Analysis of the Spatial Distribution of Aedes Albopictus by Indicator Kriging in an Urban Area of Shanghai, China

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Research

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Abstract

Background: *Aedes albopictus* is a well-recognized vector of major arboviral diseases and a primary pest in tropical and temperate regions of China. In the current monitoring system for the spread of *Ae. albopictus* based on the sub-district scale in most cities of China, spatial distribution has not been considered for the analysis of the density of species. So, the system is not accurate enough for epidemic investigations, especially in big cities like Shanghai.

Methods: In this study, an improved surveillance program integrating the actual monitoring locations was used to investigate the temporal and spatial distribution of *Ae. albopictus* abundance in an urban area of Shanghai, China, from 2018 to 2019 by using the mosquito-oviposition trap (MOT) method. The study area of 14 sub-districts was divided into 133 grids. The vector abundance and spatial structure of *Ae. Albopictus* were predicted by the indicator Kriging based on eight MOTs in each grid. Meanwhile, the light trap (LT) method was also used for the analysis and compared with the MOT method.

Results: A total of 8,192 MOTs were placed in the study area in 2018, and 7,917 (96.6%) were retrieved with a positive rate of 6.45%, while in 2019, 22,715 (97.0%) of 23,408 MOTs were recovered with a positive rate of 5.44%. When using the LT method, 273 (93.5%) and 312 (94.5%) adult female *Ae. albopictus* were gathered in 2018 and 2019, respectively. The *Ae. albopictus* populations in the urban area of Shanghai increased slowly from May, reached a peak in July, and declined gradually from September. The **MOT positivity index (MPI)** showed a significant positive spatial autocorrelation across the study area, while LT collections indicated a non-significant spatial autocorrelation. The MPI was suitable for spatial interpolation by using the indicator Kriging and showed different hotspots in different years.

Conclusions: The improved surveillance system integrating geographic information can help improve our understanding of the spatial and temporal distribution of *Ae. albopictus* in urban areas of Shanghai and could provide a practical method for decision-makers to implement vector control and management of mosquitoes.

Background

Aedes albopictus (Diptera: Culicidae), also known as the Asian Tiger Mosquito, has invaded all continents except Antarctica during the last 30-40 years [1, 2]. It is a primary human-biting pest species that significantly reduces the quality of life of infected persons, and an aggressive vector of major arboviral diseases such as dengue, chikungunya, yellow fever, and Zika. In China, *Ae. albopictus* is a primary nuisance pest and disease vector in the tropical and temperate regions after having adapted to low temperatures [3]. *Ae. albopictus* is present in regions where *Aedes aegypti* is absent, including Shanghai [4], and dengue is one of the most widely transmitted diseases by *Ae. albopictus* in China [5]. *Ae. albopictus* was reported as the primary vector of several epidemics in Guangzhou Province (37,354 laboratory-confirmed cases) in 2014 [6] and Zhejiang Province (adjacent to Shanghai) in 2004 [7], 2009 [8] and 2017 [9].

The dengue case reported in 2017 in Shanghai was the first autochthonous dengue case in the last five decades in Shanghai [10]. In the following years, three cases have been reported [11]. Since then, *Ae. albopictus* has been on the top of the list for vector control and surveillance in Shanghai. The Public Health Service developed a monitoring system for *Ae. albopictus* to obtain information regarding its temporal evolution by using the light trap (LT) and mosquito-oviposition trap (MOT) methods in 2010. This system is used for surveillance of *Ae. albopictus* population and biting rates based on data collected from sub-districts. However, a disadvantage of the surveillance network is that it does not integrate geographic information, and the sub-district scale, which is mostly more than 3 km, is also large. As a result, only the regional average density of *Ae. albopictus* population can be obtained with this monitoring system.

