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Fine-scale spatial modeling and mapping of Aedes aegypti and Culex spp. adults' abundances in a large and heterogeneous city, Southeast Brazil

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Abstract

Background: Arboviruses transmitted by *Aedes aegypti* and *Culex* spp. are of great public health importance. Tools used to measure mosquito infestation based on immature vector forms have been questioned for their ability to predict transmission risk. Indicators based on adult mosquitoes have proven more effective for this purpose.

Objectives: evaluate the association between *Aedes* and *Culex* adults' abundances and socioeconomic, land-use and land-cover, and climate covariates measured in 20-100m buffers around adultrap installation sites and map them on a fine scale in a large and heterogeneous city.

Methods: BG-Mosquitito adultraps were installed in 200 residences throughout the Campinas urban area, a municipality with 1.2 million inhabitants, São Paulo state, Brazil. Six installations were carried out in each residence during the summers of 2021/22 and 2022/23. The number of females and the total *Ae. aegypti*, and total *Culex* spp. were summed per trap, and modeled in a Bayesian geostatistical framework. The Brazilian Deprivation Index was used as a socioeconomic covariate. Land-use and land-cover data were obtained from high-resolution satellite imagery, and climatic data were obtained from the CHELSA website. After choosing the best models, the abundances were mapped.

Results: The female and total *Ae. aegypti* and *Culex* spp. abundances were positively associated with lower socioeconomic status, and the first two with a higher proportion of trees. The females and the total number of *Ae. aegypti*were positively associated with shade and cement, respectively. *Culex*spp. was positively associated with cement and negatively with ceramic tile. Climatic covariates were excluded from the final models, probably because we collected mosquitoes during the most suitable period for them. We created maps predicting *Ae. aegypti* and *Culex* spp. abundances for the study area, at a fine-scale spatial resolution.

Conclusions: The study enabled modeling of infestation by adult *Ae. aegypti* and *Culex* spp. Their levels were predicted across the study area at a fine spatial scale, independent of administrative boundaries. The covariates included in the models improved predictions at unsampled locations. This enables the identification of high-risk areas for infestation and arbovirus transmission, enabling targeted control measures to be implemented.

Background

Aedes mosquitoes are important vectors of arboviruses to humans. *Ae. aegypti* is recognized as the primary vector of the dengue virus (DENV) worldwide, also transmitting the yellow fever, Zika, and chikungunya viruses. *Ae. albopictus* is a potential vector of DENV in the Americas [1]. *Culex* mosquitoes transmit filaria, West Nile virus, and Saint Louis encephalitis virus, among others. These can coexist with *Aedes*, and the two can benefit from combined control measures [2]. Among these diseases, dengue is considered the most prevalent, being endemic in tropical regions [3]. In 2024, dengue cases reached record highs in the Americas and Brazil, with 13 million and 10 million cases reported, respectively [4].

The Integrated Vector Management (IVM) [5] guides entomological surveillance and control measures for mosquitoes. It aims to optimize available resources by maximizing the effectiveness and efficiency of surveillance and control programs, prioritizing sustainable, ecologically appropriate methods. An essential aspect of IVM is the entomological monitoring of vector infestation levels. For a long time, this monitoring for *Ae. aegypti* was based exclusively on infestation measurements using larvae and/or pupae, which are known as Stegomyia indices [6, 7].

Although they have helped measure infestation and vector control for yellow fever, they have proven ineffective at identifying areas at risk for arboviruses transmitted by *Ae. aegypti*. Bowman et al.[8] found that this method is unreliable for measuring arbovirus risk. They also indicated that, ideally, adult mosquitoes should be used routinely for this purpose, given their closer association with viral transmission. Another method is that proposed by Fay and Eliason [9], which measures vector infestation using oviposition traps. However, it shares the same inadequacy as Stegomyia indices; it is also based on the immature stage of the vector [10]. Previous results indicate that adult monitoring is more effective at estimating the risk of arbovirus occurrence than indices based on mosquito larval stages [7, 11].

Among the methods using adult mosquitoes is the Nasci capturer [12], which is currently considered the gold standard for assessing adult mosquito infestation. A significant number of mosquitoes are generally captured; however, this method has high operational costs, since collection is conducted house by house [7].

Another option for capturing adult mosquitoes is the adultraps, such as MosquiTRAP, BG Sentinel, and BG Mosquitito. The first was developed in Brazil (ECOVEC Ltda, Belo Horizonte, Brazil), and the latter two by Biogents, a German company. MosquiTRAP is not sold separately; instead, it is offered as an installation and monitoring service, which makes it quite expensive [13]. Unlike MosquiTRAP, Biogents' adultraps require an electrical power source. On the other hand, they are more sensitive and capture a greater number of mosquitoes, since they target females seeking blood feeding rather than oviposition. *Ae. aegypti* females feed on blood regardless of the stage of the gonotrophic cycle [14]; therefore, these adultraps can capture adult females throughout their entire lifespan.

Although recently developed vaccines may help reduce dengue cases, entomological surveillance of *Ae. aegypti* and other mosquitoes will remain a significant public health concern [15]. And the best approach for it is the use of adult mosquitoes for risk measurement [7, 8, 11]. This surveillance should consider the factors that influence mosquito infestations and the diseases they carry. Among these, the most relevant factors are socioeconomic level, land-use and land-cover, and climate [16–21]. Given this, our objectives were to evaluate the association between the abundances of *Aedes* and *Culex* adults and covariates measured around adultrap installation sites and to map them at a fine scale across the whole Campinas urban area, a large and heterogeneous city in Brazil.

Methods

Study type and area

We conducted a cross-sectional study in Campinas, São Paulo, Brazil (22°53'03" S, 47°02'39" W) (Fig. 1), with a population of 1.2 million inhabitants, of whom 99.5% reside in urban areas. It is a regional center, considered an industrial, commercial, educational, and healthcare hub, 100 km from the state capital. Its Human Development Index at the municipal level (HDI-M) was 0.805 in 2010, the infant mortality rate was 10.12 deaths of children under one year old per 1,000 live births in 2022, and 99% of the population had access to piped water. Its northern and central areas have better infrastructure, in contrast to the southern region, which has less access to urban services [22].

Campinas has a tropical climate, favoring *Ae. aegypti* infestation and arbovirus incidence, with rainy summers (December to March) and dry winters (June to September). The first dengue autochthonous cases occurred in 1996. Since then, the municipality has experienced its autochthonous transmission, with peaks in 2007, 2015, and 2024. The latter had the highest incidence of the historical series, reporting more than 120,000 autochthonous cases (10,500 cases per 100,000 inhabitants). The first cases of chikungunya and Zika occurred in 2014 and 2015, respectively, with incomparably lower incidences than those of dengue [22, 23] .

