



OPEN Assessing and correcting neighborhood socioeconomic spatial sampling biases in citizen science mosquito data collection

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Climatic, ecological, and socioeconomic factors are facilitating the spread of mosquito-borne diseases, heightening the importance of vector surveillance and control. Citizen science is proving to be an effective tool to track mosquito populations, but methods are needed to detect and account for small scale sampling biases in citizen science surveillance. In this article we combine two types of traditional mosquito surveillance records with data from the Mosquito Alert citizen science system to explore the ways in which the socioeconomic characteristics of urban neighborhoods result in sampling biases in citizen scientists' mosquito reports, while also shaping the spatial distribution of mosquito populations themselves. We use Barcelona, Spain, as an example, and focus on *Aedes albopictus*, an invasive vector species of concern worldwide. Our results suggest citizen scientists' sampling effort is focused more in Barcelona's lower and middle income census tracts than in its higher income ones, whereas *Ae. albopictus* populations are concentrated in the city's upper-middle income tracts. High resolution estimates of the spatial distribution of *Ae. albopictus* risk can be improved by controlling for citizen scientists' sampling effort, making it possible to provide better insights for efficiently targeting control efforts. Our methodology can be replicated in other cities faced with vector mosquitoes to improve public health responses to mosquito-borne diseases, which impose massive burdens on communities worldwide.

Keywords Mosquito-borne diseases, Vector control, Vector surveillance, *Aedes albopictus*, Citizen science, Social inequality

Climatic, ecological and socioeconomic factors are shifting and expanding the ranges, seasons, and fecundity of disease vector mosquitoes^{16,55,62,73,78,79,86}, while also driving faster and earlier multiplication of pathogens^{14,83}, all of which heightens the importance of vector surveillance and control efforts^{18,92}. In the absence of viable vaccines, the World Health Organization (WHO) has long highlighted vector control as an essential but underutilized strategy for addressing the increasing global burden of vector-borne disease⁹⁰, and the calls for member states to strengthen vector control and surveillance are becoming increasingly urgent^{3,91,92}.

Responding to these calls requires adding new tools and new ways of thinking to traditional entomological approaches^{26,58,74}. Citizen science is proving to be a particularly effective one^{5,12,29,70}, so much so, that it is now being incorporated explicitly into national and local vector control strategies^{60,61}. Citizen science involves participation in scientific research by members of the public who need not be professional scientists^{37,41,66}.

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Participation ranges from “classical” scientific observation (like the century-old Christmas Bird Count), to networked citizen science that harnesses the internet and digital sensors to link participants and enable involvement in different parts of the research process³⁶.

One of the main challenges of citizen science is to collect reliable data that can be used to make unbiased inferences. This is especially important for projects that rely on citizen scientists’ observations and reporting but have no participation restrictions—i.e., people can participate whenever and wherever they want. In these types of projects, it is generally necessary to distinguish between variation in the phenomenon of interest and variation in citizen scientists’ sampling effort²² because citizen scientists tend to sample some areas more than others⁴⁶. For example sampling may be more intense in areas closer to participants’ homes²¹ or closer to cities or roads⁹. Sampling effort may also be mediated by a variety of other physical and socioeconomic spatial characteristics, including human population density, altitude, land cover type, degree of urbanization, and aggregate income levels of resident populations^{32,81}.

From a vector surveillance perspective, this issue is crucial because human-related factors generally have the most unpredictable influence on vector dynamics in urban ecosystems⁴⁹. A better understanding of the role of these factors in citizen science participation makes it possible to learn more about their influence on vectors themselves. The analysis of potential spatial sampling biases in mosquito vector population estimates that use data collected from citizen scientists is also crucial from a health equity perspective, as these estimates are increasingly used by local, regional, and national public health authorities as an integral part of vector surveillance and control⁶⁰. Reducing spatial biases in these estimates allows for more efficient control interventions and targeting of surveillance, consequently reducing the risk of diseases that place massive burdens on society around the world and that widen existing health inequalities^{8,56}.

In the present study, we investigate how socioeconomic census tract characteristics in Barcelona shape reporting patterns in Mosquito Alert, a networked citizen science platform used for vector mosquito surveillance^{5,47,70}. We untangle the effects of census tract characteristics on participation from their effects on mosquito populations and the risk of exposure using ground truth data about the presence of mosquitoes. This allows us to reduce spatially structured socioeconomic biases in estimates of mosquito distributions relied on by public health authorities.

Mosquito Alert leverages mobile phone sensors, the Internet, expert validation, and artificial intelligence to enable people without any prior training to identify and report vector mosquitoes^{5,47,70}. Since its launch in 2014, the Mosquito Alert system has been operational in Barcelona^{67,70}, and Barcelona’s public health agency, the *Agència de Salut Pública de Barcelona* (ASPB), has gradually incorporated it into its vector surveillance program^{59,61}.

Since June 2014 Mosquito Alert has received over 197,353 reports from 67,276 citizen scientists in 183 countries. Of these reports, 54% represent adult mosquitoes, 35% mosquito bites, and 10% mosquito breeding sites. (For the latest participation statistics, updated daily, see <https://labs.mosquitoalert.com/participation/>.) Seventy-seven percent of adult and site reports are accompanied by at least one photograph, and all adult reports with photographs are validated within Mosquito Alert’s Digital Entolab system by entomologists who review the photographs and score each report’s probability of representing one of five vector species (or species complexes) of public health concern: *Ae. albopictus*, *Ae. aegypti*, *Ae. japonicus*, *Ae. koreicus*, or *Culex pipiens*⁴⁷.

The Mosquito Alert system was designed to collect not only citizen scientists’ reports of vector mosquitoes, but also information about sampling effort that can be used to correct for bias. To protect participants’ privacy, however, its approach relies on anonymized background tracking masked to a grid of 0.025 degrees latitude and longitude (see Suppl. Info. Fig. 1)^{12,47,70}. This makes it possible to estimate variation in sampling effort between cells of approximately 4 km², but not within these cells. Yet, smaller-scale variation in sampling effort may well be an important source of bias in the type of census tract-level analysis necessary for effective mosquito surveillance and control in cities.

In Barcelona, the mosquito species of primary concern is the tiger mosquito, *Ae. albopictus*, an invasive species that poses a nuisance and a public health risk through its aggressive daytime biting and its ability to transmit dengue, chikungunya, Zika and a wide range of other viruses^{15,20,38,77}. Although autochthonous transmission of these viruses has not yet been detected in Barcelona, the presence of an established *Ae. albopictus* population in the city is particularly worrying given this species’ high vector competence and the city’s position as a major travel and tourism hub, with frequent cases of imported mosquito-borne infections^{7,34,35,52,59}.

Barcelona contains 1068 census tracts, with important variation along many socioeconomic dimensions including income (Fig. 1). Our key variable of interest is the yearly net mean income per consumption unit of each census tract, which we use as a proxy for area-level socioeconomic status. Worldwide, evidence suggests that *Aedes* mosquitoes often cluster in poorer areas^{17,76,80,87,89} due to community features such as higher concentrations of unmanaged water containers (e.g., flower pots), overgrown vegetation, and poorly maintained or abandoned buildings^{17,49,65,76,87}. Nevertheless, *Aedes* mosquito populations are also capable of clustering in census tracts with high socioeconomic status due to the availability of breeding sites created through gardening and other activities involving water inputs⁴⁹ like swimming pools¹⁷. In the case of Barcelona, very little is known about the relationship between census tract socioeconomic characteristics and *Aedes* mosquito populations. Our analysis helps to address this gap for the first time, while also adding to the literature on this topic globally.

Results

We examine citizen scientists’ reporting through Mosquito Alert in Barcelona from the time of the system’s launch in June 2014 through December 2023. This period encompasses 10 mosquito seasons, with the seasons running each year from approximately April through November. We start by examining overall participation by citizen scientists in the form of their submission of adult mosquito reports and mosquito bite reports through the system (Section “General participation model”). We then analyze citizen scientists’ Mosquito Alert reports in

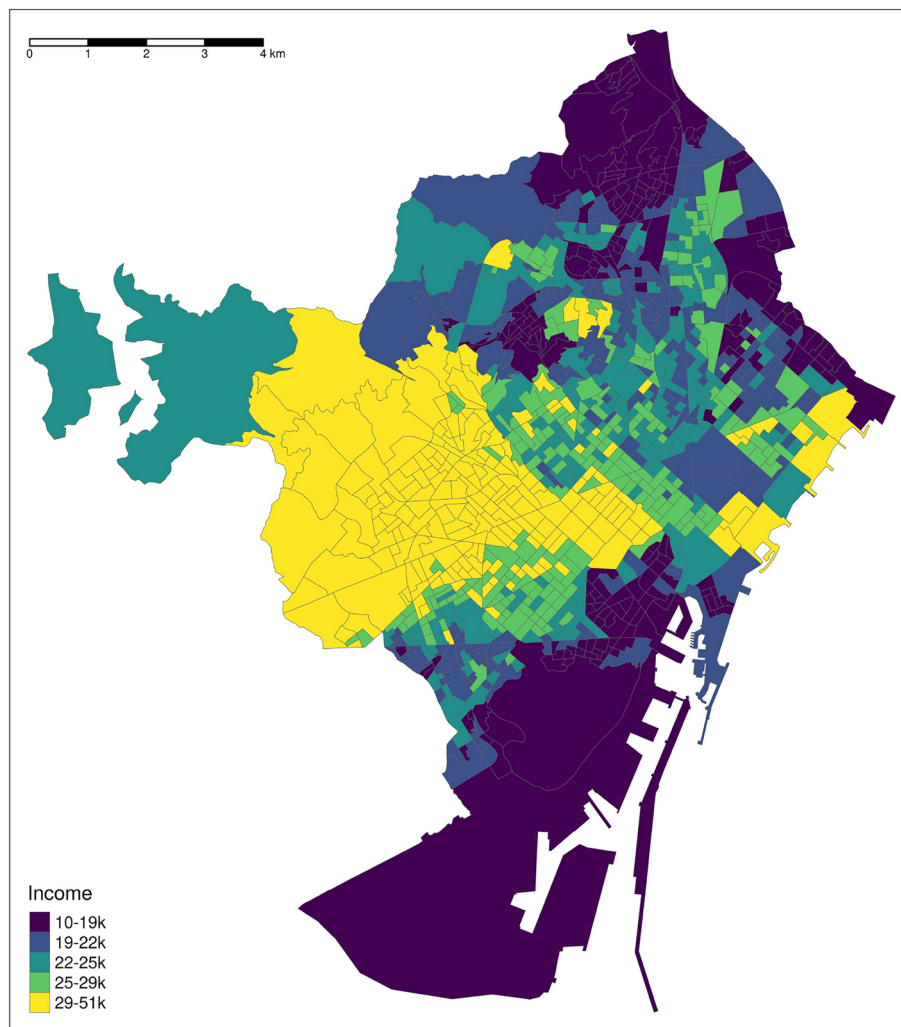


Fig. 1. Map of Barcelona municipality showing census tracts colored by yearly net mean income per consumption unit. Cartographic image created by the authors from the the INE's Digital Cartography Files⁴⁴ using R 4.4.1⁷² with ggplot2 3.4.4⁹³ and ggspatial 1.1.9²⁴.

