spatial variability. The Table 2 shows the parameters of the adjusted models in semivariograms, theoretical models, the coefficient of determination (R^2), the index relative nugget effect (E) and k parameter in which it is observed that for the variables studied, the semivariogram parameters were adjusted considering the degree of fit of the models, verified by R^2.

Table 2- Parameters of semivariograms models, R^2, relative nugget effect (E) and K parameter to the larvae incidence vector *Aedes aegypti* in neighborhoods of Train and New City for the two seasons of collection

Neighborhood	Variables	Parameters			Model	R^2	E	K
		C_0	C_1	a(m)				
Train	Dry period (Out/05)	0.03	0.09	150	Exponential	0.99	0.33	0.25
	Rainy period (Fev/06)	0.05	0.12	120	Exponential	0.98	0.42	0.30
New City	Dry period (Out/05)	0.06	0.11	120	Exponential	0.99	0.55	0.35
	Rainy period (Fev/06)	0.12	0.10	160	Exponential	0.98	1.20	0.55

The semivariogram and the parameters of the fitted model to the incidence vector *Aedes aegypti* larvae to dry and rainy periods in Train district are shown in Figure 3 A and B, which show that the exponential model fit the incidence of data larvae to both the dry and rainy seasons, with a spatial dependence (range) of 150m and 120m, respectively. For the dry season the relative nugget effect (E) is approximately 0.33 and the ratio (k) is equal to 0.25. In the rainy season the Train district has E = 0.42 and k = 0.30, thus indicating the existence of significant randomness in both the samples for the two seasons.

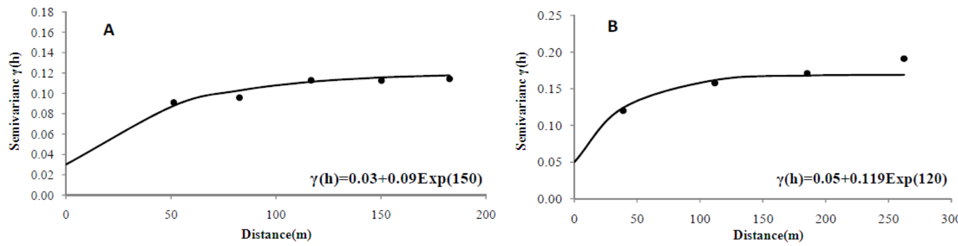

Figure 3 - Semivariograms larvae vector incidence of *Aedes aegypti* in the neighborhood of Train: (A) dry season (Oct / 2005) and (B) rainy season (Feb / 2006).

You can see in Figure 4 A and B maps for vector *A. aegypti* larvae variable estimated by kriging and the average of 100 conditional simulations to the Train neighborhood for both the dry and rainy seasons.

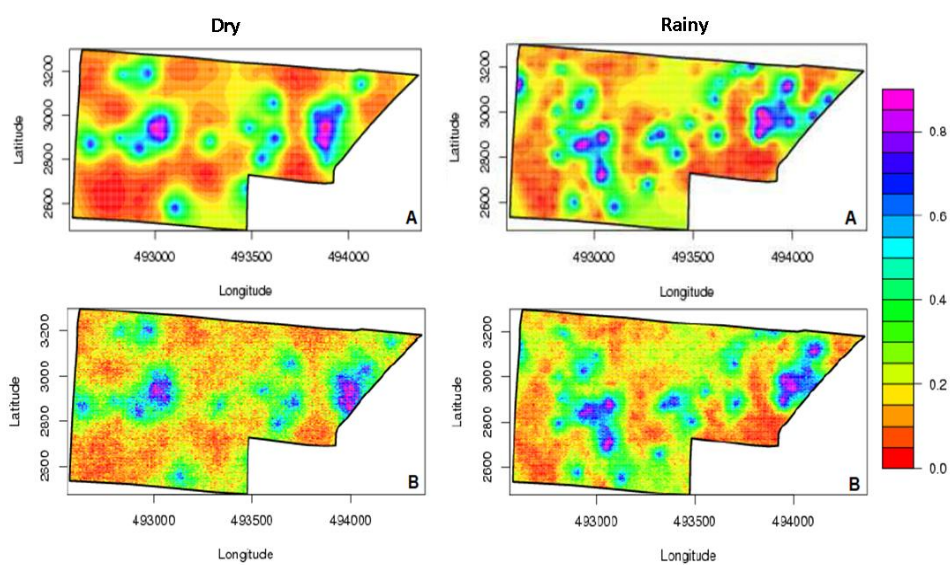

Figure 4- Maps of variable larvae vector *Aedes aegypti* estimated by kriging indicative (A) and average of 100 conditional simulations (B) in the neighborhood Train for dry and rainy periods.