Geostatistical methods, which integrate the actual locations of samples, have been used to investigate the spatial distribution of mosquitoes [12] and several mosquito-transmitted diseases, including malaria [13, 14] and Dengue fever

[15, 16]. Global and local indicators of spatial autocorrelation such as Moran's I [17] or LISA (local indicators of spatial association) [18] have been applied to study pests, including mosquitoes [19, 20]. These indicators can detect hot spots of mosquito abundance and predict the significance of clustering and the effect of disease control [21]. Among the geostatistical methods, Kriging interpolation [22] can predict the vector abundance in unsampled areas. Albieri et al. have used the Kriging interpolation to predict mosquito population distribution at the provincial and municipal scales in northern Italy [23]. Azil et al. have used Kriging to analyze the costs of dengue vector surveillance and control programs in Australia [24]. In addition, Giordano et al. conducted a more efficient larvicide control program for West Nile virus awareness campaigns in Canada by using the Kriging interpolation technique [25].

In China, assessment of the density of *Aedes albopictus* is usually made based on the *Aedes* positive rate in ovitrap monitoring, and MOT is a standard method for surveillance of the temporal and spatial distributions of container-inhabiting mosquitoes including *Ae. albopictus* [26]. However, there have been rare reports [27] on the spatial interpolation of positive rates and the indicator Kriging.

The present study was set out to evaluate the temporal and spatial distributions of *Ae. albopictus* using the MOT method, investigate the autocorrelation of *Ae. albopictus* abundance and estimate *Ae. albopictus* abundance at non-sampling locations using the indicator Kriging [28] in an urban area of Shanghai, and identify hotspots and risk areas of high infestation. We conducted an improved surveillance program, which additionally included the location of the traps and changed the monitoring unit from 14 sub-district to 133 grids, for *Ae. albopictus* in an urban area of Shanghai from 2018 to 2019. Eight MOTs in each grid were applied to predict *Ae. albopictus* abundance and spatial structure. Meanwhile, the LT method of the original monitoring scheme was also used for the analysis and compared with the improved MOT method.

Methods

Selection of the study area

Shanghai is situated at 31°12'N north latitude and 121°30'E east longitude in the east part of the alluvial plain of the Yangtze Delta, adjacent to the Yangtze River estuarine and the East China Sea. It has four distinct seasons (spring from March to May, summer from June to August, autumn from September to November, and winter from December to February) and abundant precipitation with a subtropical monsoon climate. The mean annual temperature in Shanghai is approximately 17 °C, and the mean annual precipitation is more than 1100 mm, with 53% occurring between June and September. The study area is situated in the center of Shanghai, China, with a total area of 37.37 km², measuring 6.15 km from east to west and 11.93 km from south to north (Fig. 1). In 2018, the study region included 14 sub-districts with a resident population of 1,057,700 [29].

Meteorological data

The monthly total precipitation and monthly mean maximum and minimum temperatures were calculated based on data from the China Meteorological Administration [30]. Weather variables were recorded at Xujiahui, which is located approximately 2 km from the study area.

Entomological survey

The abundance of *Ae. albopictus* was analyzed by using the MOT (Tian[®], Kaiqi Co. Ltd, Shanghai, China) and LT methods. The MOT provides artificial breeding sites for container-breeding mosquitoes including *Ae. albopictus*, and those with *Aedes* eggs are positive. LT attracts adult mosquitos baited with carbon dioxide, and the number of female adult mosquitoes captured was used as the index.

The MOT [31] consists of a transparent cylindrical plastic jar (100 mm high, 70 mm diameter, 66 mm internal diameter) with a concave bottom (20 mm inward) and a black top cover with three conical openings of 100 mm diameter. When used as a collection container, a white filter paper of 70 mm diameter, used as an egg deposition substrate, was placed inside the bottom of the MOT, and 25 ml of dechlorination water was poured into the jar to keep the paper moist but not submerged. MOTs were placed outdoors on grasslands, kept away from direct sunlight, rain, and wind at ground level by a skilled technician, and maintained unchanged until the end of the study.