We delineate the study area using a shapefile of the Campinas urban census tracts, which is available from the Brazilian Institute of Geography and Statistics (IBGE). This file, containing 1,347 census tracts, was overlaid on a 30 cm resolution satellite image acquired by the WorldView-3 satellite between May 2019 and March 2020. Only census tracts with at least 50% of their area covered by this image were retained in the study area. Furthermore, the tracts were associated with values from the São Paulo Social Vulnerability Index (IPVS) and the Brazilian Deprivation Index (IBP). Only tracts with no zero IPVS values and those with an IBP value were used. Tracts that lacked this information but were bordered by another tract were merged with the adjacent tract, avoiding gaps in the final study area. Ultimately, the study area comprised 1,293 census tracts (96.0% of the urban area).

The IPVS is a socioeconomic indicator that combines socioeconomic and demographic data and classifies census tracts into six levels of social vulnerability [24]. The IBP is an indicator of socioeconomic status composed of data on education, income, and household conditions. The higher its value, the greater the level of deprivation in the census tract [25]. Both were obtained from the 2010 census.

Study period, data collection and source, and variables

Mosquito collection occurred during the most favorable period for the vector in the region [26, 27], spanning two cycles: November 2021 to March 2022 and December 2022 to April 2023. Data from both cycles were considered together.

Before sampling, census tracts with fewer than 20 houses were also excluded. Given that installations require resident cooperation, potential refusals may make installations infeasible in sectors with a small number of dwellings, resulting in a final sample size that falls short of the pre-established target. Of the 1,293 census tracts, 1,054 remained. These were ordered according to IPVS categories, proportions of houses, and the average annual soil temperature, obtained from daily Moderate-resolution Imaging Spectroradiometer (MODIS) Collection 6 [28](MYD11A1) data between June 2019 and June 2021.

A sample of 200 census tracts was randomly selected and systematically sampled for the installation of traps. The Campinas Municipal Health Department (CMHD)'s professionals chose a block in each tract for trap installation, selecting those with a large number of houses to minimize the chance that the traps would be unfeasible due to residents' refusal. Houses in the designated blocks were selected at the time of trap installation, following specific guidelines: they were preferably located in the center of the blocks, had a covered area around the home, and had plants nearby where the trap could be installed. During each trap placement cycle, three installations were made (one per month) to capture adult mosquitoes, preferably in the same house within the selected census tract of the study area. The sampling design and field procedures described in this study were identical to those described by Laranjeira et al. [28].

The field workers were employees of the São Paulo State Health Department, and all underwent training at the CMHD before beginning collections. The collections were continuously monitored by a researcher, who actively participated in the work and supervised the field activities. Data were collected in printed bulletins and later typed by the researcher who oversaw the activities.

To capture adult mosquitoes, we used BG-Mosquitito with Lurex, an attractant containing an odorous substance that simulates the odors emitted by human skin, both produced by Biogents. This trap features a fan connected to a battery, enabling it to operate continuously for 24 hours. During operation, the mosquitoes were attracted to the odorous substance and sucked in by the fan, which prevented them from escaping. The mosquitoes were kept in an internal bag inside the trap and, upon removal, were placed in sealed plastic containers. These were sent to the CMHD for identification of the genus, and, if belonging to *Aedes* genus, for species and sex determination, using Consoli and Lourenço-de-Oliveira's [29] mosquito taxonomic key. The traps were placed in the peridomiciles of selected residences and remained in place for an average of 24 hours.

To georeference the 200 trap installation houses as points for analysis, we first verified the addresses of the installations. In sectors where all six installations (three per cycle) happened in the same residence, this location was used to assign the point. Where it was impossible to perform all installations at the same residence, we chose to maintain the address of the residence where the majority of installations took place. In cases where the same number of installations occurred in different locations, we decided to verify the number of female *Ae. aegypti* mosquitoes and use the location where the most mosquitoes were captured. If ties persisted, we chose the location most centrally located within the block. Once the address representing the installation site was established, it was geocoded using the WGS-84 latitude-longitude coordinate system and subsequently transformed to the UTM 23S SIRGAS 2000 plane

coordinate system. All addresses were manually verified to minimize errors. For each trap, all six installations were made in the same block chosen in each drawn census tract.

Satellite imagery with a 30 cm spatial resolution was used to classify the study area into 10 pre-established land-use and land-cover categories. This image was acquired by the WorldView-3 satellite on May 13, 2019, and March 5, 2020. The images were acquired and delivered pre-processed (orthorectified and enhanced) in 8-bit GeoTIFF format, in UTM projection and SIRGAS 2000 datum. We use the IBP, instead of IPVS, to represent census tract socioeconomic levels because the former is continuous, whereas the latter is categorical, both providing analogous information.

Climatic data from the CHELSA (Climatologies at High Resolution for the Earth's Land Surface Areas) satellite-derived [30] dataset were used to characterize the study area. The images have a spatial resolution of approximately 1 km (30 arc-seconds) and represent the monthly mean values of climatic variables. We used images from December 2018 to March 2019 to compute the mean for this period, capturing the average seasonal conditions. These images were the most recent available at this spatial resolution. The CHELSA data were obtained in GeoTIFF format, referenced initially to the WGS84 coordinate system. They were subsequently reprojected to the UTM 23S SIRGAS 2000 plane coordinate system to ensure spatial consistency with other datasets.

Dependent variables for analysis were the number of female *Ae. aegypti*, the sum of males and females, and the number of *Culex* spp.. Male and female *Ae. albopictus* mosquitoes were also collected and analyzed. Independent variables included the IBP, average air temperature, humidity, and precipitation, as well as land-use and land-cover. The last one was predefined in ten categories[19, 20] : cement, tree, asbestos tile, swimming pool, exposed soil, grass, asphalt, zinc tile, shade, and ceramic tile. They were obtained through pixel-wise supervised classification of satellite imagery (semantic segmentation), which consists of categorizing all pixels in an input image into a predetermined set of classes. This process was performed using a supervised learning approach, with the provided labels (pixel-level annotations) serving as training data for the model. To train the model, we used previously annotated polygons from a different set of aerial images of Campinas. For validation, polygon annotations were made on the available image. With this set of labels, the model was able to classify the image into the ten pre-defined categories. The IBP was included in the model as an adjustment variable for socioeconomic level.

