Acta Tropica 205 (2020) 105398

Contents lists available at ScienceDirect

Acta Tropica

journal homepage: www.elsevier.com/locate/actatropica

Remote sensing for risk mapping of *Aedes aegypti* infestations: Is this a practical task?

Camila Lorenz[a,1,*], Francisco Chiaravalloti-Neto[a,1], Mariana de Oliveira Lage[b], José Alberto Quintanilha[b], Maisa Carla Parra[c], Margareth Regina Dibo[d], Eliane Aparecida Fávaro[c], Marluci Monteiro Guirado[e], Maurício Lacerda Nogueira[c]

[a] *Departamento de Epidemiologia, Faculdade de Saúde Pública, Universidade de São Paulo, Av. Dr. Arnaldo, 715, São Paulo, SP, Brazil*
[b] *Divisão Científica de Gestão, Ciência e Tecnologia Ambiental do Instituto de Energia e Ambiente - IEE da Universidade de São Paulo, São Paulo, SP, Brazil*
[c] *Laboratório de Pesquisa em Virologia, Faculdade de Medicina de São José do Rio Preto, São José do Rio Preto, SP, Brazil*
[d] *Laboratório de Entomologia, Superintendência de Controle de Endemias, São Paulo, SP, Brazil*
[e] *Laboratório de Vetores, Superintendência de Controle de Endemias, São José do Rio Preto, SP, Brazil*

ARTICLE INFO

Keywords:
Mosquito control
Bayesian approach
Landscape
Geostatistical analysis

ABSTRACT

Mosquito-borne diseases affect millions of individuals worldwide; the area of endemic transmission has been increasing due to several factors linked to globalization, urban sprawl, and climate change. The *Aedes aegypti* mosquito plays a central role in the dissemination of dengue, Zika, chikungunya, and urban yellow fever. Current preventive measures include mosquito control programs; however, identifying high-risk areas for mosquito infestation over a large geographic region based only on field surveys is labor-intensive and time-consuming. Thus, the objective of this study was to assess the potential of remote satellite images (WorldView) for determining land features associated with *Ae. aegypti* adult infestations in São José do Rio Preto/SP, Brazil. We used data from 60 adult mosquito traps distributed along four summers; the remote sensing images were classified by land cover types using a supervised classification method. We modeled the number of *Ae. aegypti* using a Poisson probability distribution with a geostatistical approach. The models were constructed in a Bayesian context using the Integrated nested Laplace Approximations and Stochastic Partial Differential Equation method. We showed that an infestation of *Ae. aegypti* adult mosquitoes was positively associated with the presence of asbestos roofing and roof slabs. This may be related to several other factors, such as socio-economic or environmental factors. The usage of asbestos roofing may be more prevalent in socioeconomically poor areas, while roof slabs may retain rainwater and contribute to the generation of temporary mosquito breeding sites. Although preliminary, our results demonstrate the utility of satellite remote sensing in identifying landscape differences in urban environments using a geostatistical approach, and indicated directions for future research. Further analyses including other variables, such as land surface temperature, may reveal more complex relationships between urban mosquito micro-habitats and land cover features.

1. Introduction

Aedes aegypti (Linnaeus, 1762) mainly inhabits urban and suburban environments in close association with humans (Service, 1992; Gibbons and Vaughn, 2002) and is considered the primary vector of the etiological agents of dengue, Zika, chikungunya, and urban yellow fever (Kyle and Harris, 2008; Paupy et al., 2010). It is estimated that every year, approximately 3 billion people in the world are at risk of dengue infection (Bhatt et al., 2013; WHO, 2016). In 2016, in Brazil alone, 802,249 new suspected cases of dengue fever, 63,810 confirmed cases of chikungunya, and 64,311 confirmed cases of Zika fever were reported in 1840 municipalities (MS, 2019). Female *Ae. aegypti* mosquitoes blood-feed during the day and usually lay their eggs in artificial containers such as buckets, drums, and tires, where water accumulates and remains for several days (Service 1992; Focks and Chadee, 1997; Gubler, 1998; Calderón-Arguedas et al., 2004). The presence of *Ae.*

Abbreviations: INLA, Integrated Laplace Approximations; PCA, principal component analysis; PC, principal components; NAM, number of *Ae. aegypti* adult mosquitoes; SPDE, stochastic partial differential equations; W, intercept and the spatial dependence; DIC, Deviance Information Criteria; RC, rotated components

* Corresponding author.
E-mail address: camilalorenz@usp.br (C. Lorenz).

[1] These authors contribute equally.

https://doi.org/10.1016/j.actatropica.2020.105398
Received 23 January 2020; Received in revised form 12 February 2020; Accepted 13 February 2020
Available online 14 February 2020

aegypti is also strongly associated with poor sanitary conditions and a lack of residual waste recycling, typical of rapidly expanding urban areas; these are considered important contributory factors to epidemics of vector-borne diseases (Costa et al., 2017). Source reduction by the elimination of larval habitats is an important measure for mosquito eradication efforts in Brazil (MS, 2019). However, *Ae. aegypti* generally breeds in small artificial habitats (Chadee et al., 2004; Calderón-Arguedas et al., 2004), thereby complicating environmental management. The local habitat conditions that influence mosquito life history often vary at spatial scales significantly finer than the land use and census tract boundaries that inform many social and ecological variables (Leisnham et al., 2014; Little et al., 2017). *Aedes aegypti* infestation is likely influenced by local biophysical conditions that support larval development, resting survivorship, and host access, all within the hundred-meter flight range (Marini et al., 2010; Little et al., 2017). However, the identification of these mosquito breeding hotspots over a large geographic region based on field surveys alone is labor-intensive, time-consuming, and ineffective. Hence, more efficient tools for the accurate and rapid determination of mosquito habitat distribution are essential to implement larval and adult mosquito control.

Remotely sensed data can supply spatial information to study the epidemiology of many vector-borne diseases (Bergquist, 2001; Correia et al., 2004; Mushinzimana et al., 2006; Fuller et al., 2010). Previous studies have proven the utility of remote sensing technology in the estimation of vector populations on a large spatial scale. For instance, Welch et al. (1989) used infrared aerial photos in Texas to detect potential *Psorophora columbiae* breeding sites, such as ditches, low-lying areas, and tire tracks. Roberts et al. (1996) surveyed southern Mexican villages and showed that aerial photos were useful for the identification of oviposition sites of *Anopheles albimanus*. They discovered that low elevations in flooded, unmanaged pastures were the most important determinants for adult *Anopheles* abundance. Moloney et al. (1998) tested aerial photography as a surveillance tool for identifying residential premises at high risk of *Ae. aegypti* breeding and found that the premise condition index could be accurately identified from these infrared photographs. Moreover, newly developed remote sensors with high spatial resolution may be particularly useful for determining mosquito habitat distribution in urban areas, and for supporting vector control measures. Commercial imaging satellites such as WorldView-3 offer new opportunities to evaluate urban habitats for disease vectors providing very high spatial resolutions (0.3 m), which are appropriate for identification of city blocks, roadways, buildings, individual roads, tree crowns, and rooftops. Thus, the aim of our study was to assess the suitability of high-resolution (0.3 m) WorldView-3 imagery to assess urban structural variables that may be associated with *Ae. aegypti* infestation. We analyzed empirical relationships between these variables derived from the classification of WorldView-3 imagery and adult mosquito habitats in an endemic area in Brazil.