The MOTs were placed once a month in 2018 between April and November. To enhance the data in the peak period, in 2019, the frequency was increased to once a week in week 20, week 23, week 25, weeks 27-39, and weeks 41-46. MOTs that were removed, emptied, or interfered with for any reason were excluded from further analysis. After four days, each MOT was collected to the laboratory. Species identification was performed with a stereomicroscope, and the MOT positivity index (MPI) was calculated as: $MPI = \text{number of the } Aedes\text{-positive MOTs} / \text{total number of MOTs retrieved} \times 100\%$.

There were 14 sub-districts in the study area which contained 276 neighborhood residents' committees. Each grid was set to be composed of 2 or 3 neighborhood residents' committee as the surveillance unit, with a side length close to 500 m. Based on the original monitoring program, 50 MOTs were placed in each sub-district. Under the premise of not increasing the cost as much as possible, MOTs were evenly distributed to each grid. Most sub-districts were made up of 6-10 grids, so we decided to place 8 MOTs in each grid. In 2018, the center of the study area was under construction and could not be placed with MOTs, so we chose the rest area and divided it into 128 grids (Fig. 1). We found a residential area with vegetative coverage as the monitoring point in each unit and put eight MOTs around a center point (Fig. 1). The MPIs of the eight MOTs were used to represent the *Ae. albopictus* density at that point. In 2019, we added five surveillance units in the middle of the study area, which lead to a total of 133 surveillance units in 2019.

On the third Wednesday of each month from May to November, the Centers for Disease Control and Prevention set two LTs in every sub-district throughout Shanghai as part of a city-wide mosquito surveillance program. LTs were usually collected from 4 pm to 10 pm. Contents of LTs were sent to the laboratory for species identification and only female *Ae. albopictus* from the traps were collected for data analyses.

The locations of MOTs and LTs were georeferenced using GPS CHCNAV X360H (WGS 1984 coordinate system) and later projected to the Shanghai local coordinate system. The georeferenced positions of MOTs and LTs in 2018 and 2019 are presented in Fig 1.

Cluster analysis

The monitoring data were assigned into MOT2018, MOT2019, LT2018, and LT2019 groups and analyzed. The yearly total collections of each LT and the mean MPI of each unit were calculated. Geostatistical analyses were conducted using ArcGIS 10.3 Spatial Statistics Tools (ESRI, China), and data in Microsoft Excel 2019 were imported into ArcGIS.

The average nearest neighbor (the mean distance from each feature to its nearest neighboring feature) analysis was then performed to calculate the nearest neighbor index. The index compared the mean distance to the null hypothesis states in which traps were randomly distributed, with index < 1 indicating a trend of clustering, while index > 1 indicating dispersion or competition. The area of the study region was used to the average nearest neighbor analysis based on the Euclidean distance.

We evaluated whether the mosquito abundances were spatially autocorrelated by calculating the incremental spatial autocorrelation (Global Moran's I at multiple distances). The Global Moran's I [17] was tested using the permutation procedure based on feature locations and attribute values (total collections of each LT and mean MPI of each unit) against the null hypothesis (the absence of spatial autocorrelation). This analysis identifies the spatial patterns in the

study area but did not indicate where such clusters occur, which could be determined by Local Moran's I [18]. The local Moran's I analysis was performed to assess the presence of hot spots with statistically significant clusters, cold spots, and spatial outliers.