the immediate vicinity of catch basin drains with known mosquito activity to better isolate the socioeconomic determinants of participation levels from those of mosquito populations (Section "[Active catch basin drain participation model](#)"). We combine these results with expert-validated *Ae. albopictus* reports from Mosquito Alert to analyze the socioeconomic determinants of this species' populations in Barcelona's census tracts and improve high resolution estimates (Section "[Mosquito Alert vector model](#)"). Finally, we compare our findings to an independent set of estimates based on data from 51 traditional adult mosquito traps positioned around the city between 2018 and 2022 (Section "[Mosquito trap vector model](#)"). We focus our discussion on our estimated coefficients on the income variable, but we include coefficient estimates for other variables and tables of model comparisons in the Supplemental Information.

Citizen scientist participation patterns

From June 2014 through December 2023 Mosquito Alert received a total of 5,393 adult mosquito and mosquito bite reports in Barcelona (3,563 adults and 1,830 bites). These reports were heterogeneously distributed across the city and covered most of its area (79% of its census tracts). We observe a lower density of reports in the southernmost area of the city, which is an industrial and commercial area, as well as the northeastern and northern border zones of the city, which mostly consist of natural areas like a marsh and lands covered by forest (Fig. 2a).

The distribution of mean income by consumption unit (from now on referred to as "income"; we describe its calculation in the Methods section) across Barcelona's census tracts ranges from 10,399 euros to 51,033, with a median of 23,510 (calculated in terms of the number of tracts, not people). Twenty-five percent of Barcelona's census tracts have mean incomes below 19,970 euros; 75% have mean incomes below 27,517 euros. Spatially, income is highly autocorrelated in Barcelona (Fig. 1), with a correlation coefficient of 0.84 between the income of each census tract and that of its neighboring tracts. Overall, we find 60% of Mosquito Alert reports in census

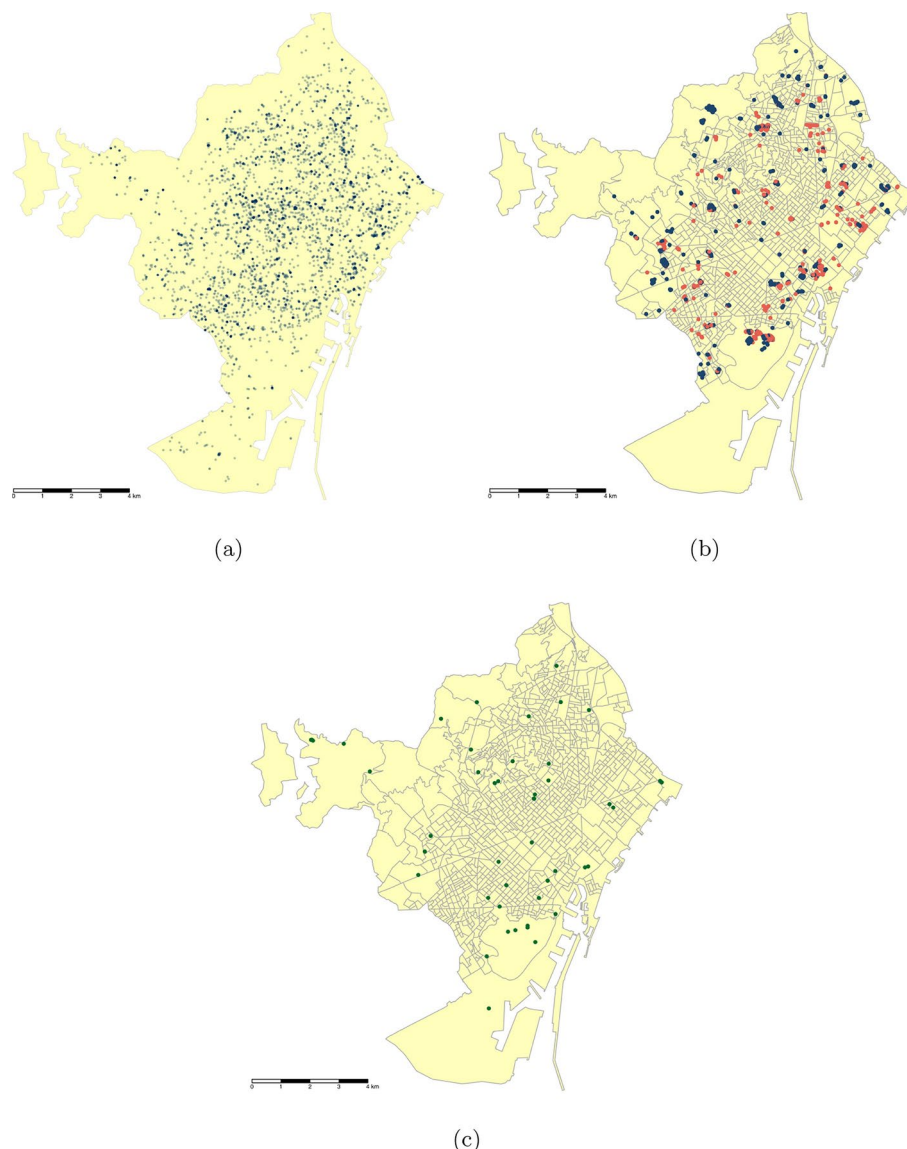


Fig. 2. Maps of the census tracts of the municipality of Barcelona showing: (a) locations of adult mosquito and mosquito bite reports sent through Mosquito Alert during 2014–23, a darker shade of blue indicates a higher concentration of reports; (b) locations of catch basin drains in which mosquito activity was detected by ASPB during 2019–23, with colors indicating whether any (red) or no (blue) adult mosquito or mosquito bite report was sent from within 200 m of the drain during same year in which the ASPB detected the activity; (c) locations of adult mosquito traps from which data was collected between 2018 and 2022. Cartographic image created by the authors from the the INE’s Digital Cartography Files⁴⁴ using R 4.4.1⁷² with *tmap* 3.3.4⁸².

tracts above the median; we find 25% in census tracts in the highest income quartile (over 27,517 euros), and 19% in the lowest quartile (under 19,970 euros).

General participation model

We analyze the Mosquito Alert participation data in a Bayesian logistic regression framework, modeling the log odds of a report being sent from a given point in Barcelona as a function of census tract income, population density, mean age, and proportion of households composed of only a single member (see Methods section for a description) using an intrinsic conditional auto-regressive term to account for the spatial autocorrelation of our covariates across neighboring census tracts. We transform our presence-only data (reports of mosquitoes) to a binary variable by randomly sampling pseudo-absences within the perimeter of the city of Barcelona (we describe this in detail in the Methods section). In this model (hereinafter General Participation Model) we find that, all else equal, the probability of citizen scientists’ participation has a very weak inverted-U-shaped relationship with income (Fig. 3), but there is too much uncertainty to draw firm conclusions about this relationship. We do see a clearly positive relationship between the probability of submitting a report to Mosquito Alert and population density, with the effect diminishing as density increases (Suppl. Info. Fig. 2). We also see a positive relationship

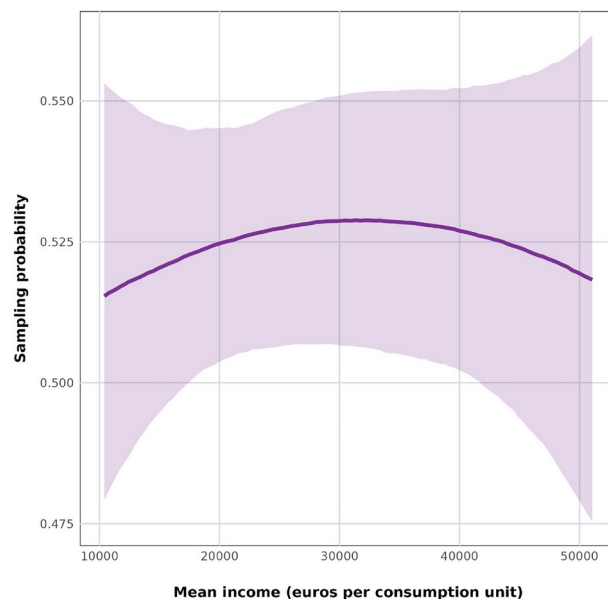


Fig. 3. Conditional effects plot of the relationship between mean income per consumption unit (in euros) and predicted probability of citizen scientists reporting adult mosquitoes or mosquito bites in the Mosquito Alert General Participation Model, with all other variables held at their means.

with the proportion of single-member households (Suppl. Info. Fig. 3), and a negative relationship with age (Suppl. Info. Fig. 4), but in both cases there is a lot of uncertainty in the estimate. This model does not allow us to untangle whether the predicted probabilities of submitting a mosquito report are due to socioeconomic neighborhood-level processes (e.g., a higher concentration of residents with more free time), a higher (or lower) density of mosquitoes, or both. Testing this requires some independent source of information about the actual mosquito population, and for this, we turn to official mosquito surveillance and control data from the ASPB.