Data analysis

Modeling was performed in a Bayesian and geostatistical context, using the integrated nested Laplace approximation (INLA) and stochastic partial differential equations (SPDE) approaches [31]. IBP, land-use and land-cover, and climatic variables were considered as fixed effects with non-informative priors. The latent, stationary Gaussian field with penalized-complexity priors was treated as a random effect [32]. The analyses were performed in R (R Core Team, 2025) using the R-INLA package [31]. Each dependent variable was initially modeled using a Poisson distribution; however, due to indications of overfitting and

overdispersion in some models, the negative binomial distribution was adopted. The models accounted for trap installation locations and a latent, stationary Gaussian field that captured the spatial dependence of the phenomena under study. This Gaussian field had a multivariate normal distribution with a mean of 0, a covariance structure modeled by a Matérn function, and was represented by a Gaussian Markov random field [33].

To perform the analyses, we constructed a mesh of 6,867 non-overlapping triangles interconnecting the entire study area [34, 35]. This mesh had maximum internal and external edge parameters of 400 and 1200 m, respectively, an offset of 600 m for the inner extension and 4800 m for the outer extension, a minimum triangle angle of 25°, and a cutoff value of 25 m.

For regression analyses, buffers with radii of 20, 30, 50, and 100m were created around each trap location, based on the estimated *Ae. aegypti* flight radius [19, 36]. For each buffer size, the areas corresponding to each land-use and land-cover category were obtained. These, divided by the sum of the areas, produced the respective percentages for each class in each buffer. The average air temperature, humidity, and precipitation were also calculated for each buffer size. These values were aggregated into the file containing mosquito information, along with the IBP data for the census tract where the trap was located. The colinearity analysis of all covariates (Fig. 2) showed that precipitation and temperature were highly correlated and they were not considered together in the same model. Given that the land-use and land-cover variables presented outliers, we transformed them using their square root. All covariates were standardized, except IBP, which was standardized in its original formulation.

To predict mosquito numbers across the entire study area, a 200-by-200 grid was created, resulting in a final grid of 17,741 points after cropping the area. Buffers with radii of 20, 30, 50, and 100m were also made at each of these points. As with the 200 trap points, the values of IBP, land-use and land-cover, and climatic variables were obtained for each point in the final grid, considering its respective buffers. This information was aggregated into the final grid data.

To select the best models, initially, each of the three dependent variables was modeled: first, only with the intercept; and second, univariately as a function of each covariate, for each buffer size. Once the independent variables with a 95% credible interval (95% CI) that did not contain zero (or one on the natural scale) were identified, these were reanalyzed and combined to select the final models. The best models, including IBP and excluding those models that presented unrealistic maximum grid prediction values, were selected based on the lowest Watanabe–Akaike Information Criterion (WAIC) value [37]. After obtaining the best models, they were used to map female and total *Ae. aegypti* and *Culex* spp. abundances in the study area. Maps were also produced, considering only the intercept models. We removed from these maps the values considered outliers (i.e., greater than the third quartile plus 1.5 times the interquartile range). The code used in this study is available on GitHub at https://github.com/LAES-USP/fine-scale-mosquito-modeling.git.

Results

A total of 1,307 *Ae. aegypti* (556 male, 737 females, and 14 unspecified), and 1,924 *Culex* spp. mosquitoes were collected. Their descriptive statistics are presented in Table 1. We also collected 18 *Ae. albopictus* mosquitoes (five males and 13 females), and their small numbers prevented regression analyses. Their spatial distributions are shown in the Additional file 1: Fig. S1. The 10 predefined land-use and land-cover categories obtained by supervised classification (Additional file 2: Fig. S2) resulted in an output that achieved 94% overall accuracy, 74% balanced accuracy (taking into account the proportion of each class), and 88% Kappa score. The statistical summary of their percentages is presented in Table 2 for the 50m buffers, corresponding to the best model. These results for the other buffers are presented in Additional file 3: Table S1-S3. The IBP presented in Table 2 corresponds to the census tract values.

In the univariate analysis, all three dependent variables were positively associated with IBP: the lower the socioeconomic status, the greater the number of mosquitoes. In univariate analyses of the number of female *Ae. aegypti* mosquitoes (Additional file 4: Table S4 - S7), the variables that showed significant association besides IBP were: tree, asbestos tile, shade, exposed soil, ceramic tile, asphalt, and precipitation, across the four buffer dimensions. The first three showed a positive association, and the last four showed a negative association. After running all possible combinations (Additional file 6: Table S8 - S11), the model with the lowest WAIC included IBP, tree, and shadow (Table 3), with 50m buffers.

In the univariate analyses with the total number of *Ae. aegypti* mosquitoes (Additional file 6: Table S12 - S15), the associated variables, besides the IBP, were trees, cement, asbestos tile, exposed soil, asphalt, and ceramic tile. The first three showed a positive association, while the last two showed a negative association across the four buffer dimensions. In the final analysis, the best model (lowest WAIC) included IBP, cement, and trees (Additional file 7: Table S16 - S19) for the 50m buffer (Table 3). In univariate analyses of the number of *Culex* spp. (Additional file 8: Table S20 - S23), the variables associated with the number of Culex spp., in addition to IBP, were trees, cement, temperature, shade, exposed soil, asphalt, precipitation, and ceramic tiles. The first five showed a positive association, while the last four showed a negative association across the four buffer dimensions. In the final analyses, the best model (lowest WAIC) was with IBP, cement, and ceramic tile for the 50m buffer (Table 3) (Additional file 9: Table S24 - S27).

Figures 3, 4, and 5 show the fine-scale spatial predictions of the number of *Ae. aegypti* females and total, and *Culex* spp., respectively, considering the intercept and final models for the whole study area. Table 4 shows the outlier values we excluded from these maps. All three final models showed lower WAIC than their respective intercept models (Table 3), resulting in better mosquito number prediction.

Discussion

We examined the relationship between adult *Ae. aegypti* and *Culex* spp. abundances and socioeconomic, land-use and land-cover, and climatic data around the trap installation sites. Few studies have evaluated these relationships with *Aedes* mosquitoes, especially using adult traps and at scales compatible with

their flight radius. Furthermore, there is still no consensus on how they relate to infestation [18–21]. We estimated the spatial distribution of adult *Ae. aegypti* and *Culex* spp. abundances continuously, producing high-resolution maps with fine-scale detail across the territory. They enable the identification of areas with higher infestation risk at appropriate spatial resolution to guide vector and arbovirus control [38].

We identified a positive association between lower socioeconomic levels and higher levels of *Ae. aegypti* adult infestation. Several studies have shown this for immature forms [26, 39]. Donnelly et al.[40] also found it for adult *Ae. aegypti*, while Coalson et al.[21] found a positive association with higher socioeconomic levels. Lorenz et al. [19] found associations between adult *Ae. aegypti* and the presence of asbestos roofs and slabs, and attributed them to poorer socioeconomic conditions.