2. Materials and methods

2.1. Study area and mosquito collection

Our study was conducted in the Vila Toninho neighborhood (20°49′11″ S and 49°22′46″ W), in the city of São José do Rio Preto, Brazil (Fig. 1). This study site encompasses an area of approximately 4×10^6 m², at an elevation of 475 m above sea level (CPTEC, 2015). Census data indicated the presence of approximately 2000 households in the neighborhood, with a human population of about 6000. The climate is tropical, with an average temperature of 25 ºC, and a yearly average rainfall of 1410 mm. Reinfestation by *Ae. aegypti* in São José do Rio Preto was detected in 1985 (Chiaravalloti-Neto, 1997). Dengue was first reported in this municipality in 1990, and it has been significantly affected by the disease ever since. In 2019 alone, more than 10,000 cases of dengue were reported by the Ministry of Health (MS, 2019). We chose the neighborhood of Vila Toninho for our study because this area shows a high prevalence and incidence of dengue (Chiaravalloti-Neto et al., 2019). This study area represents the most vulnerable part of the city for the occurrence of dengue. Additionally an ongoing arbovirus surveillance is being conducted in this area on a cohort of the general population (Chiaravalloti-Neto et al., 2019).

The procedures followed in our study were based on a study by Parra et al. (2018). To capture adult mosquitoes, we used 30 BG Mosquitito™ traps (Biogents BGS) installed on 2016 until 2019 between December and February of each year, a time of peaking *Aedes* infestation, near plant pots, with no direct exposure to the sun and rain in preselected residences with shaded areas. These traps were installed twice a week, once per month, allowing us to gather data from up to 60 houses per week. Traps were installed on Mondays and Thursdays and collected respectively on Tuesdays and Fridays. The traps set always at the same houses and they were maintained at each residence for 24 h. The Cartesian coordinates (UTM 22 zone, SIRGAS 2000) of these houses were obtained using a GPS for each specific trap. Mosquitos collected from the traps were identified at the Laboratory of Entomology from Medical School of São José do Rio Preto (FAMERP) with specific taxonomic keys (Consoli and Oliveira, 1994; Forattini, 2002).

2.2. Remote sensing data acquisition and classification

Cloud-free images of the study area were obtained from WorldView-3 satellite (0.31 m in panchromatic mode and 1.24 m in the multispectral – resampled accordingly) and were acquired on March 2017. The datasets are composed of one panchromatic band (450–800 nm) and four multispectral bands comprising blue (450–510 nm), green (510–580 nm), red (630–690 nm), and near-infrared (770–895 nm). Urban land cover maps were generated by applying supervised image classifiers. Classification algorithms included the following classifiers: maximum likelihood, mahalanobis distance, and minimum distance. These classifiers assigned each pixel to specific, predetermined 10 land cover classes including: asphalt, tile roof, asbestos roof, roof slab, tree, grass, exposed soil, pavement, water, and shadow areas. We precisely selected training samples (50 per class) and test samples (50 per class) corresponding to these 10 categories. The classification accuracy was quantitatively assessed by test samples using a confusion matrix and the kappa coefficient. The overall, user's, and producer's accuracies were defined for testing the classification accuracy (Congalton, 1991). The kappa coefficient is a statistical measure of agreement that considers all of the categories. It has a value close to zero when the observed agreement is the same as expected by chance and a value approaching one with perfect agreement (Monserud and Leemans, 1992).

For the 60 traps, buffers of 30 m, 50 m, and 100 m radii were constructed around each trap, representing the assumed mean distance traveled by an *Ae. aegypti* mosquito (Muir and Kay, 1998; Getis et al., 2003). A study by Getis et al. (2003) showed that *Ae. aegypti* adults clustered strongly within houses and weakly at a distance of 30 m beyond the household. We calculated the percentage of each remote sensing image category into each buffer to relate with the number of *Ae. aegypti* adult females and males found in each trap.

2.3. Data analysis

Initially, an exploratory analysis of the covariates was performed to detect possible outliers. Once detected, the covariates containing these outliers were transformed by logarithm or square root. A principal component analysis (PCA) was performed, for each buffer, among 10 land cover categories to reduce the complexity related to these variables. We chose this approach because of the comparatively lesser mosquito data (60 traps) in relation to the number of classes (10). We standardized the 10 variables and obtained the principal components (PC) and their respective eigenvalues. For each buffer we retained the PC whose eigenvalues were greater than one. Next we rotated the obtained PC for each buffer using varimax and produced the scores to