Active catch basin drain participation model

The ASPB regularly monitors mosquito activity in and around catch basin drains in public spaces of Barcelona, recording mosquito activity whenever detected³⁰. We rely on the locations of 1024 drains in which the ASPB recorded mosquito activity from 2019–23. We model the presence or absence of citizen scientists' Mosquito Alert reports within 200 m of those drains in which the ASPB detected mosquito activity during the year in which the report was sent (Fig. 2b) as a function of Mosquito Alert sampling effort (described in Methods) along with the set of independent variables used in the Mosquito Alert General Participation Model. This enables us to estimate the probability of a citizen scientist reporting mosquito activity to Mosquito Alert given that mosquito activity was actually occurring. We again use a Bayesian logistic regression, but in this case, instead of fitting a spatial autocorrelation term, we take a multilevel approach, giving each drain a random intercept to account for the fact that some of the drains are observed as active repeatedly (in multiple years). We refer to this model as our Active Catch Basin Drain Participation Model.

The Active Catch Basin Drain Participation Model shows a concave and mostly negative relationship between census tract income and probability of reporting (Fig. 4). We find the highest probabilities of reporting mosquitoes in census tracts with incomes just below 30,000 euros (the highest income quartile among Barcelona's census tracts), with probabilities then dropping at higher and lower incomes. Holding our other covariates at their means, the probability of a citizen scientist reporting mosquito activity near an active drain is between 40% and 50% in census tracts with incomes under 30,000 euros, and it drops to 30% in the highest-income tracts (Fig. 4). We also see the same positive, diminishing effect of population density as in the General Participation Model (Suppl. Info. Fig. 5), and here we see clear positive relationships with the proportion of households composed of a single person (Suppl. Info. Fig. 6) and with Mosquito Alert sampling effort (Suppl. Info. Fig. 7) and a clear negative relationship with age (Suppl. Info. Fig. 8).

As a robustness check, we test whether the relationships estimated in this model hold if we randomly eliminate catch basin drains from the dataset to ensure that no two modeled drains are within 200 m of one another. We find largely the same relationships in this case, albeit with more noise (Suppl. Info. Figs. 9, 10, 11, 12). The relationship between the probability of reporting a mosquito and income appears more like an inverted U in this model, showing a larger variation of sampling probability values, with much lower sampling effort in both lower and higher income tracts (Suppl. Fig. 9). Nonetheless, we attribute this to the loss of data from eliminating the drains closer than 200 m to one another.

Vector-mosquito risk

We interpret the relationships estimated in the Active Catch Basin Drain Participation Model as reflecting sampling biases—systematic differences in the probabilities of citizen scientists reporting mosquitoes when

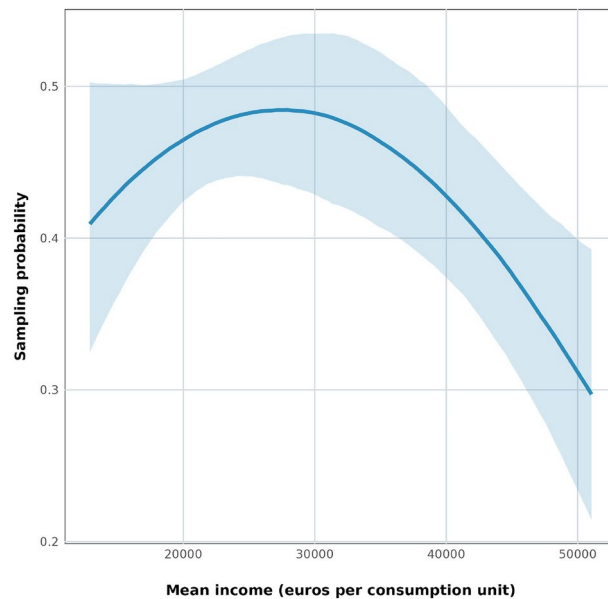


Fig. 4. Conditional effects plot of the relationship between mean income per consumption unit (in euros) and predicted probability during a given year of citizen scientists reporting adult mosquitoes or mosquito bites within 200 m of a catch basin drain with known mosquito activity that year in the Active Catch Basin Drain Participation Model, with all other variables held at their means.

mosquitoes are present, based on socioeconomic neighborhood characteristics. These sampling biases are important not just for what they tell us about the socioeconomic determinants of citizen science participation, but also because correcting for them should make it possible to disentangle the determinants of mosquito population sizes from the determinants of citizen scientists' participation. In the same way that we use ASPB data on mosquito activity in the sewage system to control for variation in the actual mosquito distribution, we can use the predictions from the Active Catch Basin Drain Participation Model to control for sampling bias in a mosquito distribution model.

Mosquito Alert vector model

Specifically, we model the probability of *Ae. albopictus* presence, as measured through validated Mosquito Alert reports, controlling for the predicted sampling effort from our Active Catch Basin Drain Participation Model. We again rely on Bayesian logistic regressions. As in the General Participation Model, we use an intrinsic conditional auto-regressive term to account for the spatial autocorrelation of our covariates across neighboring census tracts. In this case, however, the presences in our outcome variable are locations of expert-validated *Ae. albopictus* reports (as opposed to all adult and bite reports, regardless of validation status, as modeled in the General Participation Model). In this case we generate pseudo-absences by sampling random points across Barcelona with sampling weights proportional to the sampling probabilities predicted from the Active Catch Basin Drain Participation Model. In addition to using the predicted sampling probabilities as sampling weights, we also use the log of these probabilities as an offset in the model to control for any extra socioeconomic bias for which the sampling weights do not account. Finally, we control for proximity to privately owned spaces with green land cover, a variable that the ASPB regularly uses in its mosquito surveillance and control planning based on habitat suitability of green land cover and the difficulty of carrying out mosquito control in privately-owned spaces due to lack of access.

This model estimates the relationship between census tract mean income and the probability of *Ae. albopictus* presence to be concave, but mostly increasing (Fig. 5). Holding the other variables at their means, the probability is lowest, below 1%, in the lowest-income census tracts. It increases to a maximum of just over 5% in census tracts with mean incomes between 40,000 and 50,000 euros and then decreases beyond that point, dropping to 5% in the highest-income tracts. The model also estimates a clear positive relationship between the probability of *Ae. albopictus* presence and proximity to privately owned spaces with green land cover (Suppl. Info. Fig. 13).

Figure 6 shows the predicted probabilities from this model on a regular lattice of 256,898 points across Barcelona, spaced at 20 m intervals, and it compares these predictions to those from the same model without controlling for sampling effort. The map in Figure 6a shows the predictions from the model with sampling effort, i.e., the predicted probabilities of reporting a mosquito from our Active Catch Basin Drain Participation Model, while the one in Figure 6b shows the differences between these predictions and those from the model without sampling effort, subtracting the no-sampling-effort model predictions from the sample-effort-model predictions. In this second map, the orange and red areas are those in which the model without sampling effort under-predicts the probability of *Ae. albopictus* presence, while the green and blue ones are those in which it over-predicts the probability. The model without sampling effort mostly over-predicts the probability of *Ae. albopictus* presence. It does so by more than 10 percentage points in 9 out of Barcelona's 10 districts (Suppl. Info.

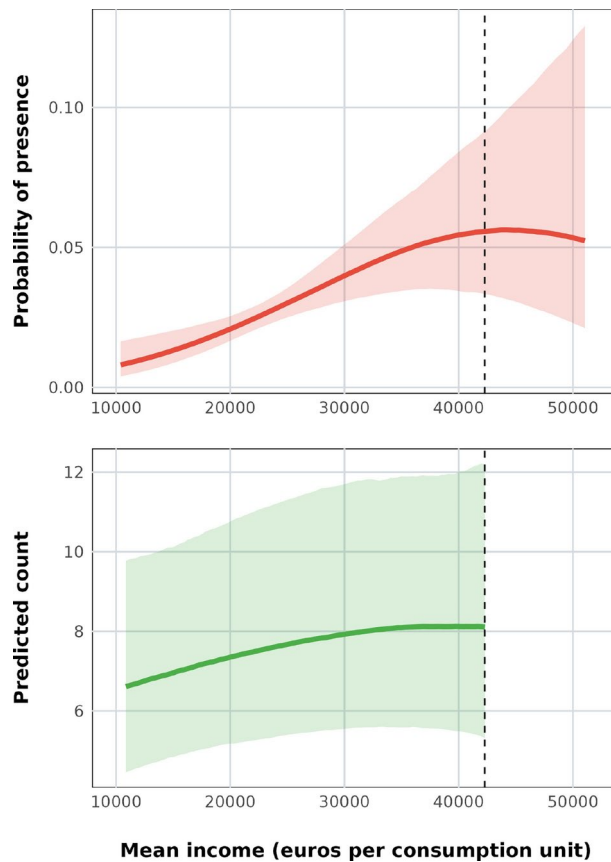


Fig. 5. Top: Conditional effects plot of the relationship between mean income per consumption unit (in euros) and predicted *Ae. albopictus* probability in the Mosquito Alert Vector Model, with all other variables are held at their means. Bottom: Conditional effects plot of the relationship between mean income per consumption unit (in euros) and predicted *Ae. albopictus* counts in the Mosquito Trap Vector Model, with all other variables are held at their means. Dotted vertical line in both plots indicates maximum income modelled in the Mosquito Trap Vector Model.

Tab. 1). Under prediction by more than 10 percentage points is seen in only 3 of the 10 districts (Suppl. Info. Tab. 1).