Geostatistical analysis

The indicator Kriging [28] was used for geostatistical analysis. It is a geostatistical approach to geospatial modeling. Instead of assuming a normal distribution at each estimate location, indicator kriging builds the cumulative distribution function (CDF) at each point. The Kriging and Co-Kriging techniques were performed using the ArcGIS 10.3 Geostatistical Analyst extension, including exploratory statistical analysis, variogram modeling, and producing a probability or standard error of indicator. The Kriging interpolation method was used to quantify the spatial structure of the data and predict species abundance at unsampled locations on the basis of the mean MPI of each unit. We chose MPI of 5 as the threshold for indicator Kriging, which was also used as the threshold for early warning of dengue fever in Shanghai, China [32]. MPI less than 5 suggests a lower risk of an outbreak of dengue fever according to the "Implementation Program of National Vector Surveillance" launched by China's Center for Disease Control and Prevention. In the emergency response of dengue fever, MPI less than 5 is also an indicator of the control program. Here, MPI was made into a binary (0 or 1) variable, where 1 means MPI value above the threshold, and 0 means MPI value below the threshold. The resulting interpolation map shows the probabilities of exceeding the threshold. The Co-Kriging uses information on several variables. We used several thresholds for MPI and then the binary data on each threshold (covariable) to predict the threshold of primary interest by Co-Kriging. The prediction surface with the lowest error output and standard error surface was clipped to the study area boundary file. A leave-one-out cross-validation method was used to determine whether the Kriging interpolation provided reliable estimates of the indicator at unsampled locations. The criteria used for accurate prediction in the cross-validation were requested to be the following: root mean square standardized (RMSS) approximately 1, mean standardized (MS) approximately 0, and root mean square (RMS) approximately the average standard error (ASE).

Results

Mosquito collection

A total of 8,192 MOTs were placed in the study area, and 7,917 of them (96.6%) were retrieved with a positive rate of 6.45% in 2018, while in 2019 22,715 (97.0%) of 23,408 MOTs were recovered with a positive rate of 5.44%. LTs collected both male and female adult *Ae. albopictus*, with females constituting the majority, and 273 (93.5%) and 312 (94.5%) adult female *Ae. albopictus* were gathered in 2018 and 2019, respectively.

Monthly distribution of *Aedes albopictus*

The monthly mean temperature reached a peak in July (33.2°C) in 2018 and in August (32.9°C) in 2019. The monthly precipitation was highest in August in both 2018 (230.5 mm) and 2019 (369.5 mm) (Figs. 2 and 3). From May to October, the total precipitation in 2019 (1345.8 mm) was almost twice of that in 2018 (709.7 mm). Besides, from July to September, the mean monthly maximum temperature was higher in 2018 (31.9°C, Fig. 2) than in 2019 (30.9°C, Fig. 3).

As shown in Figs. 4 and 5, lower levels of oviposition were detected by MOTs in April 2018, and May 2019, with both MPIs peaking in July. In 2018, the monthly MPI peaked at 14.08, whereas in 2019, it peaked at 8.28 in the 29th week (July). The MPI peak during the 2018 mosquito season was higher than that in the 2019 season. There was also a significant peak in the number of female adults collected by LTs from July to September, in both years.

In 2018, the number of adult female *Ae. albopictus* collected by LT reached a peak in July, consistent with that by MPI. The number of female adults collected by LT increased from May to July, reached the highest values in July and August, and then decreased in September. In general, the curves of seasonal fluctuation in 2018 and 2019 indicated that *Ae. albopictus* populations in the urban area of Shanghai slowly increased from May, reached a peak in July, and declined gradually from September to October. Spearman correlation coefficient (r) between the monthly number of adult female *Ae. albopictus* collected by LT and monthly MPI was 0.792 8 ($P = 0.033$ 4, $df = 6$) in 2018 and 0.756 8 ($P = 0.048$ 9, $df = 6$) in 2019.

Spatial distribution of MOT and LT traps

We used the average nearest neighbor analysis to estimate whether the spatial autocorrelation of *Ae. albopictus* abundance was influenced by the locations of MOTs and LTs. The average nearest neighbor analysis tested whether the traps were randomly distributed within the study area, and produced the mean, minimum, and maximum distances between traps (Table 1). The results showed that both the MOTs and LTs exhibited a dispersed distribution pattern in 2018 and 2019.

The dispersed distribution of MOTs and LTs indicated that the distribution patterns of *Ae. albopictus* abundance monitored by the traps were not due to the location of the traps in the study area.

Cluster analysis of *Aedes albopictus* abundance

We performed the incremental spatial autocorrelation analysis to evaluate the spatial autocorrelation of *Ae. albopictus* abundance across the study area. Only the MOT method demonstrated statistically significant positive spatial autocorrelation based on the mean MPI of each unit, which peaked at 609 m in 2018, and 542 m in 2019. The LT method did not show statistically significant spatial autocorrelation of *Ae. albopictus* abundance based on the total collections of each LT (Table 2).