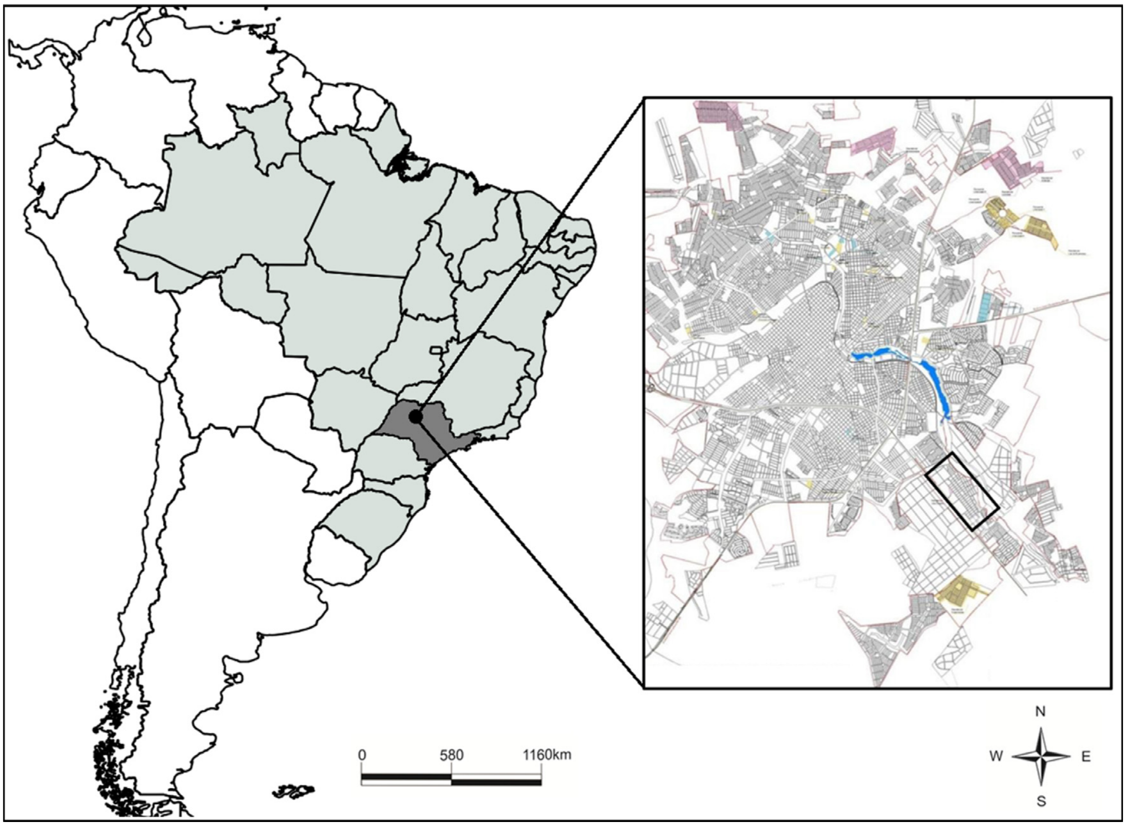

Fig. 1. Left: Municipality of São José do Rio Preto, state of São Paulo, Brazil, South America; Right: Vila Toninho neighborhood (study area) in the municipality of São José do Rio Preto.

calculate the values of PC for each trap. These procedures were performed using *psych* package (Revelle, 2017) of R statistical software.

Next, the number of *Ae. aegypti* adult mosquitoes (NAM) that were found in each trap between 2016 and 2019 was modeled using a Poisson probability distribution in a Bayesian context, which is represented by the following equations:

$$NAM \sim P(\mu_i)$$
$$\log(\mu_i) = \alpha + \sum_{p=1}^{p} \beta_p X_{pi} + W(s_i)$$

where:

- $i = 1,\ldots, 60$ represents the ID of a particular house with mosquito adult traps
- μ_i: mean
- α: intercept
- β: regression parameters
- X: matrix of PC values for each house with adult traps (for buffer of 30, of 50 and of 100 m)
- s_i: Cartesian coordinates of each house with adult traps
- $W(s_i)$: realization of a latent stationary Gaussian field

W, which modeled the spatial dependence among the locations of the houses with adult mosquito traps, has a multivariate normal distribution with zero mean and a spatially structured covariance matrix. To obtain this matrix, we considered the Euclidean distance between the houses with traps and used a Matérn function (Cressie, 1993). We also used a Gaussian Markov random field to represent the Gaussian field. Bayesian inference was performed using the Integrated Nested Laplace Approximations (INLA) and a geostatistical approach, with stochastic partial differential equations (SPDE) (Rue et al., 2009). For these procedures we used the R statistical software suite and the R library INLA (www.r-inla.org).

First, we modeled the NAM alone considering the intercept and the spatial dependence (W) using only females mosquitoes. Then we modeled using both sexes. Next, we considered each PC and modeled the total possible combinations among the obtained components for each buffer. To identify the best model, for each buffer and among all buffers, we used the Deviance Information Criteria (DIC) (Blangiardo and Cameletti, 2015) and the models with lowest values of DIC were considered to be the best. To build an infestation map of NAF we used ordinary kriging technique. We performed a statistical interpolation of data using geoR package of R statistical software. Weight was defined using a semivariogram estimated from core parameters, contribution, and amplitude (Ribeiro-Jr and Diggle, 2001). The maps were edited using QGis software 2.10.1.

3. Results

Our traps captured 705 *Ae. aegypti* adults (460 females and 245 males) in the four-summer study period. Ordinary kriging at different levels of spatial aggregation showed an important local variability in vector infestation (Fig. 2). It is possible to note that the areas of greatest infestation are essentially the same in both maps. Regarding World-View-3 image classification, the most accurate thematic map resulted from Maximum Likelihood classifier, with images accurately classifying 90.6% of the urban land cover and having a Kappa index of 0.89. The confusion matrix was used to provide a site-specific assessment of the correspondence between image classification and ground conditions (Foody, 2002). The global accuracy index of the classification was satisfactory.

Exploratory analysis for the 30 m buffers covariates revealed outliers in the asbestos roof, roof slab, and grass covariates, which were transformed by logarithms. For the 50 m buffers, this analysis revealed outliers in the asbestos roof, grass, and tree covariates, the first two