Mosquito trap vector model

As a final step, we partially validate these results by testing the relationship between census tract income and a total of 1368 female *Ae. albopictus* counts that we recorded in 51 BG Sentinel-2 adult mosquito traps placed around Barcelona between 2018 and 2022 (Fig. 2c). These counts and the sampling process on which they are based have no connection to citizen scientists and so provide an independent source of information about the mosquito distribution in Barcelona. Controlling for the effects of weather (since traps were checked at different times throughout the mosquito season) and land cover, we find a similar relationship with income as in the Mosquito Alert Vector Model: The predicted counts of female *albopictus* in traps go up as we move from the lowest income census tracts to the tracts with mean incomes of 40,000 euros (Fig. 5). The predictions appear to peak at slightly lower incomes than in the Mosquito Alert Vector Model, but they are also much more noisy (Fig. 5). We hypothesize that this is due to the fact that there were very few traps in high income tracts: only 89 out of 1368 (6.5%) trap counts are from traps in tracts with mean income over 35,000 euros, and none are over 42,283. In contrast, the Mosquito Alert Vector Model is estimated using reports (both presences and pseudo-absences) from tracts with mean incomes up to 51,000.

Discussion

These results show how spatially structured socioeconomic characteristics shape sampling bias in the Mosquito Alert citizen science reporting in Barcelona. In addition, they show how a better understanding of that bias makes it possible to learn more about the socioeconomic determinants of the small-scale spatial distribution of disease vector mosquitoes and to improve our predictive models of mosquito populations at high resolution (20m).

We find a predominantly negative relationship between census tract mean income and the probability of submitting a mosquito report to Mosquito Alert (Fig. 4). Once we control for this sampling bias, the modeled citizen science data shows a positive relationship between census tract mean income and *Ae. albopictus*

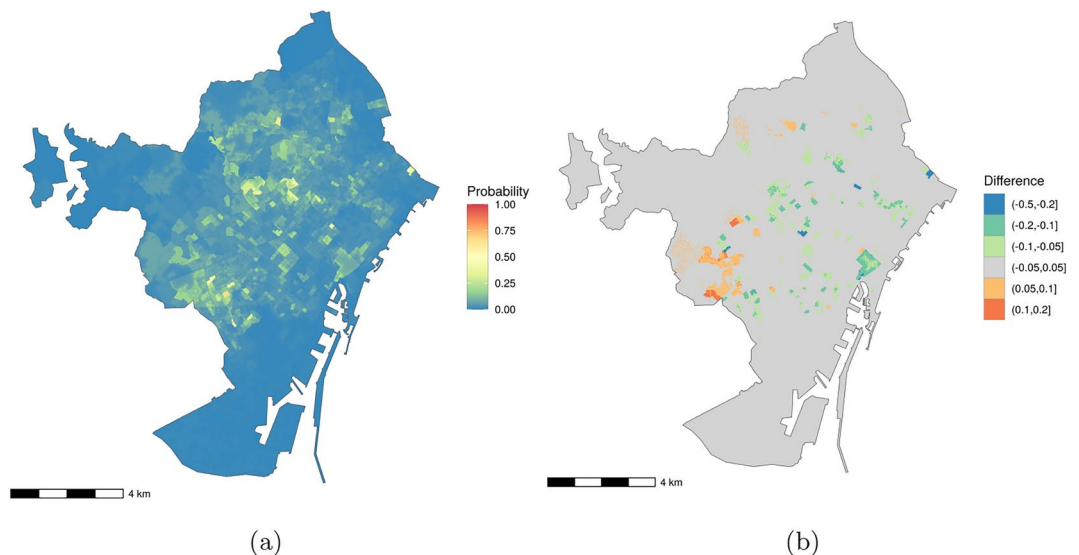


Fig. 6. Maps of Barcelona municipality showing: (a) predicted probability of *Ae. albopictus* presence based on the Mosquito Alert Vector Model controlling for sampling effort, and (b) differences between these predictions and those made without controlling for sampling effort. The differences are calculated as predictions controlling for sampling effort minus those not controlling for sampling effort, so values above zero (oranges and reds) represent zones where probabilities would be under-predicted without controlling for sampling effort, and values below zero (greens and blues) represent zones where those probabilities would be over-predicted. Cartographic image created by the authors from the INE's Digital Cartography Files⁴⁴ using R 4.4.1⁷² with *ggplot2* 3.4.4⁹³ and *ggspatial* 1.1.9²⁴.

probabilities up to incomes above 40,000 euros, which is largely the same as the relationship we find when we model mosquito trap data. Beyond these tract mean incomes the citizen science data suggests that probabilities begin to decrease, but there is little mosquito trap data with which to make a comparison at this income range values. Note also that 40,000 euros is at the top of Barcelona's census tract mean income distribution, only 5% of Barcelona's census tracts have higher mean incomes.

Whereas citizen science often faces criticism for insufficiently including communities with lower resources^{42,71}, our results suggest that citizen science mosquito sampling effort in Barcelona is actually higher in these areas than in others. We hypothesize that higher-income census tracts in Barcelona have lower probabilities of submitting reports to Mosquito Alert because their residents are less exposed to mosquitoes, irrespective of mosquito prevalence, because they have higher access to air conditioning, private transportation, mosquito window nets, mosquito repellents, indoor working environments, and other amenities that reduce human-mosquito contact.

From a health and spatial inequality perspective, hazards are theorized to accumulate in poorer areas as a reflection of inequality processes at the individual level as well as structural decisions to organize space in ways that perpetuate inequality^{23,33,40}. Empirical evidence supports this idea worldwide, e.g.^{13,94}, even in spaces that make substantive efforts to make themselves more equitable⁸⁵. This is also the case in Barcelona when it comes to hazards such as air pollution⁵³.

Our models suggest a more complicated story when it comes to vector mosquitoes, with higher prevalence in wealthier areas. Although this is not the most common distribution pattern observed worldwide, our results emphasize the heterogeneous and location-specific nature of the association between socioeconomic status and *Aedes* mosquito presence that has been recently highlighted by other scholars⁸⁸. In the case of Barcelona, the positive association between tract-level income and *Ae. albopictus* presence makes sense since higher income housing in Barcelona is characterized by having higher access to outdoor private spaces like terraces and gardens, where mosquitoes can proliferate easily. This does not mean that mosquito-borne disease infections should be expected to follow the same pattern as mosquito vector prevalence. Were an outbreak to occur in Barcelona, many factors could cause transmission to amplify in different parts of the city. For example, human mobility flows can facilitate the rapid spread of infected people in the viremic phase, moving the virus between mosquito subpopulations across neighborhoods¹. Moreover, disease transmission depends not just on the density of mosquito populations but also on mosquito behavior, the density of human populations and on individuals' exposure to mosquito bites.

Notably, the Agència de Salut Pública de Barcelona (ASPB) is making an effort to monitor mosquito presence in the city and avoid the production of mosquito-related health inequalities. In its latest report⁶¹, ASPB found that 59% of potential mosquito risk factors (e.g., public catch basins or fountains) were in the low-income areas of the city. Consequently, the ASPB decided to increase monitoring of mosquito activity and related risk factors in these areas, which now represent 67% of its monitoring activity⁶¹. This may well explain our finding, from both the Mosquito Alert Vector model and the Mosquito Trap Vector model, that *Ae. albopictus* probabilities are lower in the low-income areas.

The prevalence of *Ae. albopictus* in higher-income census tracts also suggests a mechanism by which this species' population may be supported in Barcelona: metapopulation stability. A set of interconnected *Ae. albopictus* subpopulations utilizing different types of breeding sites, some in public spaces and others in private spaces, is more likely to survive and rebound after concerted control programs¹. For example, when control programs focus on public spaces, they may reduce the subpopulations there, but those subpopulations can be replenished through in-migration from subpopulations in private spaces. Even with their limited dispersal capacity, *Ae. albopictus* individuals can cross the boundaries between high and low-income areas by flying between adjacent sites, through human-aided dispersal in vehicles^{28,54}, or through slower multi-generational processes.

In addition to these findings about citizen science participation and the spatial distribution of mosquito populations, our approach here offers a reliable and replicable method for other citizen science projects that collect anonymized data to assess their socioeconomic spatial sampling biases as long as they have access to some source of ground truth data about the presence of the phenomenon they study. Studying the socioeconomic distribution of the underlying phenomena observed by citizen scientists in any field is crucial, as it can overlap with detrimental outcomes and trigger a process of widening social inequality.

Methods

The core of the data for this study consists of anonymous geolocated reports sent by citizen scientists through the Mosquito Alert citizen science system^{5,47,70}. We combine these reports with data from mosquito traps that we collected during 2018–22, data from the ASPB's surveillance of catch basin drains during 2019–23, sociodemographic data from the Spanish National Statistical Institute (<https://www.ine.es>) and the Barcelona City Council's Open Data Portal (<https://opendata-ajuntament.barcelona.cat>), and weather data from the Meteorological Service of Catalonia.

We estimate all models using Hamiltonian Monte Carlo Markov chain sampling with the no U-turn sampler implemented by *brms* 2.19.0^{10,11}, *cmdstanr* 0.7.1, and *cmdstan* 2.32.2³¹ in R 4.4.1⁷². We use weakly informative priors for our population effects and estimate complete posterior distributions for each parameter through 4 parallel chains and 2000 iterations.

Mosquito Alert data

We rely on descriptive content of the Mosquito Alert reports and the report dates and locations, along with optional anonymous background tracking masked to a grid of 0.025 degrees latitude and longitude (approx. 4 km², see Supplemental Fig. 1). Anyone can participate in Mosquito Alert as a citizen scientist if they are 18 or older. Citizen scientists participate by using a mobile phone app to report adult mosquitoes, breeding sites, and mosquito bites. Participants can optionally include photographs with adult mosquito reports, and these photographs are reviewed by a large international team of entomologists, who classify them by target species using Mosquito Alert's digital Entolab⁴⁷. Mosquito Alert operates around the world and collaborates with local and national public health agencies to ensure that the vector intelligence it produces is useful and actionable^{12,29,47,60,74}. The system avoids collecting socio-demographic or economic information about participants for privacy reasons. However, a recent analysis of a voluntary sample of citizen scientists who had registered to use Mosquito Alert in Spain from August 2020 to September 2021 showed that participants are more likely to be women, middle-aged (30–49), employed, high earners, and live in urban spaces¹⁹. The tendency of higher earners to participate in Mosquito Alert in Spain as a whole contrasts with the lower propensity to report mosquitoes in the highest income areas of Barcelona. Notably, the first finding is based on a voluntary sample of the Mosquito Alert citizen scientist pool all over Spain who had begun participating in 2020–21, whilst the findings in this paper are based on mosquito bite and mosquito reports collected specifically in Barcelona and over a much wider time period (2014–23). Together, these results suggest that participation “profiles” may vary within countries and over time.