Local Moran's I was then used to determine the locations of hot spots, cold spots, and spatial outliers. Results showed 13, 14, 2, and 1 location of clusters or outliers for MOT2018, MOT2019, LT2018, and LT2019, respectively (Fig. 6).

Prediction of *Aedes albopictus* abundance at non-sampling locations

We found that the mean MPI of each unit was suitable for Kriging interpolation because it demonstrated statistically significant positive spatial autocorrelation. The probability maps were created for *Ae. albopictus* abundance exceeding MPI 5. There was no spatial autocorrelation for LT2018 and LT2019, and spatial interpolation was not permitted. We constructed the indicator Kriging interpolation by transferring the mean MPI of each unit into a binary with a threshold value of 5. Semivariograms created with indicator Kriging showed spatial dependence (range) within approximately 2000 m and 900 m for MOT2018 and MOT2019 (Figs. 7 and 8), respectively, beyond which the semivariance remained constant. The best-fitting model for 2018 was the stable model with a nugget effect value (the semivariance value at zero distance) of 0.096, and a partial sill value (the constant semivariance value beyond the range) of 0.160, and the spherical model fit the data of 2019 best, with a nugget effect value of 0, and a partial sill value of 0.259.

Prediction maps (Fig. 9) associated with those of standard errors (Fig. 10) based on MOT2018 and MOT2019 data showed that the highest mosquito abundance and strong spatial clustering were located in the south and north regions of the study area in 2018, and in the south and central areas in 2019. The prediction of standard errors quantified the degree of data uncertainty for each location on the surface. According to this analysis, the prediction error was the lowest around where MOTs were set in the study area. Overall, the leave-one-out cross-validation statistics (Table 3) with the value of RMSS approaching 1 showed that the predicted models were reliable for map production.

Furthermore, Co-Kriging improved the prediction of indicator Kriging. By using the Co-Kriging method, the inclusion of multiple thresholds of MPI generated several indicator variables for the same dataset. We took MPI of 1–4 and 6–10 as co-variables respectively, then selected the best two combinations with MPI 5 together, and compared all the results to select the best one. The use of covariables in the Co-Kriging analysis resulted in lower root mean square errors (RMS) for prediction (Table 3).

Discussion

According to the “Implementation Program of National Vector Surveillance” launched by China’s Center for Disease Control and Prevention, MOT and LT should be routinely applied for *Ae. albopictus* monitoring in China. In this project, each sub-district as a monitoring unit in Shanghai has a sample size of 2 LTs and 50 MOTs in a park and a residential area, but the spatial scale is limited for evaluating *Ae. albopictus* distribution [33, 34]. To obtain more accurate seasonal and spatial distribution density of species, we developed this scheme without additional fund demand by dividing the sub-district into grids. We also evaluated the feasibility and accuracy of MOTs in combination with geostatistical analysis as a practical tool for monitoring the spatial distribution of *Ae. Albopictus* in an urban area of Shanghai. Using this improved monitoring program, more information including the spatial distributions of *Ae. albopictus* was obtained without increasing the economic cost.

The results showed that MPI peaked in July in both 2018 and 2019, while the LT collections peaked in July in 2018 and in August in 2019. However, the indices of LT remained at a high level from July to September in both years. Consistent with the study by Gao et al., there was a significant correlation between monthly sampling yields [32]. The *Ae. albopictus* populations in the urban area of Shanghai slowly increased from May, peaked from July to September, and declined after September, which is coincident with the seasonal high temperatures and precipitation, and also consistent with previous reports [35, 36]. Moreover, although there was little difference in the quantity of *Ae. albopictus* captured by the LT method between 2018 and 2019, the MPI in 2018 was higher than that in 2019. This can be explained by more precipitations in the 2019 mosquito season, which bought more water-filled habitats for mosquito reproduction. As *Ae. albopictus* has a strong oviposition preference for physical and chemical stimuli over a range of distances [37], the increased number of water-filled containers would distract gravid *Ae. albopictus* females from laying eggs in the MOTs [38, 39]. Therefore, our results indicated that both MOT and LT could be applied for surveillance of the seasonal fluctuation of *Ae. albopictus*, but MPI and LT might be different between years.