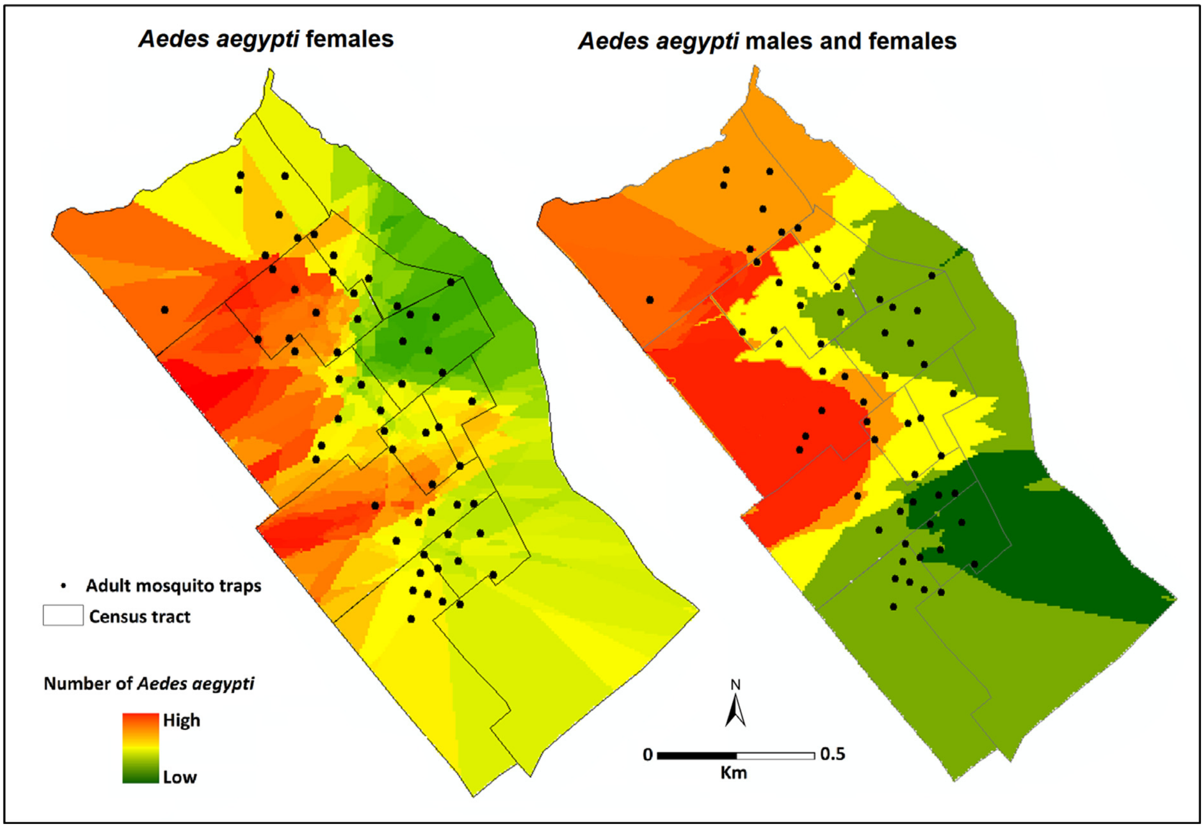

Fig. 2. *Aedes aegypti* infestation map obtained by ordinary kriging in Vila Toninho neighborhood, São José do Rio Preto, São Paulo State, Brazil.

Table 1
Standardized PCA loadings of each land use category based upon correlation matrix.

Classes	Buffer 30m					Buffer 50m					Buffer 100m			
	%	RC1	RC2	RC3	RC4	%	RC1	RC2	RC3	RC4	%	RC1	RC2	RC3
Water	1.83	0.14	0.16	0.26	0.85	1.71	0.05	0.17	0.21	0.11	1.5	0.67	0.11	0.18
Tree	11.35	0.75	−0.40	−0.19	0.15	12.1	−0.55	−0.69	−0.01	−0.25	12.56	−0.53	−0.72	−0.25
Asphalt	16	−0.87	−0.02	0.05	−0.17	14	0.88	0.09	−0.06	−0.05	11.2	0.85	0.41	0.07
Pavement	24.57	−0.59	−0.56	−0.38	0.00	24.01	0.88	−0.06	0.22	−0.02	20.01	0.93	0.19	0.00
Shadow areas	9.38	0.04	−0.34	−0.33	0.73	8.21	0.23	−0.21	0.26	−0.19	7.02	0.85	−0.02	−0.04
Exposed soil	18.95	0.08	0.73	−0.20	−0.05	19.45	−0.04	0.79	0.05	0.09	14.97	0.31	0.55	−0.16
Tile roof	8.25	−0.06	0.87	0.10	0.02	8.75	0.02	0.84	−0.05	−0.29	6.71	0.01	0.90	−0.07
Asbestos roof*	3	0.00	−0.39	**0.65**	−0.36	3.5	−0.04	−0.20	**0.54**	0.87	3.54	−0.11	−0.12	**0.95**
Grass	5.95	0.77	0.19	−0.05	−0.07	7.45	−0.70	−0.07	−0.30	−0.33	8.24	−0.73	−0.01	−0.33
Roof slab	0.72	−0.14	0.09	**0.80**	0.16	0.8	0.20	0.22	**0.32**	0.53	0.8	0.37	0.15	**0.86**

* The term "asbestos" is used to refer to a group of fibrous silicate minerals.

being transformed by logarithm and the third one by square root. For the 100 m buffers, the covariates asbestos roof, roof slab, grass, and trees, all transformed by logarithm, were identified with outliers. Regarding PCA, the first four components presented eigenvalues greater than one for 30 m and 50 m buffers and explained at least 75% of the variation; for 100 m buffers, the first three components presented eigenvalues greater than one and explained 76% of the variation. The proportion explained by each component is presented in Supplementary Material 1 (S1). Standardized PCA loadings (rotated components) based upon correlation matrix can be visualized in Table 1. The percentage of each land cover category was similar in all buffers. Vila Toninho neighborhood is an urban area, so the categories with the largest percentage were pavement, exposed soil, and asphalt.

We tested all possible combinations among RCs using INLA; this can be visualized in Supplementary Material 2 (S2). The best models (with the lowest values of DIC) obtained for all buffers are presented in Table 2. Each mean in the tables represents the variation in the mean of

Table 2
Posterior mean fixed effects and 95% credible intervals (CI) of the best DIC models for the number of *Ae. aegypti* adult females and both sexes for the 30 m, 50 m, and 100 m buffers, Vila Toninho neighborhood, São José do Rio Preto, state of São Paulo, Brazil.

		Only females mosquitoes			Both males and females		
	Covariate	Mean	95% CI	DIC	Mean	95% CI	DIC
Intercept model		0.54	0.16 to 0.9	979.5	0.89	0.4 to 1.3	1202.66
Buffer 30m	RC3	0.12	0.05 to 0.2	977.8	0.075	0.01 to 0.17	1200.47
Buffer 50m	RC3	0.09	0.02 to 0.18	977.9	0.08	0.003 to 0.18	1201.53
Buffer 100m	RC3	−0.004	−0.08 to 0.07	978.2	0.005	−0.07 to 0.08	1202.19

the logarithm of the NAM for the variation of one standard deviation of a specific RC. The best models considering each buffer separately were as follows: for 30 m buffers, RC3 was the most significant, with best Deviance Information Criterion (DIC), indicating better fit of this model. RC3 is negatively associated with asbestos roof and roof slab (Table 1). In the same way, buffers of 50 m and 100 m had the best DIC using RC3, also represented mainly by asbestos roof and roof slab. The best model of all was the RC3 in the 30 m buffers, because it was the one that lowered the DIC value the most compared to the intercept model. In this type of modeling, a covariable model is considered to be good if it presents a DIC lower than the DIC of the intercept model; in this case, DIC using only females decreased from 979.5 to 977.8 and DIC using both sexes decreased from 1202.66 to 1200.47. Although these results do not show statistical significance, they are all consistent with the finding of higher number of *Ae. aegypti* mosquitoes in areas with a large proportion of asbestos roofing and roof slabs. Modeling using both sexes and only females mosquitoes showed essentially the same results. We also performed the modeling using only male mosquitoes, but no model had a DIC lower than the DIC of the intercept model (data not shown).