Visual inspection of Figure 4 shows that it is possible to see that both have similar results. But, the difference between these figures is on the surface of the region, while Figure 4A produces the most smoothed spatial variation to the actual values in Figure 4B best represents the data variability (Figure 3), being necessary to analyze the parameters in Table 3.

Table 3 presents S and the CV of observed and estimated values by indicative kriging and conditional simulation used in vector spatial distribution *A. aegypti* in the district Train to the dry and rainy seasons.

Table 3- Average, S and CV values of observed (OV) and estimated values by indicative kriging and conditional simulation used in spatial distribution of the vector *Aedes aegypti* for the Train district for both the dry and rainy seasons.

	Dry period			Rainy period		
	OV	KRIG	SC	OV	KRIG	SC
Average	0.1300	0.1401	0.1562	0.1200	0.1186	0.1335
S	0.3371	0.1514	0.3585	0.3258	0.1281	0.3389
CV	25.931	10.807	22.951	2.7150	10.801	25.386

Note: CV = S/Average. that S: Deviation; and CV: Coeficient of Variation.

It is observed in Table 3 that when comparing the average of the values estimated by kriging and conditional simulation with the average of the observed values, the neighborhood Train, both in the dry season and in the rainy season, both presented averages of approximately equal estimators of the observed values. So, making an analysis from the deviation of the observed values, where the deviation of the estimation should be as close as possible deviation of the observed values. In doing so, it is observed that the deviation of the conditional simulation for the rainy and dry seasons was more close to the observed values. Then calculate the CV of the observed values and estimated, it noted that both the dry and rainy seasons, the estimation method for simulation was the most appropriate for this study because it presents the CV near the CV values observed.

It is observed in Figure 5 A and B that the exponential model fit both the incidence data larvae for both the dry and rainy season, with a spatial dependence (range) of 120m and 160m respectively. It is noted also that the dry period on the nugget effect (E) is of the order of 0.55, which indicates that the random component is very important, and the parameter k was 0.35, indicating that about 35% of the variance of the samples is random. For the rainy season and was around 1.20 and k equal to 0.55. Thus, they are close to the sampling units were this variability is present.

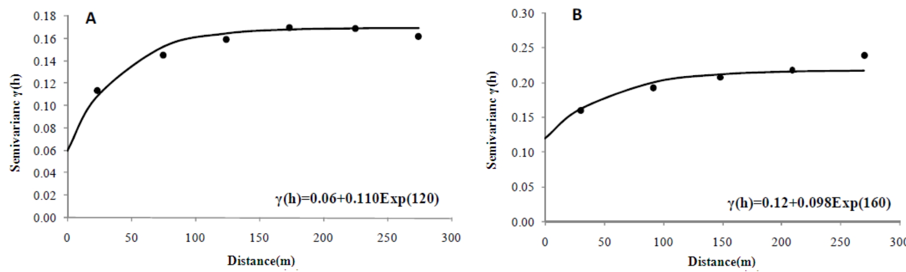

Figure 5- Semivariograms larvae vector incidence of *Aedes aegypti* in the neighborhood of New City: (A) dry season (Oct / 2005) and (B) rainy season (Feb / 2006).

Figure 6 (A and B) shows the map of the variable vector *A. aegypti* larvae estimated by kriging and the average of 100 conditional simulations in the New City neighborhood to the dry and rainy seasons. For visual comparison of the maps obtained, it can be seen that these images show only changes with regard to the variability of the data.

It is observed from Table 4, which shows the values of S and the CV of observed and estimated values of indicative kriging and conditional simulation used in vector spatial distribution *A. aegypti* in the New City neighborhood, for dry periods and rainy that the kriging estimation and conditional simulation are approximately equal. thus indicating that it is not only necessary to evaluate these estimators. Note that for the New City neighborhood, during the two periods studied. The estimation by simulation presents the best S in relation to indicative kriging estimation. From the CV of observed and estimated values, it turns out that the conditional simulation was the most appropriate method for the study in the New City neighborhood to the dry and rainy seasons.