In this study, we did not observe spatial autocorrelation for the LT collections of different periods, possibly due to the small number or the low density of LTs during those periods. Since the spatial analyses used distances to establish neighbors, low amounts of neighbors might result in lower statistical significance. The spread of *Ae. Albopictus* is limited by a short-range flight at a maximum distance of 600 to 800 m [40, 41], which is close to the distance of peak Global Moran’s *I* of MOT. Duncombe et al [42] suggested that the mosquito traps be placed at a distance of less than 1200 m from each other, while in this study the maximum distance of LT to the nearest neighbor was over 1500 m (Table 1). The spacing of LTs was too large to detect spatial autocorrelation in the sample area [43]. In our study, there were 2 LTs arranged in each sub-district with different areas, which contributed to the different spatial density of traps. More LTs are needed and should be well distributed for *Ae. albopictus* surveillance in Shanghai.

In this study, there was significantly positive spatial autocorrelation of MOT2018 and MOT2019 across the study area with a maximum distance of peak Global Moran’s *I* around 600 m (Table 2). The semivariograms showed that mosquito collections from MOT more than 2000 m in 2018 and 900 m in 2019, did not show spatial autocorrelation (Figs 7 and 8). In this study, we focused more on the spatial relationship with the risk of dengue fever, we used the indicator Kriging as it is more suitable for MOT data which is not normally distributed, with the advantage of applying binominal variables. Then MPI of 5 was chosen as the threshold of indicator, which was also used as the threshold for the risk of dengue

fever in China [32]. The indicator Kriging maps revealed different oviposition hot spots in 2018 *versus* 2019, which may be attributed to the following reasons: first, the mosquito abundance and seasonal distribution vary from year to year due to changes in temperature, precipitation, and humidity [44, 45]; second, the result of MOT2018 may provide a reference for strict vector control in high-density areas in 2019, causing a lowered MPI density in these sites compared to other regions in 2019. The Co-Kriging is recommended to improve the accuracy of spatial interpolation and the prediction of *Ae. albopictus* abundance [46]. The cross-validation results indicated that the estimated MPI at unsampled locations was reasonably acceptable, despite some limits due to the uneven distribution of the data.

As far as we know, this is the first study to apply MOT together with geostatistical methods to develop a routine surveillance program in China. MOT and LT could be used to monitor the relative size of mosquito populations [47] and that there was a significant correlation between monthly MPI and LT in our study. Although LT data were not suitable for Kriging interpolation, the correlations between LT and MOT can help set a threshold of MOT with different LT values. Then we can obtain a probability map of LT estimated by the MOT indicator Kriging.

This study was limited by the lack of combination of the breeding sites and habitats of *Ae. Albopictus*, such as the Breteau index. Future studies should include the preferred larva breeding sites and adult habitats, as well as NDVI (Normalized Difference Vegetation Index) and the human population in spatial modeling of abundance, which will increase the accuracy and comprehensiveness of the model [24, 25].

Conclusions

In conclusion, the improved surveillance system with MOT based on grids is affordable and can predict areas of high and low vector density in Shanghai. It can improve our understanding of the spatial and temporal distribution of *Ae. Albopictus* in urban regions of Shanghai and is a practical method for decision-makers to use for vector control and management of mosquitoes. In future studies, the exploration of larger-scale use of this monitoring program is needed, and more data are needed to validate this improved method.

Abbreviations

MOT: Mosquito oviposition trap; LT: Light trap; MPI: MOT positivity index

Declarations

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Ethics approval and consent to participate

This study did not involve vertebrate animals or human subjects.

Consent for publication

Written informed consent for the publication of the images was obtained from all individuals involved in this study.