4. Discussion

Although the results presented here are preliminary, our study indicates the direction that further research may focus on. Most research till date has focused on sylvatic mosquitoes such as *Anopheles* (Mushinzimana et al., 2006) and *Culex* (Lacaux et al., 2007). However, we have shown the utility of remote sensing in the prediction of *Ae. aegypti* infestations in urban scenarios. The identification of essential features of households that are hotspots for *Ae. aegypti* breeding has been a goal to facilitate surveys (Tun-Lin et al., 1995). Our findings align with those of Little et al. (2017) and highlight the huge fine-scale spatial heterogeneities in mosquito habitats within urban environments. We showed that the higher the percentage of asbestos roof and roof slabs used in a given area, the greater the number of adult *Ae. aegypti* mosquitoes found there. This may be related to several other factors, such as socioeconomic and environmental factors. For example, asbestos roof is an inexpensive type of construction, generally used in poor areas with precarious infrastructure (Berman, 1986). The positive association between socioeconomically poor areas and a higher incidence of dengue or a higher number of mosquito infestations confirms the findings of several other studies (Chan et al., 1971; Oliveira and Valla, 2001; Ferreira and Chiaravalloti-Neto, 2007). LaDeau et al. (2013) showed that *Aedes* immatures were more likely to be found in neighborhoods categorized as being below the median income level and the *Aedes* pupae density was greater in container habitats found in these lower income neighborhoods. Socioeconomic factors have been shown to have a significant effect on the reproductive rates of *Ae. aegypti* (Reiter, 2007). According to Kuno (1995), social factors that influence the occurrence of larval habitats depend on two main factors: (i) human community behavior, which is related to factors such as education, income, occupation, and population density in an area, and (ii) the condition of human habitations, including sanitation of the surrounding environment. Infrastructural systems prevalent in many neighborhoods also limit human–mosquito exposure, including regular waste management, which limits larval habitats, and screens and air conditioning, which reduce vector–host contact rates (Reiter et al., 2003; Little et al., 2017). Urban areas with unsanitary conditions tend to create more larval habitats for *Ae. aegypti* (Souza-Santos and Carvalho, 2000; Ferreira and Chiaravalloti Neto, 2007; Scandar et al., 2010; Teixeira and Cruz, 2011). As our study was conducted in a small area of approximately 4×106 m^2, it is possible that sanitary conditions were similar for the entire area.

However, the association of asbestos roofing with *Ae. aegypti* infestations may be related to the ability of asbestos to retain heat at the specific site (i.e., balconies or garages with this type of roof tend to be much warmer than those with ceramic tiles), optimizing the reproduction and life cycle of mosquitoes. Breeding sites do not necessarily form on the asbestos roof itself, but in the places that are covered by it. Cator et al. (2013) analyzed urban resting habitats of *Anopheles* mosquitoes and found that homes with asbestos roofs were the warmest habitats, with a mean temperature of 30–33ºC throughout the year. Azevedo et al. (2018) demonstrated that even when temperature conditions adversely affected the occurrence and development of *Ae. aegypti* infestations, oscillations in urban microclimates were responsible for alterations in the usual patterns of mosquito dispersal and activity. Temperatures between 20°C and 31°C can increase the metabolic rate of mosquitoes, shorten the larval development period, and optimize foraging and egg-laying behavior, leading to increased mosquito abundance when larval habitats become available (Scott et al., 2000; Araujo et al., 2015; Misslin et al., 2016; Murdock et al., 2017). Thus, the higher temperatures generated by materials such as asbestos could increase mosquito infestation in specific areas. Flat slab roofing can retain rainwater and contribute to the generation of temporary mosquito breeding sites. Tinker (1964) found a positive association between the infestation levels and the density of containers per house. Regarding container capacity, Vezzani et al. (2004) and Abe et al. (2005) reported that *Ae. aegypti* productivity was higher in containers with a capacity of 1–5 L than in those with capacities up to a liter; thus, flat slab roofing may provide a major temporary breeding site for mosquitoes.

We found little correlation between tree cover and *Ae. aegypti* infestation; this negative association was observed mainly in 50 m buffers. Troyo's (2007) analysis using QuickBird imagery showed that moderately built-up residential areas with moderate tree cover were likely to contain relatively high numbers of habitats positive for *Ae. aegypti* larvae. This is also supported by studies that indicate that tree crowns reduce the evaporation from containers, thus providing some benefit to *Ae. aegypti* larvae (Vezzani et al., 2004; Barrera et al., 2006; Bisset-Lazcano et al., 2006). This inconsistency with our results may be due to the difference between habitats of immature forms and adult mosquitoes or due to indoor breeding sites. Getis et al. (2003) noted that there were significant differences in spatial structure of adult mosquito populations compared with immature mosquito populations. Adult mosquitoes cluster most at distances of approximately 10 m and to a lesser extent up to 30 m, which could include neighboring houses. McDonald (1977) found that most adult *Ae. aegypti* dispersed to less than 20 m, and the majority of those recaptured were collected in the same house where they were released. Edman et al. (1998) similarly collected most of their recaptured *Ae. aegypti* in Puerto Rico from their release house. Accordingly, these evidences indicate that in urbanized areas such Vila Toninho neighborhood most adult *Ae. aegypti* do not fly far from the container where they developed as larvae and pupae inside households.

Our findings are in disagreement with other studies carried out in Thailand (Morrison et al., 2004) and in Peru (Getis et al., 2003) that concluded that homes infested by *Ae. aegypti* were randomly scattered in the neighborhood. We showed that physical characteristics of landscape can influence the distribution of adult mosquitoes. However, it is worth mentioning that the association between the existence of mosquito clusters and occurrence of dengue cases is an issue that needs to be further investigated. According to Getis et al. (2003), "until we quantitatively define the relationship between mosquito density and risk of virus transmission, we cannot predict the effect that eliminating key premises will have on the risk of human infection and disease. For example, eliminating key premises may not reduce the adult mosquito population below the threshold density and, depending on the nature of the relationship between virus transmission and vector density, the pattern of human infections could continue unabated". Another study carried out in Puerto Rico (Morrison et al., 1998) suggested that control measures should be adopted uniformly throughout the whole area affected by arbovirus transmission to be efficient, because clusters of dengue cases were identified within very short distances, most probably in the same homes (Ferreira and Chiaravalloti-Neto, 2007).