Regarding land-use and land-cover and *Ae. aegypti*, several studies also found a positive association between the presence of trees and higher levels of infestation [21, 41, 42]. Chen et al. [18] found the same result for adult *Ae. albopictus*. On the other hand, Lorenz et al. [20] found a negative association between *Ae. aegypti* and vegetation. The studies conducted by Chen et al. [18]and Coalson et al. [21], similar to ours, installed adultraps in large cities with varying socioeconomic levels and land-use gradients, accounting for territory heterogeneity. They also used 30-50m buffers for modeling, values for which we obtained our best-fitting models. This may reflect the fact that mosquitoes congregate around properties because of the availability of food sources [36].

The positive association between the presence of trees and higher levels of infestation is related to the availability of resting places and habitat for mosquitoes [43]. It is consistent with the degree of shading component of the Premise Condition Index (PCI) [44]. The higher the PCI, the greater the risk of *Ae. aegypti* presence in a given property. Shading, among other possibilities, results from the presence of trees inside or around properties. The PCI has been incorporated into arbovirus control programs and used to identify priority properties for vector control [45].

In contrast to other studies, our final models did not include climatic variables [46]. One explanation is that we collected mosquitoes during the most suitable period of the year in our study area, characterized by small variation ranges of the climatic variables considered in our models [26, 27]. Apart from being a limitation of our study, mapping mosquito infestation during this period could be both helpful and cost-effective for assessing the risk of arbovirus transmission.

Improving knowledge about the relationship between socioeconomic levels, land-use and land-cover has been the subject of numerous studies conducted worldwide. They have sought to associate terrestrial observations with infestations by different vector types [47]. These studies have been undertaken in several scenarios, sometimes yielding inconsistent results. Holeva-Ekland et al.[41] and Coalson et al. [21] conducted studies in large cities with a desert climate and low humidity. Our study and that of Chen et al.[18] were conducted in large cities with tropical and subtropical climates, respectively. The study of Myer et al.[42] was conducted in a medium-sized town with a subtropical climate. Those by Lorenz et al. [19, 20] were conducted in a small, restricted area of a medium-sized city with a tropical climate. Despite

the discrepancies in the results obtained so far, they generally indicate potential use in routine vector and arbovirus control programs.

Incorporating land-use and land-cover, as well as socioeconomic variables, into the mosquito number modeling improved our models. Other studies have also shown that remote sensing images, combined with geostatistical analysis techniques, enable the identification of land-use and land-cover types that are favorable or unfavorable for vector infestation [19, 20, 48]. Teillet et al. [49] [51] incorporated artificial intelligence techniques into remote sensing and achieved good results in predicting *Ae. aegypti* infestation in French Guiana.

Our models generated fine-scale, high-resolution abundance maps that accounted for territory heterogeneity and were not constrained by political-administrative boundaries. This enables the aggregation of infestation information at various geographic scales, ranging from the finest levels, such as blocks and census tracts, to the coarsest, such as neighborhoods and districts [11, 50, 51]. Furthermore, more important than knowing the number of mosquitoes present is understanding the relative distribution of vectors, thereby enabling classification of areas according to risk levels. Therefore, mapping will enable targeting control measures to regions with the highest levels of vector infestation [18, 21]. Moreover, among the available entomological methods, the use of adult *Ae. aegypti* is recognized to be a better alternative than Stegomyia indices and ovitraps to measure infestation and evaluate the arbovirus risk [6–8, 10, 11, 50, 52–54]

Other advantages of using adult traps over Stegomyia indices include their lower sample cost and the quality and flexibility of infestation mapping. Parra et al. [50] demonstrated that adult traps require significantly less sampling effort than the House and Breteau indices, given the lower positivity rates in the latter. Furthermore, there is a lower need for human resources and vehicles to install adultraps than for measuring Stegomyia indices [50]. However, an important issue to consider is the cost of the adultraps, and seeking more viable alternatives for routine use should be pursued.

The low positivity of properties, in general, as measured by Stegomyia indices, does not preclude but somewhat limits the scope of mapping. On the contrary, mapping adult mosquitoes enables going beyond political and administrative boundaries, producing information aggregated by blocks, census tracts, neighborhoods, and districts, in addition to the various advantages already mentioned [11, 50, 51]. Mapping larval infestation by neighborhoods and districts is feasible; however, the sampling effort required to perform mapping at finer scales, depending on the entomological situation of the territory, would be very costly and likely prohibitive for countries where arboviruses represent significant public health problems. Shen et al. [51] employed resampling techniques to generate maps at reduced scales from monthly larval infestation data initially collected at the city scale. Although this is a possibility worth considering, it still does not overcome the issue of the more distant relationship between this type of indicator and the transmission of arboviruses compared to information based on adult mosquitoes [7, 8, 11, 50].

We also estimated *Culex* spp. abundance across the territory and assessed its association with socioeconomic levels, as well as land-use and land-cover variables. A positive relationship between infestation and lower socioeconomic status has also been observed in other studies [55, 56]. In Brazil, this association is linked to the breeding sites of the vector. Although *Culex* spp. is also present in the types of breeding sites occupied by *Ae. aegypti*, the main breeding sites are stream banks and open sewers, often found in urban areas with lower socioeconomic levels [57].

The considerations made so far regarding *Ae. aegypti* also apply to this vector, given its importance as a vector of filariasis and West Nile virus, as well as encephalitis viruses, among others. Currently, in Brazil, Culex spp. poses a significant nuisance to the population rather than a risk of disease transmission. Filariasis was declared eliminated from Brazil by the WHO in 2024 [3]. Regarding West Nile fever, despite the record number of cases in South America, there have been no major epidemics, unlike in other parts of the world. Among the various hypotheses raised is the possibility of cross-protection due to other flaviviruses [58]. However, given the favorable conditions for the occurrence of these diseases in Brazil, *Culex* spp. surveillance must be maintained. The mapping produced and the identification of areas of higher risk are fundamental tools for entomological surveillance and the prevention or control of transmitted diseases [59].

From the perspective of *Ae. aegypti* entomological surveillance, our methodology has the potential to be reapplied for research and adapted as a routine activity in other municipalities, especially medium- and large-sized ones in tropical and subtropical regions. Measuring adult mosquito infestation during the months most favorable for them can be an interesting strategy for optimizing the use of human and financial resources. These periods are reasonably well characterized and precede the peaks of epidemics in dengue-endemic regions. Adapting this methodology to other contexts will depend on understanding the ideal period for measuring infestation. It will also depend on identifying the covariates associated with infestation, which, as seen in this study, produced better-fitting predictive models.