The present study uses 3563 reports of adult mosquitoes and 1830 reports of mosquito bites collected from Barcelona Municipality from June 2014 through December 2023 through Mosquito Alert⁶⁹. The study also relies on a subset of 992 of the adult mosquito reports that contained photographs assessed by a team of expert entomologists as showing *Ae. albopictus*. That subset was derived from the full dataset of expert-validated adult reports downloaded on 20 February 2024⁷⁵. Barcelona is the city with the highest concentration of reports in the Mosquito Alert system, in part because it is where the system was first launched and has received press attention for the longest time.

Mosquito Alert sampling effort data is taken from the open data published by Mosquito Alert daily and downloaded on 20 February 2024⁶⁴. Specifically, we rely on the `SE_expected` variable in the `sampling_effort_daily_cellres_025.csv.gz` dataset. The dataset provides values on a grid of 0.025 degrees longitude and latitude (see Suppl. Info. Fig. 1). Each cell in the grid is referred to as a sampling cell, and it is used to protect the anonymity of the sampling effort data collected from participants⁷⁰. The `SE_expected` variable represents the estimated expected number of participants sending at least one report from each sampling cell during each day from 2018 to present. The estimates are calculated by first estimating the discrete hazard function²⁵ for participants' reporting over time since registering with Mosquito Alert. In other words, we calculate the empirical probability of participants sending a report through Mosquito Alert on each day since they register, treating reporting as a repeated event². We then apply this empirical probability to each participant in the background tracking data to estimate their probability of sending a report on the date in question. For the `SE_expected` variable, we aggregate these probabilities by summing them by sampling cell (see Suppl. Info. Fig. 1) and by day to get the expected number of participants sending at least one report from each cell each day. In other words, `SE_expected` for sampling cell *c* on day *d* is:

$$SE_expected_{cd} = \sum_{i=1}^{N_{cd}} P(x_{icd}) \quad (1)$$

where $P(x_{icd})$ is the probability of participant i sending at least one report from cell c on day d and N_{cd} is the total number of participants observed in cell c on day d .

We incorporate this variable into the dataset used here by further aggregating each cell by year, summing the daily expected values to get the expected number of participants sending at least one report from each cell each year.

Mosquito trap data

We rely on data that we collected from BG Sentinel-2 mosquito traps with BG lures (BioGents Corporation, Regensburg, Germany). These traps attract adult, host-seeking female mosquitoes using air currents, visual queues, and (optionally) chemical queues, and capture them with a small suction fan^{6,48,51}. We deployed 51 traps, between 12 and 24 per year, over four years and four mosquito seasons in cooperation with the ASPB. Trap locations are shown in Fig. 2c. Each trap was checked and mosquitoes were classified and counted approximately every week over the course of each mosquito season. There are a total of 1368 trap observations, 453 in 2018, 165 in 2020, 426 in 2021, and 324 in 2022.

Catch basin drain data

The drain data were collected by the ASPB from 2019 to 2023 as part of its continuous surveillance and control of mosquitoes in the city³⁰. This involves inspecting possible breeding sites in public spaces and applying anti-larval treatments as needed. The triggers for these inspections include direct communications about mosquito nuisance from city residents, Mosquito Alert reporting, and communications of arboviruses cases from relevant authorities, i.e. humans infected with mosquito-borne viruses. Some drain inspections are also part of regular surveillance that is carried out in different risk areas of the city (around 80 areas each year). These risk areas are inspected from April to November with an inspection frequency per drain of approximately 1 visit every 3 weeks. In these inspections, all possible sources of breeding sites found in public spaces (mainly streets and roads) are checked (mainly catch basins but also ornamental fountains or other elements that can accumulate water), and data is collected on whether or not mosquito activity is detected.

Socio-demographic data

Our principal socioeconomic indicator in all of our models is the yearly net mean income per consumption unit of each census tract in 2021, measured in euros, obtained from the most recent atlas of income distribution provided by the Spanish National Statistics Institute (INE)⁴³. This variable is calculated as the sum of net incomes generated in a household divided by the units of consumption living in it. Adults are assigned a weight of one unit of consumption, individuals 14–18 years old are given a weight of 0.5, and individuals younger than 14 are assigned a weight of 0.3⁴³. Adjusting household incomes by consumption unit in this way is intended to provide a value that can be more meaningfully compared across families by correcting for differences in consumption needs⁹⁵. This variable is correlated with standard measures of inequality such as the Gini index, with a Pearson correlation coefficient of 0.54.

We obtain the percentage of census tract households composed of a single member and mean age of the census tract residential population from INE's atlas of income distribution⁴³. We estimate the population density of each census tract by dividing each tract's population by its area, in square kilometers, which we obtain from INE's cartography of census tracts⁴⁴.

Landcover data

We use data provided by the ASPB on green areas located in private spaces. This data is generated from Normalized Difference Vegetation Index (NDVI) values taken from 2019 orthophoto data available from the Cartographic and Geographic Institute of Catalonia⁴⁵, cropped to private spaces in Barcelona. The ASPB uses this dataset as part of its surveillance planning based on its experience that these private green spaces serve as important mosquito breeding sites, particularly when breeding sites in public areas are being effectively suppressed. The data consists of a set of polygons indicating private green spaces in Barcelona, and we use this to generate a proximity variable calculated based on the distances between each observation and the closest green area. We transform these distances into a Green Proximity Index (GPI) using the following standard distance decay function:

$$GPI = e^{-a+d^b} \quad (2)$$

where d is distance in meters and we set constants a to 0.01 and b to 1. This function takes the value of 1 when the distance is 0, and decreases with greater distances, quickly approaching zero at distances beyond 200 m, which corresponds roughly to the maximum flight-based dispersal distance of *Ae. albopictus*⁵⁷.

Weather data

Our Mosquito Trap Vector Model relies on historical temperature data obtained from the Meteorological Service of Catalonia. We calculate the 30-day average temperature of each trap observation using data from the five

weather stations across Barcelona. The average takes the 30 days up to and including each day on which the trap was checked. We label this variable TMP.

General participation model

Our first model (General Participation Model) estimates the probability of finding any type of mosquito report (adult or bite) in a given point location, conditional on the mean income, population density, mean age, and percentage of households composed of a single person for the census tract in which the point lies. We include population density to account for potential differences in participation across census tracts due to the amount of people living in them—assuming that higher-density areas have higher levels of participation. We include the percentage of single person households to account for the possibility that individuals living alone may have more time and motivation to participate in citizen science. We include mean age of the census tract population to account for the possibility that younger people may be more likely to participate using smartphone technology and may be more aware of Mosquito Alert.

We analyze a total of 5,393 reports (adult mosquitoes pooled with mosquito bites) covering 10 mosquito seasons from 2014 to 2023. Initially, our data is presence-only: We know locations where mosquitoes have been observed, but we have no direct data about locations in which a citizen scientist looked for mosquitoes but did not observe them. This limits our ability to make comparisons across spaces and it is a common challenge in species distribution models²⁷. We deal with this by randomly sampling pseudo-absences from a uniform distribution within the perimeter of Barcelona municipality. We then generate a binary variable (1 for the presence of a report and 0 for a pseudo-absence), which we use as the outcome in our model. To minimize the impact of the influence of the distribution of our pseudo-absences in our models we sample a large number of pseudo-absences equal to our number of presences and we weight both of them equally. This approach has been shown to provide the best predictive distributions for regression-like models⁴. Our final sample consists of 10,786 observations, with the same number of presences and pseudo-absences.

The General Participation Model is a logistic regression that includes an intrinsically conditional autoregressive (ICAR) logistic term⁶³ based on neighboring census tracts. ICAR models assume full spatial autocorrelation, which is empirically consistent with the overall levels of Moran's I observed in our covariates. We treat each observation i as the realization of a Bernoulli random variable with mean π_i , and we model π_i as:

$$\log\left(\frac{\pi_i}{1-\pi_i}\right) = \alpha + \beta_1 \text{INC}_i + \beta_2 \text{INC}_i^2 + \beta_3 \log(\text{POP}_i) + \beta_4 \text{PSH}_i + \beta_5 \text{AGE}_i + Zu \quad (3)$$

where Z represents a symmetric (if $i \sim j$ then $j \sim i$) and positive spatial effects matrix specified using first-order queen contiguity, with random effects modeled as a multivariate Normal distribution: $u \sim N(0, \sigma_u^2 \Sigma)$. In other words, each census tract is neighbors with all the census tracts with which it shares a border. The covariates in this model are census tract mean income per consumption unit (INC), population density (POP), proportion of households composed of a single member (PSH), and mean population age (AGE). The β terms represent the estimated coefficients on each variable. Table 2 in the Supplemental Information shows the degree of collinearity across our covariates, which is low and does not threaten our inferences.

Table 3 in the Supplemental Information section provides coefficient estimates for this model (GPM5) along with estimates for alternative specifications. GPM1–GPM3 take the same approach to spatial autocorrelation as GPM5 but include different combinations of covariates: GPM1 includes only mean income, GPM2 includes mean income and population density, GPM3 includes mean income, population density and mean age. GPM4 has the same covariates as GPM5 but it does not control for spatial autocorrelation. All five models have Bayes R-squared values of 0.35 and all have essentially the same expected log pointwise predictive density (ELPD) based on leave-one-out cross validation⁸⁴ (the small differences in ELPD are overwhelmed by the ELPD standard errors). We focus on GPM5 in our analysis in order to highlight the estimated coefficients on all variables of interest.