In this study we demonstrated the utility of satellite remote sensing to identify landscape differences in an urban environment approach. It is believed that this modern high-resolution remotely sensed approach of assessing adult mosquito habitats, if combined with monitoring activities and if properly coordinated by entomologists, could improve the understanding of factors involved with urban *Ae. aegypti* infestation and arboviruses dissemination. However, this application is surely more difficult than others, because of the epidemiological complexity and the involvement of pathogens and vectors in an urban environment. Deducing specific associations for areas that are biologically different is not an easy task. Complementary methods at different scales and resolutions might confront this problem, but the legitimate use of remote sensing data is still dependent of the quality of information coming from the field (Rocque et al., 2004). Besides, further analysis using other variables, such as land surface temperature and precipitation, may present more complex relationships between urban mosquito habitats and landscape features.

Several limitations of our study are worth noting. We do not directly consider environmental data in the model, such as thermal temperature of the surfaces of each urban material. Nevertheless, these results should be of concern to public health professionals looking to improve control measures in areas where asbestos roof and roof slab are preponderant landscape features. In future studies we suggest including different types of areas and different seasons of the year in the model, which may contribute to further understanding of mosquito habitat abundance, although insufficient sample size of 60 traps in our study precluded the use of more independent variables in the analysis. For building the buffers, we assumed the average flight radius of an adult *Ae. aegypti*, but depending on environmental conditions they might fly further than this distance. Among the strengths of our study, it should be mentioned that the statistical model selected (INLA) allowed the control of the spatial correlation between the number of mosquitoes and traps.

We encourage future studies to expand their study area and test models using freely available images such as those obtained from Landsat 8. Medium-resolution images may also identify patterns in the urban landscape useful for identifying *Ae. aegypti* habitats. In addition, it would be interesting to correlate infestation rates with surface temperatures within the urban environment and define landscapes more likely to be infested with adult mosquitoes. Urban land cover maps obtained from such imagery may initiate the development of arbovirus risk maps that support the prediction and identification of priority zones for vector control measures, particularly in areas where prompt action is needed and detailed epidemiological and entomological data are unavailable or restricted.

5. Conclusions

This study provides promising descriptive results and proposes insights that need to be tested over longer periods of time using satellite data from larger areas. We showed that the physical characteristics of a landscape can influence the distribution of *Ae. aegypti* adult mosquitoes: it was found to be positively associated with the presence of asbestos roofing and roof slabs. This may be related to several other specific features of the landscape, such as socioeconomic or environmental factors. The usage of asbestos roofing may be more prevalent in poorer areas. Moreover, roof slabs can retain rainwater and increase the number of temporary mosquito breeding sites. We also demonstrated the utility of a high-resolution satellite remote sensing approach in identifying landscape differences in an urban environment. We believe that applying this modern remote sensing approach towards studying adult mosquito habitats and their characteristics will improve the understanding of factors associated with urban *Ae. aegypti* infestations and arbovirus dissemination.

Ethics

This study was approved by the Internal Review Board from the Medical School of São José do Rio Preto (FAMERP) (protocol #02078812.8.0000.5415). Homeowners who had traps installed on their properties signed an informed consent form.

Financial support

São Paulo Research Foundation (FAPESP) grants 2017/10297-1 (C.L.) and 2013/21719-3 (M.L.N. and F.C.N.). MLN and FCN are CNPq Research Fellow. This work was supported by CAPES (Grant # 001).

CRediT authorship contribution statement

Camila Lorenz: Formal analysis, Investigation, Software, Project administration, Writing - original draft. **Francisco Chiaravalloti-Neto:** Conceptualization, Formal analysis, Investigation, Supervision, Writing - review & editing. **Mariana de Oliveira Lage:** Formal analysis, Investigation, Software, Writing - review & editing. **José Alberto Quintanilha:** Investigation, Writing - review & editing. **Maisa Carla Parra:** Data curation, Visualization, Writing - review & editing. **Margareth Regina Dibo:** Visualization, Writing - review & editing. **Eliane Aparecida Fávaro:** Visualization, Writing - review & editing. **Marluci Monteiro Guirado:** Visualization, Writing - review & editing. **Maurício Lacerda Nogueira:** Conceptualization, Funding acquisition, Supervision, Writing - review & editing.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.actatropica.2020.105398.

References

Abe, M., McCall, P.J., Lenhart, A., Villegas, E., Kroeger, A., 2005. The Buen pastor cemetery in Trujillo, Venezuela: measuring dengue vector output from a public area. Trop. Med. Int. Health 10 (6), 597–603.
Araujo, R.V., Albertini, M.R., Costa-da-Silva, A.L., Suesdek, L., Franceschi, N.C.S., Bastos, N.M., Allegro, V.L.A.C., 2015. São Paulo urban heat islands have a higher incidence of dengue than other urban areas. Braz. J. Infect. Dis. 19 (2), 146–155.
Azevedo, T.S., Bourke, B.P., Piovezan, R., Sallum, M.A.M., 2018. The influence of urban heat islands and socioeconomic factors on the spatial distribution of *Aedes aegypti* larval habitats. Geospat Health 13 (1).
Barrera, R., Amador, M., Clark, G.G., 2006. Ecological factors influencing *Aedes aegypti* (Diptera: Culicidae) productivity in artificials containers in Salinas, Puerto Rico. J. Med. Entomol. 43 (3), 484–492.
Bergquist, N.R., 2001. Vector-borne parasitic diseases: new trends in data collection and risk assessment. Acta Trop. 79 (1), 13–20.
Berman, D.M., 1986. Asbestos and health in the third world: the case of Brazil. Int. J. Health Services 16 (2), 253–263.
Bhatt, S., Gething, P.W., Brady, O.J., Messina, J.P., Farlow, A.W., Moyes, C.L., Myers, M.F., 2013. The global distribution and burden of dengue. Nature 496 (7446), 504.
Lazcano, Bisset, A., J., Marquetti, M.D.C., Portillo, R., Rodríguez, M.M., Suárez, S., Leyva, M., 2006. Factores ecológicos asociados con la presencia de larvas de *Aedes aegypti* en zonas de alta infestación del municipio Playa, Ciudad de la Habana, Cuba. Rev. Panamer. Salud Publ. 19, 379–384.
Blangiardo, M., Cameletti, M., 2015. Spatial and Spatio-Temporal Bayesian Models with R-INLA. John Wiley & Sons.
Calderón-Arguedas, Ó., Troyo, A., Solano, M.E., 2004. Caracterización de los sitios de multiplicación de *Aedes aegypti* (Diptera: Culicidae) en el caserío La Carpio, San José, Costa Rica durante la estación seca del año 2003. Rev. Biomed. 15 (2), 73–79.
Cator, L.J., Thomas, S., Paaijmans, K.P., Ravishankaran, S., Justin, J.A., Mathai, M.T., Eapen, A., 2013. Characterizing microclimate in urban malaria transmission settings: a case study from Chennai, India. Malar. J. 12 (1), 84.
Chadee, D.D., 2004. Key premises, a guide to *Aedes aegypti* (Diptera: Culicidae) surveillance and control. Bull. Entomol. Res. 94 (3), 201–207.