As limitations of the study, we highlight that in some situations, the traps could not be kept in the same residences during both installation cycles, primarily due to residents' refusal to participate. The condition of choosing a central residence in the block was not always feasible due to the lack of a suitable location with the necessary characteristics for installing a trap. In addition, the socioeconomic covariate used (IBP) was based on 2010 census data, the most recent nationwide source available. Although it may not capture recent local changes, it remains widely used in spatial and epidemiological studies in Brazil due to its consistency and coverage. Another limitation is failing to account for climatic variables in our models properly. We used soil temperature from MODIS satellite images as a proxy for air temperature for stratification and systematically sampled census tracts. This was the finest-scale, lowest-resolution, and most closely aligned with the study period available. For modeling, we sought more appropriate climate data. There are several options [60, 61]; however, those with more current data have spatial resolutions not suitable for working intramunicipally. Then, we preferred to use the fine-scale climatic data from CHELSA, even though it did not cover our study period. This limitation was mitigated by conducting our work during the most favorable period for mosquitoes in the study area.

Despite these limitations, this study has several strengths. We highlight the use of traps to capture adult mosquitoes in a populous and heterogeneous city over two consecutive summers. Also noteworthy is the use of high-resolution remote sensing images for land-use and land-cover classification, which has been recommended and used by several authors [18–21, 38, 47] as an available tool to aid in mapping vector abundance. Modeling using a Bayesian approach is another point worth highlighting. Combined with high-resolution satellite imagery, this allowed us to extrapolate the information obtained from the traps to the entire study area, enabling us to aggregate infestation information from coarser scales, such as city blocks and census tracts, to finer scales. The Bayesian approach also helped us to account for the spatial dependence of the phenomenon under study.

Conclusions

The female and total *Ae. aegypti* and *Culex* spp. abundances were positively associated with lower socioeconomic status, and the first two were associated with a higher proportion of trees. The females and the total number of *Ae. aegypti* were positively associated with shade and cement, respectively. *Culex* spp. was positively associated with cement and negatively with ceramic tile. All the final models were for 50m buffers. We created maps predicting the number of females and the total adult *Ae. aegypti*, and total *Culex* spp. for the entire study area, at a fine-scale spatial resolution and independent of the administrative boundaries. The covariates included in the models improved predictions at unsampled locations. Besides quantifying the number of mosquitoes, these maps display the relative distribution of mosquitoes, enabling the identification of higher-risk areas for infestation. Our methodology and results, using adult mosquitoes, have the potential to be both helpful and cost-effective for measuring the occurrence of arbovirus risk and guiding control actions.

Declarations

Ethics approval:

The School of Public Health - University of São Paulo, Committee for Ethics in Research (COEP), the Plataforma Brazil system, Ministry of Health, approved the study, number CAAE: 46655121.0.0000.5421.

Availability of data and materials:

Scripts used in this study were deposited in a publicly accessible repository: https://github.com/LAES-USP/fine-scale-mosquito-modeling.git. Sensitive data are protected by law and were obtained through the Research Ethics Committee. This data may be made available upon reasonable request, provided that the requester obtains appropriate ethical approval. All additional results supporting the findings of this study are available within the article and its Supplementary Information files.

Competing interests:

The authors declare no competing interests.

Authors' contributions:

CMF, JAS, GLB, VRA, KN, JAQ, FCN: conceptualization and writing manuscript text; CMF, MBP, PMMB, VRA: data collection; CMF: data curation; CMF, JAS, GLB, MBP, PMMB, KN, JAQ and FCN: software, formal analysis, spatial analysis, elaboration of thematic maps; FCN: supervision. All authors: investigation and methodology, discussion of the results, Writing – review and editing.

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References

1. Garcia-Rejon JE, Navarro J-C, Cigarroa-Toledo N, Baak-Baak CM. An Updated Review of the Invasive *Aedes albopictus* in the Americas; Geographical Distribution, Host Feeding Patterns, Arbovirus Infection, and the Potential for Vertical Transmission of Dengue Virus. Insects. 2021;12:967. https://doi.org/10.3390/insects12110967
2. Santana-Martínez J, Molina J, Dussán J. Asymmetrical Competition between *Aedes aegypti* and *Culex quinquefasciatus* (Diptera: Culicidae) Coexisting in Breeding Sites. Insects. 2017;8:111. https://doi.org/10.3390/insects8040111
3. WHO. World Health Organization. Brazil eliminates lymphatic filariasis as a public health problem [Internet]. 2024 [cited 2026 Jan 13]. https://www.who.int/news/item/01-10-2024-brazil-eliminates-lymphatic-filariasis-as-a-public-health-problem. Accessed 13 Jan 2026
4. PAHO. Pan American Health Organization. Epidemiological Alert Risk of dengue outbreaks due to increased circulation of DENV-3 in the Americas Region [Internet]. Washington, D.C.; 2025 Feb. www.paho.org. Accessed 13 Jan 2026
5. PAHO. Pan American Health Organization. Handbook for Integrated Vector Management in the Americas [Internet]. Washington, D.C; 2019. https://iris.paho.org/handle/10665.2/51759. Accessed 13 Jan 2026
6. Barrera R. Recomendaciones para el monitoreo de *Aedes aegypti*. Biomédica. 2016;36. https://doi.org/10.7705/biomedica.v36i3.2892
7. Wijayanti SPM, Sunaryo S, Suprihatin S, McFarlane M, Rainey SM, Dietrich I, et al. Dengue in Java, Indonesia: Relevance of Mosquito Indices as Risk Predictors. PLoS Negl Trop Dis. 2016;10:e0004500. https://doi.org/10.1371/journal.pntd.0004500
8. Bowman LR, Runge-Ranzinger S, McCall PJ. Assessing the Relationship between Vector Indices and Dengue Transmission: A Systematic Review of the Evidence. PLoS Negl Trop Dis. 2014;8:e2848.