Figure 16 in the Supplemental Information shows the prior predictive check of this model, plotting the observed number of presences and pseudo absences against the mean and central 90% of the posterior predictive distribution.

Active catch basin drain participation model

Our second model (Active Catch Basin Drain Participation Model) estimates the probability of finding an adult mosquito or mosquito bite report in a given year within a 200-meter buffer of each drain with confirmed mosquito activity that year, conditional on the same covariates as in our first model along with Mosquito Alert sampling effort. The unit of analysis in this model is a drain-year, with a total of 1437 drain-years in which ASPB detected mosquito activity (Figure 2b). Citizen scientists sent adult mosquito reports or mosquito bite reports through Mosquito Alert from within 200 m of 623 of these active drains during the years in which they were reported as active. As with the first model, we treat each observation i as the realization of a Bernoulli random variable with mean π_i . In order to account for the autocorrelation between observations that took place at the same drains in different years ($n = 74$), we give random intercepts to each drain. Thus, we model π_i as:

$$\log\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right) = \alpha + \beta_1 \text{INC}_{ij} + \beta_2 \text{INC}_{ij}^2 + \beta_3 \log(\text{POP})_{ij} + \beta_4 \text{PSH}_{ij} + \beta_5 \text{AGE}_{ij} + \beta_6 \text{SE}_{ij} + \delta_j \quad (4)$$

where δ_j represents the random intercept for each active catch basin drain and SE represents the Mosquito Alert annual sampling effort for the sampling cell in which the point drain lies. As in the first model, the covariates in this model are mean income per consumption unit (INC), population density (POP), proportion of single-member households (PSH), and mean age (AGE), with the β terms representing the estimated coefficient on each variable. Supplemental Table 4 shows the degree of collinearity across our covariates, which is low and does not threaten our inferences.

After fitting this model, we predict the probability of a citizen scientist reporting an adult mosquito or mosquito bite within 200 m of each of 256,898 points on a lattice across Barcelona spaced at 20m intervals, assuming each point represented an active catch basin drain (i.e. that mosquitoes were actually present). Each point is assigned INC, POP, PSH, AGE, and SE values based on its location. We take these predictions as a higher resolution measure of sampling effort than the one represented by the gridded Mosquito Alert sampling effort data (which uses sampling cells of approx. 4 km²), and we use them in the next model.

Table 5 in the Supplemental Information section provides coefficient estimates for this model (ACBDPM6) along with estimates for alternative specifications. ACBDPM1-ACBDPM4 include drain-level random intercepts just like ACBDPM6, but they include different combinations of covariates: ACBDPM1 includes only mean income, ACBDPM2 includes mean income and Mosquito Alert sampling effort, ACBDPM3 includes mean income, Mosquito Alert sampling effort, and population density, ACBDPM4 includes mean income, Mosquito Alert sampling effort, population density, and proportion of households composed of a single member, and ACBDPM5 includes mean income, Mosquito Alert sampling effort, population density, proportion of households composed of a single member, and mean age. ACBDPM5 has the same covariates as ACBDPM6 but it does not include any random intercepts. ACBDPM6 has the highest Bayes R-squared value (0.14) and the second highest ELPD. The model with the highest ELPD is ACBDPM5, but the difference between the two is negligible (under 2) and overwhelmed by the ELPD standard error. That ACBDPM5 and ACBDPM6 are indistinguishable in terms of predictive accuracy indicates that the random effects of ACBDPM6 do not actually improve the model—which makes sense given that there are only 74 drains that were active in multiple years and are, thus, observed more than once in the data. We focus on ACBDPM6 in our analysis simply to show that the results are not being driven by these repeated observations.

Figure 17 in the Supplemental Information shows the prior predictive check of this model, plotting the observed number of presences and pseudo absences against the mean and central 90% of the posterior predictive distribution.

Mosquito Alert vector model

Our third model (Mosquito Alert Vector Model) takes the same presence-pseudo-absence approach as the first model, but in this model we sample pseudo-absences from the 256,898 prediction points described above, with sampling weights proportional to the predicted sampling effort at each point. This third model estimates the probability of finding an expert-validated adult *Ae. albopictus* report, meaning a report with a photograph scored by the Entolab team as likely showing *Ae. albopictus*, conditional on the predicted sampling effort (SE) from the Active Catch Basin Drain Model, mean income per consumption unit (INC), and Green Proximity Index (GPI). SE is included as an offset (i.e. its coefficient is forced to 1) to control for the sampling bias that is not adequately accounted for by the sampling weights used for the pseudoabsences.

INC is our primary variable of interest and is expected to impact mosquito populations primarily through breeding site availability due to things like water inputs and the built environment. GPI is included to capture proximity to habitat often suitable for mosquito breeding sites.

The Mosquito Alert Vector Model is a logistic regression model with an intrinsically conditional autoregressive (ICAR) logistic term. It follows the same structure as our Active Catch Basin Drain Participation model, but without random intercepts because there are no repeated observations here. We treat each observation i as the realization of a Bernoulli random variable with mean π_i , and we model π_i as:

$$\log\left(\frac{\pi_i}{1-\pi_i}\right) = \alpha + \beta_1 \text{INC}_i + \beta_2 \text{INC}_i^2 + \beta_3 \text{GPI}_i + \log(\text{SE}_i) + Z u \quad (5)$$

where INC represents mean income per consumption unit, SE represents predicted sampling effort, GPI represents the Green Proximity Index, Z represents our spatial effects matrix with random effects u as in the General Participation Model, and the β terms represent the estimated coefficients on each variable. We do not include population density in this model because doing so worsened the fit of our models. Notably, the inclusion of this variable does not alter the size and direction of our predictors.

After fitting this model, we use it to make predictions on lattice of points spaced at 20 m intervals across Barcelona, based on the values of INC, log(SE), and GPI measured at each of these points.

Table 6 in the Supplemental Information section provides coefficient estimates for this model (MAVM4) along with estimates for alternative specifications. MAVM1-MAVM2 control for spatial autocorrelation, like MAVM4, using an intrinsic conditional autoregressive term, but they include different combinations of covariates: MAVM1 includes only mean income, and MAVM2 includes only the green proximity index. MAVM3 has the same covariates as MAVM4 but it does not include any spatial autocorrelation term. MAVM1, MAVM2, and MAVM4 (the models that control for spatial autocorrelation) have the same and highest Bayes R-squared value (0.21). They also have essentially the same ELPD, clearly higher than that of the non-spatial model (MAVM3). We focus on MAVM4 in our analysis in order to highlight the estimated effects of both income and green proximity, even though the addition of income to the model does not clearly improve its predictive accuracy.

Figure 18 in the Supplemental Information shows the prior predictive check of this model, plotting the observed number of presences and pseudo absences against the mean and central 90% of the posterior predictive distribution.

Mosquito trap vector model

Finally, our fourth model (Mosquito Trap Vector Model) estimates the counts of adult *Ae. albopictus* females captured in the mosquito traps described above. Each trap-count is treated as the unit of analysis, with a total of 1368 trap-counts analyzed. We used a multilevel zero-inflated Poisson regression^{39,50} in which the outcome variable is the count of adult female *Ae. albopictus* individuals found in each trap observation. The model uses trap-level random intercepts to account for the effects of the fixed trapping sites in which traps were placed. The zero-inflated Poisson model treats the observed count i from trap j as the manifestation of random variable Y_{ij} , which has the probability of taking value k given by:

$$\Pr(Y_{ij} = k) = \begin{cases} \pi_{ij} + (1 - \pi_{ij})e^{-\lambda_{ij}}, & \text{if } k = 0 \\ (1 - \pi_{ij})e^{-\lambda_{ij}}\lambda_{ij}^k/k!, & \text{if } k > 0 \end{cases} \quad (6)$$

It then estimates π_{ij} in a logistic regression specified as:

$$\log\left(\frac{\pi_{ij}}{1 - \pi_{ij}}\right) = \alpha + \beta_1\text{TMP}_{ij} + \beta_2\text{TMP}_{ij}^2 \quad (7)$$

And it estimates λ_{ij} as a Poisson regression specified as:

$$\log(\lambda_{ij}) = \alpha + \beta_1\text{TMP}_{ij} + \beta_2\text{TMP}_{ij}^2 + \beta_3\text{INC}_{ij} + \beta_4\text{INC}_{ij}^2 + \delta_j \quad (8)$$

where INC and TMP are the same as above, and where δ_j represents the random intercept for trap j .

Table 7 in the Supplemental Information section provides coefficient estimates for this model (MTVM4) along with estimates for alternative specifications. MTVM1-MTVM2 include trap-level random intercepts like MTVM4, but MTVM1 does not include a zero-inflation term, while MTVM2 does not include the income covariates. MTVM3 includes the same zero-inflation terms and covariates as MTVM4 but does not include random intercepts. MAVM1, MAVM2, and MAVM4 have the same and highest Bayes R-squared value (0.37), whereas MTVM3 has a much lower Bayes R-squared value (0.05). MAVM4 has the highest ELPD, clearly higher than that of MTVM1 and MTVM3 but not distinguishable from MTVM2 once we take the ELPD standard error into account. We focus on MAVM4 in our analysis in order to highlight the estimated effects of income even though the addition of income to the model does not clearly improve its predictive accuracy.

Figure 19 in the Supplemental Information shows the prior predictive check of this model, plotting the kernel density estimates of the observed trap counts against the posterior predictive distribution.

Data availability

All of the Mosquito Alert data used in this article is available in open access repositories hosted on Zenodo. The Mosquito Alert reporting data (all adult mosquito and mosquito bite reports as well as all expert-validated *Ae. albopictus* reports) is available at <https://zenodo.org/doi/10.5281/zenodo.10684356>⁶⁹. The Mosquito Alert sampling effort data is available at <https://doi.org/10.5281/zenodo.10674718>. We have also made the BG trap and catch basin drain data available at <https://zenodo.org/doi/10.5281/zenodo.10684356>. We have not, however, released the exact locations of the BG traps because some of them were hosted in private spaces.