Chan, Y.C., Ho, B.C., Chan, K.L., 1971. Aedes aegypti (L.) and *Aedes albopictus* (Skuse) in Singapore City: 5. Observations in relation to dengue haemorrhagic fever. Bull. World Health Org. 44 (5), 651.
Chiaravalloti-Neto, F., da Silva, R.A., Zini, N., da Silva, G.C.D., da Silva, N.S., Parra, M.C.P., Mota, M.T.O., 2019. Seroprevalence for dengue virus in a hyperendemic area and associated socioeconomic and demographic factors using a cross-sectional design and a geostatistical approach, state of São Paulo, Brazil. BMC Infect. Dis. 19 (1), 441.
Chiaravalloti Neto, F., 1997. Descrição da colonização de *Aedes aegypti* na região de São José do Rio Preto, São Paulo. Rev. Soc. Bras. Med. Trop. 30 (4), 279–285.
Congalton, R.G., 1991. A review of assessing the accuracy of classifications of remotely sensed data. Remote Sens. Environ. 37 (1), 35–46.
Consoli, R.A., de Oliveira, R.L., 1994. Principais mosquitos de importância sanitária no Brasil. SciELO-Editora FIOCRUZ.
Correia, V.R.D.M., Carvalho, M.S., Sabroza, P.C., Vasconcelos, C.H., 2004. Remote sensing as a tool to survey endemic diseases in Brazil. Cadern. Saúd. Públ. 20, 891–904.
Costa, F., Carvalho-Pereira, T., Begon, M., Riley, L., Childs, J., 2017. Zoonotic and vector-borne diseases in urban slums: opportunities for intervention. Trends Parasitol. 33 (9), 660–662.
CPTEC/INPECentro de Previsão do Tempo e Estudos Climáticos, Ministério de Ciência e Tecnologia. Available fromhttp://www.cptec.inpe.br.
Cressie, N.A., 1993. Statistics for spatial data/Noel AC Cressie. Wiley series in probability and mathematical statistics. Applied Probability and Statistics Section.
Edman, J.D., Scott, T.W., Costero, A., Morrison, A.C., Harrington, L.C., Clark, G.G., 1998. *Aedes aegypti* (Diptera: Culicidae) movement influenced by availability of oviposition sites. J. Med. Entomol. 35 (4), 578–583.
Ferreira, A.C., Chiaravalloti Neto, F., 2007. Infestação de área urbana por *Aedes aegypti* e relação com níveis socioeconômicos. Rev. Saúd. Públ. 41, 915–922.
Focks, D.A., Chadee, D.D., 1997. Pupal survey: an epidemiologically significant surveillance method for *Aedes aegypti*: an example using data from Trinidad. Am. J. Trop. Med. Hyg. 56 (2), 159–167.
Foody, G.M., 2002. Status of land cover classification accuracy assessment. Remote Sens. Environ. 80 (1), 185–201.
Forattini, O.P., 2002. Culicidologia médica: identificação, biologia e epidemiologia: v. 2. In Culicidologia Médica: Identificação, Biologia e Epidemiologia: v. 2.
Fuller, D.O., Troyo, A., Calderon-Arguedas, O., Beier, J.C., 2010. Dengue vector (*Aedes aegypti*) larval habitats in an urban environment of Costa Rica analysed with aster and Quickbird imagery. Int. J. Remote Sens. 31 (1), 3–11.
Getis, A., Morrison, A.C., Gray, K., Scott, T.W., 2003. Characteristics of the spatial pattern of the dengue vector, *aedes aegypti*, in iquitos, peru. Am. J. Trop. Med. Hyg. 69 (5), 494–505.
Gibbons, R.V., Vaughn, D.W., 2002. Dengue: an escalating problem. BMJ 324 (7353), 1563–1566.
Gubler, D.J., 1998. Dengue and dengue hemorrhagic fever. Clin. Microbiol. Rev. 11 (3), 480–496.
Kuno, G., 1995. Review of the factors modulating dengue transmission. Epidemiol Rev 17 (2), 321–335.
Kyle, J.L., Harris, E., 2008. Global spread and persistence of dengue. Annu. Rev. Microbiol. 62, 71–92.
Lacaux, J.P., Tourre, Y.M., Vignolles, C., Ndione, J.A., Lafaye, M., 2007. Classification of ponds from high-spatial resolution remote sensing: application to rift valley fever epidemics in Senegal. Remote Sens. Environ. 106 (1), 66–74.
LaDeau, S.L., Leisnham, P.T., Biehler, D., Bodner, D., 2013. Higher mosquito production in low-income neighborhoods of Baltimore and Washington, DC: understanding ecological drivers and mosquito-borne disease risk in temperate cities. Int. J. Environ. Public Health 10 (1), 1505–1526.
Leisnham, P.T., LaDeau, S.L., Juliano, S.A., 2014. Spatial and temporal habitat segregation of mosquitoes in urban Florida. PLoS ONE 9, e91655.
Little, E., Biehler, D., Leisnham, P.T., Jordan, R., Wilson, S., LaDeau, S.L., 2017. Socio-ecological mechanisms supporting high densities of aedes albopictus (Diptera: Culicidae) in Baltimore, Md. J. Med. Entomol. 54 (5), 1183–1192.
Marini, F., Caputo, B., Pombi, M., Tarsitani, G., della Torre, A., 2010. Study of *Aedes albopictus* dispersal in Rome, Italy, using sticky traps in mark-release-recapture experiments. Med. Vet. Entomol. 24, 361–368.
McDonald, P.T., 1977. Population characteristics of domestic *Aedes aegypti* (Diptera: gulicidae) in villages on the Kenya coast II. Dispersal within and between villages. J. Med. Entomol. 14 (1), 49–53.
Misslin, R., Telle, O., Daudé, E., Vaguet, A., Paul, R.E., 2016. Urban climate versus global climate change–what makes the difference for dengue? Ann. N.Y. Acad. Sci. 1382 (1), 56–72.
Moloney, J.M., Skelly, C., Weinstein, P., Maguire, M., Ritchie, S., 1998. Domestic *Aedes aegypti* breeding site surveillance: limitations of remote sensing as a predictive surveillance tool. Am. J. Trop. Med. Hyg. 59 (2), 261–264.
Monserud, R.A., Leemans, R., 1992. Comparing global vegetation maps with the Kappa statistic. Ecol. Model. 62 (4), 275–293.