https://doi.org/10.1371/journal.pntd.0002848

9. Fay RW, D. A. Eliason. A preferred oviposition site as a surveillance method for *Aedes aegypti*. Mosq News [Internet]. 1966;26:531–5. https://www.biodiversitylibrary.org/part/129402
10. Focks DA. A review of entomological sampling methods and indicators for dengue vectors [Internet]. Infectious Disease Analysis Gainsville, Florida, USA; 2003. https://iris.who.int/bitstream/handle/10665/68575/TDR_IDE_DEN_03.1.pdf. Accessed 12 Jan 2026
11. Parra MCP, Fávaro EA, Dibo MR, Mondini A, Eiras ÁE, Kroon EG, et al. Using adult Aedes aegypti females to predict areas at risk for dengue transmission: A spatial case-control study. Acta Trop. 2018;182:43–53. https://doi.org/10.1016/j.actatropica.2018.02.018
12. Nasci RS. A lightweight battery-powered aspirator for collecting resting mosquitoes in the field. 1981;41:808–11.
13. Eiras ÁE, Resende MC. Preliminary evaluation of the "Dengue-MI" technology for *Aedes aegypti* monitoring and control. Cad Saude Publica. 2009;25:S45–58. https://doi.org/10.1590/S0102-311X2009001300005
14. Barata EA de F, Costa AIP da, Chiaravalloti Neto F, Glasser CM, Barata JMS, Natal D. População de *Aedes aegypti* (l.) em área endêmica de dengue, Sudeste do Brasil. Rev Saude Publica. 2001;35:237–42. https://doi.org/10.1590/S0034-89102001000300004
15. Wilder-Smith A, Gubler DJ, Weaver SC, Monath TP, Heymann DL, Scott TW. Epidemic arboviral diseases: priorities for research and public health. Lancet Infect Dis. 2017;17:e101–6. https://doi.org/10.1016/S1473-3099(16)30518-7
16. Campbell LP, Luther C, Moo-Llanes D, Ramsey JM, Danis-Lozano R, Peterson AT. Climate change influences on global distributions of dengue and chikungunya virus vectors. Philosophical Transactions of the Royal Society B: Biological Sciences. 2015;370:20140135. https://doi.org/10.1098/rstb.2014.0135
17. Sallam M, Fizer C, Pilant A, Whung P-Y. Systematic Review: Land Cover, Meteorological, and Socioeconomic Determinants of *Aedes* Mosquito Habitat for Risk Mapping. Int J Environ Res Public Health. 2017;14:1230. https://doi.org/10.3390/ijerph14101230
18. Chen S, Whiteman A, Li A, Rapp T, Delmelle E, Chen G, et al. An operational machine learning approach to predict mosquito abundance based on socioeconomic and landscape patterns. Landsc Ecol. 2019;34:1295–311. https://doi.org/10.1007/s10980-019-00839-2
19. Lorenz C, Chiaravalloti-Neto F, de Oliveira Lage M, Quintanilha JA, Parra MC, Dibo MR, et al. Remote sensing for risk mapping of *Aedes aegypti* infestations: Is this a practical task? Acta Trop. 2020;205:105398. https://doi.org/10.1016/j.actatropica.2020.105398
20. Lorenz C, Castro MC, Trindade PMP, Nogueira ML, de Oliveira Lage M, Quintanilha JA, et al. Predicting *Aedes aegypti* infestation using landscape and thermal features. Sci Rep. 2020;10:21688. https://doi.org/10.1038/s41598-020-78755-8
21. Coalson JE, Richard DM, Hayden MH, Townsend J, Damian D, Smith K, et al. *Aedes aegypti* abundance in urban neighborhoods of Maricopa County, Arizona, is linked to increasing

socioeconomic status and tree cover. Parasit Vectors. 2023;16:351. https://doi.org/10.1186/s13071-023-05966-z

22. Johansen IC, Castro MC de, Alves LC, Carmo RL do. Population mobility, demographic, and environmental characteristics of dengue fever epidemics in a major city in Southeastern Brazil, 2007–2015. Cad Saude Publica. 2021;37:e00079620. https://doi.org/10.1590/0102-311x00079620
23. Centro de Vigilância Epidemiológica "Prof. Alexandre Vranjac." Arboviroses Urbanas [Internet]. 2026. [cited 2026 Mar 26]. https://www.saude.sp.gov.br/cve-centro-de-vigilancia-epidemiologica-prof.-alexandre-vranjac/areas-de-vigilancia/doencas-de-transmissao-por-vetores-e-zoonoses/arboviroses-urbanas/. Accessed 26 Mar 2026
24. Ferreira MP, Dini NP, Ferreira SP. Espaços e dimensões da pobreza nos municípios do Estado de São Paulo: Índice Paulista de Vulnerabilidade Social – IPVS. São Paulo em Perspectiva, São Paulo, Fundação Seade [Internet]. 2006 [cited 2026 Jan 14];20:5–17. http://www.seade.gov.br. Accessed 14 Jan 2026
25. Allik M, Ramos D, Agranonik M, Pereira E, Júnior P, Ichihara MY, et al. Small-area Deprivation Measure for Brazil: Data Documentation [Internet]. CIDACS/Fiocruz. 2020 [cited 2026 Jan 14]. https://cidacs.bahia.fiocruz.br/ibp/indice/. Accessed 14 Jan 2026
26. Ferreira AC, Chiaravalloti Neto F, Mondini A. Dengue in Araraquara, state of São Paulo: epidemiology, climate and *Aedes aegypti* infestation. Rev Saude Publica. 2018;52:18. https://doi.org/10.11606/S1518-8787.2018052000414
27. Hino P, Santos CC dos, Santos MO dos, Cunha TN da, Santos CB dos. Evolução temporal da dengue no município de Ribeirão Preto, São Paulo, 1994 a 2003. Cien Saude Colet. 2010;15:233–8. https://doi.org/10.1590/S1413-81232010000100028
28. Laranjeira C, Pereira M, Oliveira R, Barbosa G, Fernandes C, Bermudi P, et al. Automatic mapping of high-risk urban areas for *Aedes aegypti* infestation based on building facade image analysis. PLoS Negl Trop Dis. 2024;18:e0011811. https://doi.org/10.1371/journal.pntd.0011811
29. Consoli RAGB, Oliveira RL de. Principais mosquitos de importância sanitária no Brasil. Editora FIOCRUZ; 1994. https://doi.org/10.7476/9788575412909
30. Karger DN, Conrad O, Böhner J, Kawohl T, Kreft H, Soria-Auza RW, et al. Climatologies at high resolution for the earth's land surface areas. Sci Data. 2017;4:170122. https://doi.org/10.1038/sdata.2017.122
31. Rue H, Martino S, Chopin N. Approximate Bayesian Inference for Latent Gaussian models by using Integrated Nested Laplace Approximations. J R Stat Soc Series B Stat Methodol. 2009;71:319–92. https://doi.org/10.1111/j.1467-9868.2008.00700.x
32. Simpson D, Rue H, Riebler A, Martins TG, Sørbye SH. Penalising Model Component Complexity: A Principled, Practical Approach to Constructing Priors. Statistical Science. 2017;32. https://doi.org/10.1214/16-STS576
33. Cressie NAC. Statistics for Spatial Data. Wiley; 1993. https://doi.org/10.1002/9781119115151