The weather data relied on here was taken from the Meteorological Service of Catalonia's API (<https://apidocs.meteocat.gencat.cat>). Some of this data can also be accessed through the Barcelona Open Data Portal (<https://opendata-ajuntament.barcelona.cat/data/dataset/mesures-estacions-meteorologiques>). Income and population data are available from the INE's *Atlas de distribución de renta de los hogares*⁴³. Census section geographic data is available from the INE's Digital Cartography Files⁴⁴. The open code described below includes functions to merge all of these datasets.

The ASPB data on private green spaces is derived from orthophoto-based NVDI data⁴⁵ available through the Barcelona Open Data Portal (<https://opendata-ajuntament.barcelona.cat/data/en/dataset/cobertura-vegetal-ndvi/resource/0003c7ee-9b66-43f6-b9cc-ff9314c208e4>). That dataset has been cropped by the city using a shapefile of private spaces that we do not have permission to make public.

The maps shown in Figures 1, 2, and 6, and in Figure 1 of the Supplemental Information were produced by the authors with polygon data from the INE's Digital Cartography Files⁴⁴ using *ggplot2* 3.4.4⁹³ and *ggspatial* 1.1.9²⁴ (Figs. 1 and 6, and Suppl. Info. Fig. 1), and using *tmap* 3.3.4⁸² (Fig. 2).

Code availability

All code necessary for replicating this analysis is available on GitHub at <https://github.com/h-mip/citsci-spatial-bias> and archived on Zenodo at <https://zenodo.org/doi/10.5281/zenodo.10796324>⁶⁸.

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References

- Adams, B. & Kapan, D. D. Man bites mosquito: understanding the contribution of human movement to vector-borne disease dynamics. *PLoS one***4**(8), e6763 (2009).
- Allison, P. D. Discrete-time methods for the analysis of event histories. *Sociological methodology***13**, 61–98 (1982).
- Balakrishnan, V. S. WHO launches global initiative for arboviral diseases. *The Lancet Microbe***3**(6), e407 (2022).
- Barbet-Massin, M. *et al.* Selecting pseudo-absences for species distribution models: How, where and how many?: How to use pseudo-absences in niche modelling?. *Methods in Ecology and Evolution***3**(2), 327–338. <https://doi.org/10.1111/j.2041-210X.2011.00172.x> (2012).
- Bartumeus, F., Oltra, A. & Palmer, J. R. Citizen science: a gateway for innovation in disease-carrying mosquito management?. *Trends in Parasitology***34**(9), 727–729 (2018).
- Bazin, M. & Williams, C. R. Mosquito traps for urban surveillance: collection efficacy and potential for use by citizen scientists. *Journal of Vector Ecology***43**(1), 98–103 (2018).
- Bocanegra, C. *et al.* Imported cases of chikungunya in barcelona in relation to the current american outbreak. *Journal of travel medicine***23**(3), tav033 (2016).
- Borrell, C. *et al.* Veinticinco años de informes de salud en Barcelona: una apuesta por la transparencia y un instrumento para la acción. *Revista Española de Salud Pública***85**(5), 449–458. <https://doi.org/10.1590/S1135-57272011000500004> (2011).
- Botts, E. A., Erasmus, B. F. & Alexander, G. J. Geographic sampling bias in the south african frog atlas project: implications for conservation planning. *Biodiversity and Conservation***20**, 119–139 (2011).
- Bürkner, P. C. brms: An R package for Bayesian multilevel models using Stan. *Journal of Statistical Software***80**(1), 1–28. <https://doi.org/10.18637/jss.v080.i01> (2017).
- Bürkner, P. C. Advanced Bayesian multilevel modeling with the R package brms. *The R Journal***10**(1), 395–411. <https://doi.org/10.32614/RJ-2018-017> (2018).
- Carney, R. M. *et al.* Integrating global citizen science platforms to enable next-generation surveillance of invasive and vector mosquitoes. *Insects***13**(8), 675 (2022).
- Chakraborty, L. *et al.* Exploring spatial heterogeneity and environmental injustices in exposure to flood hazards using geographically weighted regression. *Environmental Research***210**, 112982. <https://doi.org/10.1016/j.envres.2022.112982> (2022).
- Chan, M. & Johansson, M. A. The incubation periods of dengue viruses. *PLOS ONE***7**(11), 1–7. <https://doi.org/10.1371/journal.pone.0050972> (2012).
- Collantes, F., Delacour, S., Alarcón-Elbal, P.M., *et al.* Review of ten-years presence of *Aedes albopictus* in Spain 2004–2014: known distribution and public health concerns. *Parasites and Vectors***8**. <https://doi.org/10.1186/s13071-015-1262-y> (2015).
- Colón-González, F. J. *et al.* Projecting the risk of mosquito-borne diseases in a warmer and more populated world: a multi-model, multi-scenario intercomparison modelling study. *The Lancet Planetary Health***5**(7), e404–e414 (2021).
- Cunha, H. S. *et al.* Water tank and swimming pool detection based on remote sensing and deep learning: Relationship with socioeconomic level and applications in dengue control. *PLOS ONE***16**(12), e0258681. <https://doi.org/10.1371/journal.pone.0258681> (2021).
- van Daalen, K. R. *et al.* The 2022 Europe report of the Lancet Countdown on health and climate change: towards a climate resilient future. *The Lancet Public Health***7**(11), e942–e965 (2022).
- Dekramanjan, B. *et al.* Demographic and motivational differences between participants in analog and digital citizen science projects for monitoring mosquitoes. *Scientific Reports***13**(1), 12384 (2023).
- Delatte, H. *et al.* Blood-feeding behavior of *Aedes albopictus*, a vector of chikungunya on la réunion. *Vector-Borne and Zoonotic Diseases***10**(3), 249–258 (2010).
- Dennis, R. & Thomas, C. Bias in butterfly distribution maps: the influence of hot spots and recorder's home range. *Journal of Insect Conservation***4**, 73–77 (2000).
- Dickinson, J. L., Zuckerberg, B. & Bonter, D. N. Citizen Science as an Ecological Research Tool: Challenges and Benefits. *Annual Review of Ecology, Evolution, and Systematics***41**(1), 149–172. <https://doi.org/10.1146/annurev-ecolsys-102209-144636> (2010).
- Diez Roux, A. V. & Mair, C. Neighborhoods and health: Neighborhoods and health. *Annals of the New York Academy of Sciences***1186**(1), 125–145. <https://doi.org/10.1111/j.1749-6632.2009.05333.x> (2010).
- Dunington, D. ggspatial: Spatial Data Framework for ggplot2. <https://CRAN.R-project.org/package=ggspatial>, r package version 1.1.9 (2023).
- Efron, B. Logistic regression, survival analysis, and the kaplan-meier curve. *Journal of the American statistical Association***83**(402), 414–425 (1988).
- Egizi, A., Fefferman, N. H. & Fonseca, D. M. Evidence that implicit assumptions of 'no evolution' of disease vectors in changing environments can be violated on a rapid timescale. *Philosophical Transactions of the Royal Society B: Biological Sciences***370**(1665), 20140136. <https://doi.org/10.1098/rstb.2014.0136> (2015).
- Elith, J. & Leathwick, J. R. Species Distribution Models: Ecological Explanation and Prediction Across Space and Time. *Annual Review of Ecology, Evolution, and Systematics***40**(1), 677–697. <https://doi.org/10.1146/annurev.ecolsys.110308.120159> (2009).
- Eritja, R. *et al.* Direct evidence of adult *Aedes albopictus* dispersal by car. *Scientific Reports***7**(1), 14399 (2017).
- Eritja, R. *et al.* At the tip of an iceberg: citizen science and active surveillance collaborating to broaden the known distribution of *Aedes japonicus* in Spain. *Parasites & Vectors***14**(1), 1–12 (2021).
- Ferraguti, M. *et al.* Spatial distribution and temporal dynamics of invasive and native mosquitoes in a large mediterranean city. *Science of the Total Environment***896**, 165322 (2023).
- Gabry, J. & Češnovar, R. cmdstanr: R Interface to 'CmdStan'. URL: <https://mc-stan.org/cmdstanr/>, <https://discourse.mc-stan.org> (2022).
- Geldmann, J. *et al.* What determines spatial bias in citizen science? Exploring four recording schemes with different proficiency requirements. *Diversity and Distributions***22**(11), 1139–1149. <https://doi.org/10.1111/ddi.12477> (2016).
- Galster, George & Sharkey, Patrick. Spatial Foundations of Inequality: A Conceptual Model and Empirical Overview. *RSF: The Russell Sage Foundation Journal of the Social Sciences***3**(2), 1. <https://doi.org/10.7758/rsf.2017.3.2.01> (2017).
- Gossner, C. M., Ducheyne, E. & Schaffner, F. Increased risk for autochthonous vector-borne infections transmitted by *Aedes albopictus* in continental Europe. *Eurosurveillance***23**(24), 1800268. <https://doi.org/10.2807/1560-7917.ES.2018.23.24.1800268> (2018). <https://www.eurosurveillance.org/content/10.2807/1560-7917.ES.2018.23.24.1800268>.
- Gutiérrez-López, R. *et al.* Vector Competence of *Aedes Caspius* and *Ae. Albopictus* Mosquitoes for Zika Virus, Spain. *Emerging Infectious Diseases***25**(2), 346–348. <https://doi.org/10.3201/eid2502.171123> (2019).
- Haklay, M. Citizen science and volunteered geographic information: Overview and typology of participation. *Crowdsourcing geographic knowledge: Volunteered geographic information (VGI) in theory and practice* pp 105–122 (2012).
- Haklay, M.M., Dörler, D., Heigl, F., *et al.* What is citizen science? the challenges of definition. *The science of citizen science***13** (2021).
- Halasa, Y. A. *et al.* Quantifying the impact of mosquitoes on quality of life and enjoyment of yard and porch activities in new jersey. *PLOS ONE***9**(3), 1–9. <https://doi.org/10.1371/journal.pone.0089221> (2014).
- Hall, D. B. Zero-inflated poisson and binomial regression with random effects: a case study. *Biometrics***56**(4), 1030–1039 (2000).
- Harvey, D. The right to the city. *International Journal of Urban and Regional Research***27**(4), 939–941. <https://doi.org/10.1111/j.0309-1317.2003.00492.x> (2003). <https://onlinelibrary.wiley.com/doi/abs/10.1111/j.0309-1317.2003.00492.x>, _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.0309-1317.2003.00492.x>.