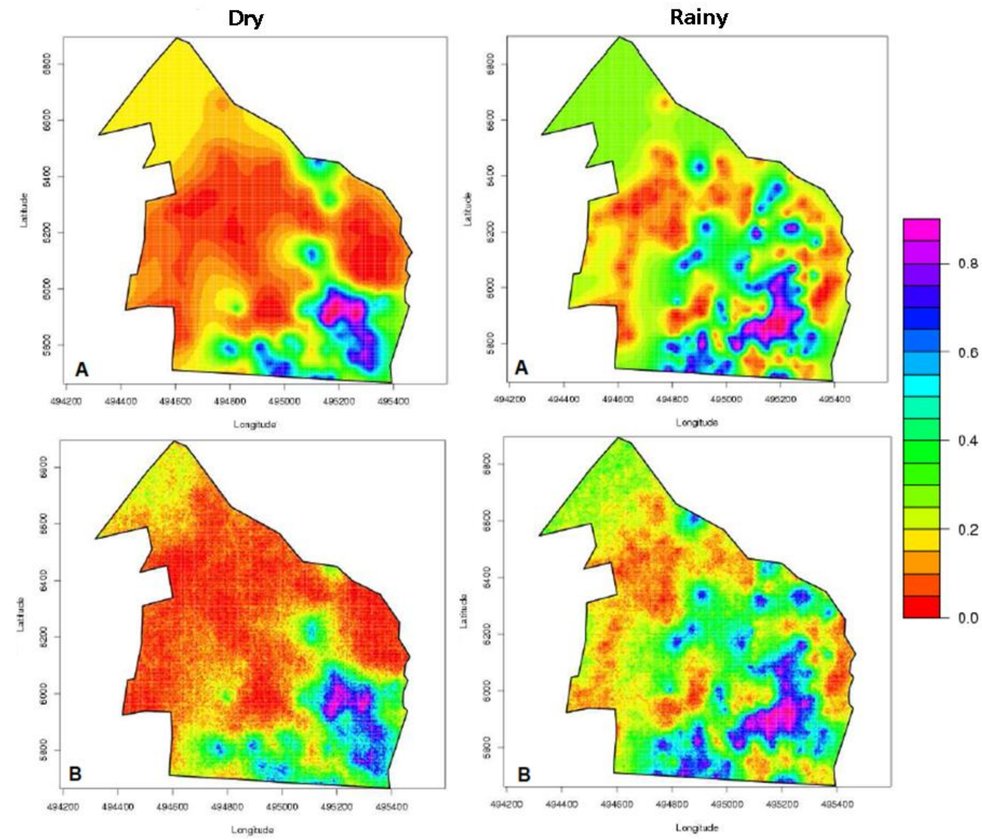

Figure 6 - Maps of variable larvae vector *Aedes aegypti* estimated by kriging indicative (A) and average of 100 conditional simulations (B) in the neighborhood New City for the dry and rainy periods

Table 4- Average. S and CV values of observed (OV) and estimated by kriging indicative and conditional simulation used in spatial distribution of the vector *Aedes aegypti* in the New City district, for the dry and rainy seasons

	Dry period			Rainy period		
	OV	KRIG	SC	OV	KRIG	SC
Average	0.1697	0.1395	0.1354	0.2844	0.2588	0.2632
S	0.3763	0.0985	0.3398	0.4522	0.1169	0.4385
CV	2.2174	0.7061	2.5096	1.5900	0.4517	1.6728

Note: CV = S/Average. that S: Deviation; and CV: Coeficient of Variation

Conclusions

Geostatistics and conditional simulation were used in this study to select best method would fit the vector distribution *A. aegypti*. From the analysis of the coefficients of variation for the neighborhoods Train and New City, located in the city of Macapá, you can see that on both locations the conditional simulation shows better performance to estimate the variable vector *A. aegypti* larvae. The importance of this study lies in the fact of being able to assess and identify possible areas with the highest incidence of dengue vector, facilitating decision making for disease control for more effective and precise methods.

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RESUMO: Este estudo foi conduzido para avaliar a distribuição espacial do Aedes aegypti e comparar os métodos de estimativa krigagem indicadora e simulação condicional. Assim, recolheu-se informação nos períodos seco e chuvoso, através de visitas domiciliares e inspeção de água contida em depósitos nas áreas de estudo (Bairros Trem e Cidade Nova) pertencentes à cidade de Macapá, Brasil. Dentre as principais descobertas destaca-se que a maior incidência de larvas foi registrada na estação chuvosa. Pode-se observar que o modelo exponencial foi o que melhor se ajustou aos dados para os dois bairros, permitindo a estimativa por krigagem indicativa. Para avaliar os métodos de estimação utilizaram-se medidas descritivas como: média, desvio padrão e coeficiente de variação para os valores observados e valores estimados, tanto pela krigagem quanto pela simulação condicional. A partir da análise das medidas obtidas, parece que a simulação condicional foi o método mais adequado ao estudo nos bairros e que apresentou os melhores resultados de estimação.

PALAVRAS-CHAVE: Dengue; epidemiologia, geostatística; interpolação, dependência espacial.

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