34. Blangiardo M, Cameletti M. Spatial and Spatio-temporal Bayesian Models with R-INLA. The Atrium, Southern Gate, Chichester, West Sussex, PO19 8SQ, United Kingdom: John Wiley & Sons, Ltd; 2015.
35. Zuur AF., Ieno EN., Saveliev AA. Beginner's guide to spatial, temporal, and spatial-temporal ecological data analysis with R-INLA. Newburgh, United Kingdom: Highland Statistics Ltd.; 2017.
36. Getis A, Morrison AC, Gray K, Scott Thomas W. Characteristics of the spatial pattern of the dengue vector, Aedes aegypti, in iquitos, Peru. Am J Trop Med Hyg. 2003;69:494–505. https://doi.org/10.4269/ajtmh.2003.69.494
37. Watanabe S. Asymptotic Equivalence of Bayes Cross Validation and Widely Applicable Information Criterion in Singular Learning Theory. Journal of Machine Learning Research. 2010;11:3571–94.
38. Yin S, Ren C, Shi Y, Hua J, Yuan H-Y, Tian L-W. A Systematic Review on Modeling Methods and Influential Factors for Mapping Dengue-Related Risk in Urban Settings. Int J Environ Res Public Health. 2022;19:15265. https://doi.org/10.3390/ijerph192215265
39. Scavo NA, Barrera R, Reyes-Torres LJ, Yee DA. Lower socioeconomic status neighborhoods in Puerto Rico have more diverse mosquito communities and higher *Aedes aegypti* abundance. Journal of Urban Ecology. 2021;7. https://doi.org/10.1093/jue/juab009
40. Donnelly MAP, Kluh S, Snyder RE, Barker CM. Quantifying sociodemographic heterogeneities in the distribution of *Aedes aegypti* among California households. PLoS Negl Trop Dis. 2020;14:e0008408. https://doi.org/10.1371/journal.pntd.0008408
41. Holeva-Eklund WM, Young SJ, Will J, Busser N, Townsend J, Hepp CM. Species distribution modeling of *Aedes aegypti* in Maricopa County, Arizona from 2014 to 2020. Front Environ Sci. 2022;10:233–8. https://doi.org/10.3389/fenvs.2022.1001190
42. Myer MH, Fizer CM, Mcpherson KR, Neale AC, Pilant AN, Rodriguez A, et al. Mapping *Aedes aegypti* (Diptera: Culicidae) and *Aedes albopictus* Vector Mosquito Distribution in Brownsville, TX. J Med Entomol. 2020;57:231–40. https://doi.org/10.1093/jme/tjz132
43. Arsenault-Benoit A, Fritz ML. Spatiotemporal organization of cryptic North American *Culex* species along an urbanization gradient. Ecological Solutions and Evidence. 2023;4. https://doi.org/10.1002/2688-8319.12282
44. Tun-Lin W, Kay BH, Barnes A. The Premise Condition Index: A Tool for Streamlining Surveys of *Aedes aegypti*. Am J Trop Med Hyg. 1995;53:591–4. https://doi.org/10.4269/ajtmh.1995.53.591
45. Barbosa GL, Lage M de O, Andrade VR, Gomes AHA, Quintanilha JA, Chiaravalloti Neto F. Use of an Extended Premise Condition Index for detection of priority areas for vector control actions. Acta Trop. 2020;209:105543. https://doi.org/10.1016/j.actatropica.2020.105543
46. Rahman MdS, Pientong C, Zafar S, Ekalaksananan T, Paul RE, Haque U, et al. Mapping the spatial distribution of the dengue vector *Aedes aegypti* and predicting its abundance in northeastern Thailand using machine-learning approach. One Health. 2021;13:100358. https://doi.org/10.1016/j.onehlt.2021.100358
47. Fornace KM, Johnson E, Moreno M, Hardy A, Carrasco-Escobar G. Leveraging Earth observation data for surveillance of vector-borne diseases in changing environments. Planetary health

approaches to understand and control vector-borne diseases. Brill | Wageningen Academic; 2023. p. 319–46. https://doi.org/10.3920/9789004688650_013

48. Lage M de O, Barbosa G, Andrade V, Gomes H, Chiaravalloti F, Quintanilha JA. Ovipositional Reproduction of the Dengue Vector for Identifying High-Risk Urban Areas. Ecohealth. 2022;19:85–98. https://doi.org/10.1007/s10393-022-01581-z
49. Teillet C, Devillers R, Tran A, Marti R, Demarchi M, Catry T, et al. Spatial and temporal predictions of mosquito potential breeding sites and densities: integration of satellite imagery, in-situ data, and process-based modeling. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. 2024;XLVIII-3–2024:539–45. https://doi.org/10.5194/isprs-archives-XLVIII-3-2024-539-2024
50. Parra MCP, Lorenz C, Dibo MR, de Aguiar Milhim BHG, Guirado MM, Nogueira ML, et al. Association between densities of adult and immature stages of Aedes aegypti mosquitoes in space and time: implications for vector surveillance. Parasit Vectors. 2022;15:133. https://doi.org/10.1186/s13071-022-05244-4
51. Shen Y, Ren Z, Fan J, Xiao J, Zhang Y, Liu X. Fine-Scale Risk Mapping for Dengue Vector Using Spatial Downscaling in Intra-Urban Areas of Guangzhou, China. Insects. 2025;16:661. https://doi.org/10.3390/insects16070661
52. Coelho GE. Challenges in the control of Aedes aegypti. Rev Inst Med Trop Sao Paulo. 2012;54:13–4. https://doi.org/10.1590/S0036-46652012000700006
53. Barbosa GL, Donalísio MR, Stephan C, Lourenço RW, Andrade VR, Arduino M de B, et al. Spatial Distribution of the Risk of Dengue and the Entomological Indicators in Sumaré, State of São Paulo, Brazil. PLoS Negl Trop Dis. 2014;8:e2873. https://doi.org/10.1371/journal.pntd.0002873
54. Bermudi PMM, Kowalski F, Menzato MM, Ferreira M da C, Passos WBS dos, Oku VJA, et al. Criadouro de Aedes aegypti em reservatório subterrâneo de água da chuva: um alerta. Rev Saude Publica. 2017;51:122. https://doi.org/10.11606/S1518-8787.2017051000087
55. Xavier A, Bonfim C, Barbosa Júnior W, Bezerra G, Oliveira C, Uchikawa R, et al. Influence of social and environmental factors for *Culex quinquefasciatus* distribution in Northeastern Brazil: a risk index. Int J Environ Health Res. 2023;33:1580–90. https://doi.org/10.1080/09603123.2022.2109603
56. Jibowu M, Nolan MS, Ramphul R, Essigmann HT, Oluyomi AO, Brown EL, et al. Spatial dynamics of Culex quinquefasciatus abundance: geostatistical insights from Harris County, Texas. Int J Health Geogr. 2024;23:23–6. https://doi.org/10.1186/s12942-024-00385-4
57. Dibo MR, Menezes RMT de, Ghirardelli CP, Mendonça AL, Chiaravalloti Neto F. Presença de culicídeos em município de porte médio do Estado de São Paulo e risco de ocorrência de febre do Nilo Ocidental e outras arboviroses. Rev Soc Bras Med Trop. 2011;44:496–503. https://doi.org/10.1590/S0037-86822011000400019
58. Lorenz C, Chiaravalloti-Neto F. Why are there no human West Nile virus outbreaks in South America? The Lancet Regional Health - Americas. 2022;12:100276. https://doi.org/10.1016/j.lana.2022.100276