Morrison, A.C., Getis, A., Santiago, M., Rigau-Perez, J.G., Reiter, P., 1998. Exploratory space-time analysis of reported dengue cases during an outbreak in Florida, Puerto Rico, 1991–1992. Am. J. Trop. Med. Hyg. 58 (3), 287–298.
Morrison, A.C., Gray, K., Getis, A., Astete, H., Sihuincha, M., Focks, D., Scott, T.W., 2004. Temporal and geographic patterns of *Aedes aegypti* (Diptera: Culicidae) production in Iquitos, Peru. J. Med. Entomol. 41 (6), 1123–1142.
MS, Brazilian Public Health, 2019. Available from http://portalsaude.saude.gov.br.
Muir, L.E., Kay, B.H., 1998. *Aedes aegypti* survival and dispersal estimated by mark-release-recapture in northern Australia. Am. J. Trop. Med. Hyg. 58 (3), 277–282.
Murdock, C.C., Evans, M.V., McClanahan, T.D., Miazgowicz, K.L., Tesla, B., 2017. Fine-scale variation in microclimate across an urban landscape shapes variation in mosquito population dynamics and the potential of *Aedes albopictus* to transmit arboviral disease. PLoS Negl. Trop. Dis. 11 (5), e0005640.
Mushinzimana, E., Munga, S., Minakawa, N., Li, L., Feng, C.C., Bian, L., Githeko, A.K., 2006. Landscape determinants and remote sensing of anopheline mosquito larval habitats in the western Kenya highlands. Malar. J. 5 (1), 13.
Oliveira, R.M.D., Valla, V.V., 2001. As condições e as experiências de vida de grupos populares no Rio de Janeiro: repensando a mobilização popular no controle do dengue. Cadern. Saúd. Públ. 17, S77–S88.
Parra, M.C.P., Fávaro, E.A., Dibo, M.R., Mondini, A., Eiras, Á.E., Kroon, E.G., Chiaravalloti-Neto, F., 2018. Using adult *Aedes aegypti* females to predict areas at risk for dengue transmission: a spatial case-control study. Acta Trop. 182, 43–53.
Paupy, C., Ollomo, B., Kamgang, B., Moutailler, S., Rousset, D., Demanou, M., Simard, F., 2010. Comparative role of *Aedes albopictus* and *Aedes aegypti* in the emergence of Dengue and Chikungunya in central Africa. Vector-Borne Zoonot. Dis. 10 (3), 259–266.
Reiter, P., Lathrop, S., Bunning, M., Biggerstaff, B., Singer, D., Tiwari, T., Baber, L., Amador, M., Thirion, J., Hayes, J., et al., 2003. Texas lifestyle limits transmission of dengue virus. Emerg. Infect. Dis. 9, 86–89.
Reiter, P., 2007. Oviposition, dispersal, and survival in *Aedes aegypti*: implications for the efficacy of control strategies. Vector-Borne Zoonot. Dis. 7 (2), 261–273.
Revelle, W.R., 2017. psych: procedures for personality and psychological research. Available from:https://CRAN.R-project.org/package=psych.
Ribeiro Jr, P.J., Diggle, P.J., 2001. geoR: a package for geostatistical analysis, R News 1/2: 15–18. Find this article online.
Roberts, D.R., Paris, J.F., Manguin, S., Harbach, R.E., Woodruff, R., Rejmankova, E., Legters, L.J., 1996. Predictions of malaria vector distribution in Belize based on multispectral satellite data. Am. J. Trop. Med. Hyg. 54 (3), 304–308.
Rocque, S., Michel, V., Plazanet, D., Pin, R., 2004. Remote sensing and epidemiology: examples of applications for two vector-borne diseases. Comparative immunology. Microbiol. Infect. Dis. 27 (5), 331–341.
Rue, H., Martino, S., Chopin, N., 2009. Approximate Bayesian inference for latent Gaussian models by using integrated nested Laplace approximations. J. R. Stat. Soc.: Ser. B (Stat. Method.) 71 (2), 319–392.
Scandar, S.A.S., Vieira, P., Junior, Cardoso, Silva, R.A.D., Papa, M., Sallum, M.A.M., 2010. Dengue em São José do Rio Preto, Estado de São Paulo, Brasil, 2005: fatores entomológicos, ambientais e socioeconômicos. Bepa. Bol. Epidemiol. Paul. 7 (81), 04–16.
Scott, T.W., Amerasinghe, P.H., Morrison, A.C., Lorenz, L.H., Clark, G.G., Strickman, D., Edman, J.D., 2000. Longitudinal studies of *Aedes aegypti* (Diptera: Culicidae) in Thailand and Puerto Rico: blood feeding frequency. J. Med. Entomol. 37 (1), 89–101.
Service, M.W., 1992. Importance of ecology in *Aedes aegypti* control. Southeast Asian J. Trop. Med. Public Health 23 (4), 681.
Souza-Santos, R., Carvalho, M.S., 2000. Spatial analysis of *Aedes aegypti* larval distribution in the Ilha do Governador neighborhood of Rio de Janeiro, Brazil. Cadern. Saúde Publ. 16 (1), 31–42.
Teixeira, T.R.D.A., Cruz, O.G., 2011. Spatial modeling of dengue and socio-environmental indicators in the city of Rio de Janeiro, Brazil. Cadern. Saúd. Públ. 27, 591–602.
Tinker, M.E., 1964. Larval habitat of *Aedes aegypti* (L.) in the United States. Mosq. News 24 (4), 426–432.
Troyo, A., 2007. Analyses of dengue fever and *Aedes aegypti* (Diptera: Culicidae) larval habitats in a tropical urban environment of Costa Rica using geospatial and mosquito surveillance technologies. Ph.D. dissertation, University of Miami, FL, USA.
Tun-Lin, W., Kay, B.H., Barnes, A.N.D.A., 1995. The premise condition index: a tool for streamlining surveys of *Aedes aegypti*. Am. J. Trop. Med. Hyg. 53 (6), 591–594.
Vezzani, D., Velázquez, S.M., Schweigmann, N., 2004. Seasonal pattern of abundance of *Aedes aegypti* (Diptera: Culicidae) in Buenos Aires city. Argentina. Memórias do Instituto Oswaldo Cruz 99 (4), 351–356.
Welch, J.B., Olson, J.K., Hart, W.G., Ingle, S.G., Davis, M.R., 1989. Use of aerial color infrared photography as a survey technique for *psorophora columbiae* oviposition habitats in Texas ricelands. J. Am. Mosq. Control Assoc. 5 (2), 147–160.
WHO, 2016. Global Vector Control Response 2017–2030. World Health Organization, Geneva.