Availability of data and materials

All relevant data are within the paper.

Competing interests

The authors declare that they have no competing interests.

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Author Contributions

Conceived and designed the experiments: HYW and YYZ. Performed the experiments: YBZ, HXL, PEL, and JZ. Analyzed the data: YBZ, SJY, and YYZ. Wrote the paper: YBZ, HXL, and YYZ. All authors read and approved the final manuscript.

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Tables

Table 1. Results of the average nearest neighbor analysis

Trap collection	MOT2018	MOT2019	LT2018 and 2019
Numbers of traps	128	133	28
Minimum distance (m) to the nearest neighbor	187.1	187.1	380.1
Maximum distance (m) to the nearest neighbor	627.0	680.9	1538.8
Observed mean distance (m)	368.5	377.2	702.1
Expected mean distance (m)	270.2	265.0	577.6
Nearest neighbor ratio	1.364	1.423	1.215
Z-score	7.875	9.337	2.180
P-value	<0.001*	<0.001*	0.029*
The distribution of traps	Dispersed	Dispersed	Dispersed

*Significant at $P < 0.05$.

Table 2. Results of incremental spatial autocorrelation analysis

Trap collection	MOT2018	MOT2019	LT2018	LT2019
Number of traps	128	133	28	28
The distance of peak Global Moran's I (m)	609*	542*	680*	716*
Global Moran's I	0.326	0.271	0.227	0.303
Z-score	4.563	3.331	1.050	1.480
P-value	<0.001**	<0.001**	0.293***	0.139***

* Some traps with no neighbors at this distance.

** Significant positive spatial autocorrelation when $P < 0.05$.

*** random patterns when $P > 0.05$.

Table 3. Leave-one-out cross-validation statistics.

MPI	Co-variables	Kriging type	RMS	MS	RMSS	ASE
2018 >5	/	Stable	0.4210	0.0024	1.0068	0.4207
2018 >5	MPI>8	Spherical	0.3472	-0.0492	0.9913	0.3513
2019 >5	/	Spherical	0.4836	0.0069	1.0348	0.4722
2019 >5	MPI>3 and MPI >8	Gaussian	0.3623	-0.0023	1.0133	0.3642

RMS: root mean square

MS: mean standardized

RMSS: Root mean square standardized

ASE: average standard error

Figures

Figure 1

Map of Shanghai, China, and locations of MOTs and LTs in the study area. Abbreviations: MOT: Mosquito-oviposition trap; LT: Light trap Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 2
Monthly maximum-minimum temperature and precipitation in 2018

Figure 3
Monthly maximum-minimum temperature and precipitation in 2019

Figure 4

The monthly MPI and number of female adult *Ae. albopictus* captured by LTs during 2018 Abbreviations: MPI: The Mosquito-oviposition trap positivity index

Figure 5

The weekly MPI and the monthly number of female adult *Ae. albopictus* captured by LTs during 2019 Abbreviations: MPI: The Mosquito-oviposition trap positivity index

Figure 6

Local Moran's I maps :(a) MOT2018 (b) MOT2019 (c) LT2018 (d) LT2019

Figure 7

Semivariograms for MOT2018

Figure 8

Semivariograms for MOT2019

Figure 9

Kriging interpolation maps in the study area. (a) Probability of MPI 5 estimated by indicator Kriging MOT2018 (b) Probability of MPI 5 estimated by indicator Kriging MOT2019 (c) Probability of MPI 5 estimated by indicator Co-Kriging MOT2018 (covariable: MPI>8) (d) Probability of MPI 5 estimated by indicator Co-Kriging MOT2019 (covariables: MPI>3 and MPI >8)

Figure 10

Standard error maps in the study area. (a) Standard error map of indicator Kriging MOT2018 (b) Standard error map of indicator Kriging MOT2019 (c) standard error map of indicator Co-Kriging MOT2018 (Covariable: MPI>8) (d) Standard error map of indicator Co-Kriging MOT2019 (Covariables: MPI>3 and MPI >8)

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