59. Ha T V., Kim W, Nguyen-Tien T, Lindahl J, Nguyen-Viet H, Thi NQ, et al. Spatial distribution of Culex mosquito abundance and associated risk factors in Hanoi, Vietnam. PLoS Negl Trop Dis. 2021;15:e0009497. https://doi.org/10.1371/journal.pntd.0009497
60. Fick SE, Hijmans RJ. WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas. International Journal of Climatology. 2017;37:4302–15. https://doi.org/10.1002/joc.5086
61. Lange S, Büchner M. ISIMIP3b bias-adjusted atmospheric climate input data (v1. 1) [Internet]. PIK: Potsdam-Institut fur Klimafolgenforschung. Germany: ISIMIP Repository; 2021 [cited 2026 Jan 13]. https://doi.org/https://doi.org/10.48364/ISIMIP.842396.1

Tables

Table 1 – Descriptive statistics of *Aedes aegypti* and *Culex* spp. adult mosquitoes collected per trap in the Campinas/SP urban area, 2021-2023.

Mosquitoes	Min	Quartiles			Max	Total	Trap positivity (%)	Average per trap	
		1º	2º	3º				positive	total
Male *Ae. aegypti*	0	0	2	4	27	556	75.5	3.73	2.78
Female *Ae. aegypti*	0	1	3	5	18	737	90.5	4.07	3.69
Total of *Ae. aegypti*	0	3	5	9	47	1,307	94.5	6.92	6.54
Culex spp.	0	1	4	8.25	331	1,924	88.0	10.93	9.62

Table 2 - Descriptive statistics of the variables representing land-use and land-cover percentages and climate, according to a 50m buffer, and IBP according to census tracts, Campinas, São Paulo, 2021-2023.

Variables		Minimum value	Maximum value	Mean	Standard deviation
Socioeconomic	IBP	-3.06	1.60	-2.03	0.94
Climate	Precipitation (mm)	12,959.63	15,814.75	14,439.94	855.34
	Temperature (°C)	24.48	25.64	25.12	0.27
	Humidity (%)	58.06	58.61	58.25	0.12
Land-use and land-cover categories (%)	Cement	0.00	40.50	6.84	7.03
	Tree	0.00	50.45	13.26	10.33
	Asbestos tile	0.40	59.96	18.04	12.55
	Swimming Pool	0.00	2.04	0.21	0.33
	Exposed Soil	0.00	55.92	11.19	10.53
	Grass	0.00	39.68	7.68	7.97
	Asphalt	2.89	44.18	21.77	8.12
	Zinc tile	0.00	29.64	4.98	5.01
	Shade	0.00	7.69	0.81	1.09
	Ceramic tile	0.00	38.56	15.24	8.96

Table 3 – Intercept and final models for *Ae. aegypti* females and total, and *Culex* spp., with 50m buffers, Campinas, São Paulo, 2021 to 2023.

Mosquito	Model	Variables*	Posterior mean (IC 95%)	Range (IC 95%)	Sd (IC 95%)	WAIC
Female *Ae. aegypti*	Intercept model	Intercept	1.13 (0.99 : 1.25)	158.14 (54.96 : 337.56)	1.04 (0.54 : 1.91)	898.08
	Best model	Intercept	1.42 (1.14 : 1.70)	115.36 (35.67 : 263.30)	1.28 0.55 : 2.72)	889.99
		IBP	0.14 (0.02 : 0.27)			
		Tree	0.19 (0.07 : 0.30)			
		Shade	0.12 (0.01 : 0.24)			
Total of *Ae. aegypti*	Intercept model	Intercept	1.65 (1.52 : 1.78)	111.67 (41.74 : 230.12)	1.57 (0.76 : 3.07)	1049.72
	Best model	Intercept	1.98 (1.71 : 2.25)	89.11 (35.11 : 175.67)	1.78 (0.87 : 3.48)	1039.20
		IBP	0.16 (0.04 : 0.28)			
		Cement	0.16 (0.04 : 0.27)			
		Tree	0.16 (0.04 : 0.27)			
Culex spp.	Intercept model	Intercept	1.38 (1.12 : 1.63)	1050.83 (899.04 : 1261.31)	1.10 0.97 : 1.21)	1062.55
	Best model	Intercept	1.90 (1.41 : 2.37)	659.14 (496.134 : 901.87)	1.03 (0.91 : 1.17)	1024.43
		IBP	0.28 (0.06 : 0.49)			
		Cement	0.18 (0.02 : 0.35)			
		Ceramic tile	-0.20 (-0.39 : -0.01)			

* Except for IBP, the other covariates were square root transformed and standardized.

Table 4 - Upper Fences and Removed Values for Descriptive Statistics for the Best Predictive Model of Each Dependent Variable

Mosquito	Descriptive statistics	Upper fence	Removed value range		Removed points	Percentage
			Minimum	Maximum		
Female *Ae. aegypti*	Mean	18.90	18.91	43.57	1269	7.15
	Standard Deviation	12.44	12.45	133.40	1648	9.29
	Coefficient of Variation	0.86	0.86	3.44	759	4.28
Total of *Ae. aegypti*	Mean	37.32	37.34	183.77	481	2.71
	Standard Deviation	28.89	28.90	819.11	1018	5.74
	Coefficient of Variation	1.02	1.02	8.18	933	5.26
Culex spp.	Mean	14.24	14.24	218.29	1021	5.75
	Standard Deviation	17.26	17.26	174.58	992	5.59
	Coefficient of Variation	1.68	1.68	1.99	884	4.98