41. Heigl, F. *et al.* Toward an international definition of citizen science. *Proceedings of the National Academy of Sciences* **116**(17), 8089–8092 (2019).
42. Hobbs, S. J. & White, P. C. L. Motivations and barriers in relation to community participation in biodiversity recording. *Journal for Nature Conservation* **20**(6), 364–373. <https://doi.org/10.1016/j.jnc.2012.08.002> (2012).
43. INE. Atlas de Distribución de Renta de los Hogares (ADRH). Metodología. Tech. rep., Instituto Nacional de Estadística, https://www.ine.es/metodologia/metodologia_adrh.pdf (2022a).
44. INE. Cartografía digitalizada de secciones censales. <https://ine.es/Satellite?c=Page&cid=1259952026632&p=1259952026632&pagename=ProductosYServicios%2FPYSLayout> (2022b).
45. Institut Cartogràfic i Geològic de Catalunya. Vegetable cover of the city of Barcelona, based on the NVDI index, seen from the sky. <https://opendata-ajuntament.barcelona.cat/data/en/dataset/cobertura-vegetal-ndvi/resource/0003c7ee-9b66-43f6-b9cc-ff9314c208e4> (2019).
46. Johnston, A. *et al.* Estimating species distributions from spatially biased citizen science data. *Ecological Modelling* **422**, 108927. <https://doi.org/10.1016/j.ecolmodel.2019.108927> (2020).
47. Južnič-Zonta, Ž., Sanpera-Calbet, I., Eritja, R., *et al.* Mosquito alert: leveraging citizen science to create a gbif mosquito occurrence dataset. *Gigabyte* **2022** (2022).
48. Kröckel, U. *et al.* New tools for surveillance of adult yellow fever mosquitoes: comparison of trap catches with human landing rates in an urban environment. *Journal of the American Mosquito Control Association* **22**(2), 229–238 (2006).
49. LaDeau, S. L. *et al.* The ecological foundations of transmission potential and vector-borne disease in urban landscapes. *Functional Ecology* **29**(7), 889–901. <https://doi.org/10.1111/1365-2435.12487> (2015).
50. Lambert, D. Zero-inflated poisson regression, with an application to defects in manufacturing. *Technometrics* **34**(1), 1–14 (1992).
51. Li, Y. *et al.* Comparative evaluation of the efficiency of the bg-sentinel trap, cdc light trap and mosquito-oviposition trap for the surveillance of vector mosquitoes. *Parasites & vectors* **9**(1), 1–8 (2016).
52. Lillepold, K., Rocklöv, J., Liu-Helmersson, J., *et al.* More arboviral disease outbreaks in continental Europe due to the warming climate? *Journal of Travel Medicine* **26**(5), taz017. <https://doi.org/10.1093/jtm/taz017> (2019). <https://academic.oup.com/jtm/article-pdf/26/5/taz017/28926801/taz017.pdf>.
53. Londoño-Cañola, C., Serral, G., Diez, J., *et al.* Retail food environment around schools in barcelona by neighborhood socioeconomic status: Implications for local food policy. *International Journal of Environmental Research and Public Health* **20**(1) (2023). <https://doi.org/10.3390/ijerph20010649>. <https://www.mdpi.com/1660-4601/20/1/649>.
54. Lucati, F. *et al.* Multiple invasions, wolbachia and human-aided transport drive the genetic variability of *Aedes albopictus* in the iberian peninsula. *Scientific Reports* **12**(1), 20682 (2022).
55. Lührsen, D. S. *et al.* Adult *Aedes albopictus* in winter: implications for mosquito surveillance in southern Europe. *The Lancet Planetary Health* **7**(9), e729–e731 (2023).
56. Mari-Dell’Olmo, M. *et al.* Climate change and health in urban areas with a mediterranean climate: a conceptual framework with a social and climate justice approach. *International Journal of Environmental Research and Public Health* **19**(19), 12764 (2022).
57. Marini, F. *et al.* Estimating spatio-temporal dynamics of *Aedes albopictus* dispersal to guide control interventions in case of exotic arboviruses in temperate regions. *Scientific Reports* **9**(1), 10281 (2019).
58. Medley, K. A., Westby, K. M. & Jenkins, D. G. Rapid local adaptation to northern winters in the invasive Asian tiger mosquito *Aedes albopictus*: A moving target. *Journal of Applied Ecology* **56**(11), 2518–2527. <https://doi.org/10.1111/1365-2664.13480> (2019).
59. Millet, J. P. *et al.* Imported zika virus in a European city: how to prevent local transmission?. *Frontiers in microbiology* **8**, 1319 (2017).
60. Ministerio de Sanidad. Plan Nacional de Prevención, Vigilancia y Control de las enfermedades transmitidas por vectores. Tech. rep., Ministerio de Sanidad, https://www.sanidad.gob.es/profesionales/saludPublica/ccayes/activPreparacionRespuesta/doc/PLAN_DE_VECTORES.pdf (2023).
61. Montalvo, T., Valsecchi, A., Peracho, V., *et al.* Vigilancia y control de mosquitos en barcelona: Informe 2021. Tech. rep., Agència de Salut Pública de Barcelona (2021).
62. Mordecai, E. A. *et al.* Climate change could shift disease burden from malaria to arboviruses in africa. *The Lancet Planetary Health* **4**(9), e416–e423 (2020).
63. Morris, M. *et al.* Bayesian hierarchical spatial models: Implementing the Besag York Mollié model in stan. *Spatial and Spatio-temporal Epidemiology* **31**, 100301. <https://doi.org/10.1016/j.sste.2019.100301> (2019).
64. Alert, Mosquito. *Sampling effort data*. [SPACE] <https://doi.org/10.5281/zenodo.10674718> (2024).
65. Murphy, A. K. *et al.* Climate variability and *Aedes* vector indices in the southern Philippines: An empirical analysis. *PLOS Neglected Tropical Diseases* **16**(6), e0010478. <https://doi.org/10.1371/journal.pntd.0010478> (2022).
66. Nov, O., Arazy, O. & Anderson, D. Dusting for science: Motivation and participation of digital citizen science volunteers. In *iConference '11.*, New York, NY., <https://doi.org/10.1145/1940761.1940771> (2011).
67. Oltra, A., Palmer, J.R. & Bartumeus, F. Atrapatigre.com: enlisting citizen-scientists in the war on tiger mosquitoes. In *European Handbook of Crowdsourced Geographic Information*. Ubiquity Press (2016).
68. Padilla-Pozo, A. & Palmer, J.R. Open Code for “Assessing and Correcting Neighborhood Socioeconomic Spatial Sampling Biases in Citizen Science Mosquito Data Collection”. <https://doi.org/10.5281/zenodo.10796342> (2024).
69. Padilla-Pozo, A., Bartumeus, F., Montalvo, T., *et al.* Untangling neighborhoods effects in citizen science vector-mosquito surveillance: Mosquito Alert Barcelona Reports Data - All Adult Mosquitoes and Mosquito Bites 2014–23. <https://doi.org/10.5281/zenodo.10684357> (2024).
70. Palmer, J. R. B. *et al.* Citizen science provides a reliable and scalable tool to track disease-carrying mosquitoes. *Nature Communications* **8**(1), 916. <https://doi.org/10.1038/s41467-017-00914-9> (2017).
71. Pandya, R. E. A framework for engaging diverse communities in citizen science in the US. *Frontiers in Ecology and the Environment* **10**(6), 314–317. <https://doi.org/10.1890/120007> (2012).
72. R Core Team. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria, <https://www.R-project.org/> (2023).
73. Rocklöv, J. & Dubrow, R. Climate change: an enduring challenge for vector-borne disease prevention and control. *Nature immunology* **21**(5), 479–483 (2020).
74. Rocklöv, J. *et al.* Decision-support tools to build climate resilience against emerging infectious diseases in Europe and beyond. *The Lancet Regional Health-Europe* **32**, 100701 (2023).
75. Rubies, A.E. & Alert, M. Mosquitoalert/data: v1.051.2024. <https://doi.org/10.5281/zenodo.10681774> (2024).
76. Scavo, N. A. *et al.* Lower socioeconomic status neighborhoods in Puerto Rico have more diverse mosquito communities and higher *Aedes Aegypti* abundance. *Journal of Urban Ecology* **7**(1), juab009. <https://doi.org/10.1093/jue/juab009> (2021).
77. Schaffner, F., Medlock, J. M. & Bortel, W. V. Public health significance of invasive mosquitoes in Europe. *Clinical Microbiology and Infection* **19**(8), 685–692. <https://doi.org/10.1111/1469-0691.12189>. [https://www.clinicalmicrobiologyandinfection.com/article/S1198-743X\(14\)61413-0/fulltext](https://www.clinicalmicrobiologyandinfection.com/article/S1198-743X(14)61413-0/fulltext), publisher: Elsevier.
78. Semenza, J. C., Rocklöv, J. & Ebi, K. L. Climate change and cascading risks from infectious disease. *Infectious Diseases and Therapy* **11**(4), 1371–1390 (2022).
79. Tajudeen, Y. A. *et al.* Tackling the global health threat of arboviruses: An appraisal of the three holistic approaches to health. *Health Promotion Perspectives* **11**(4), 371–381. <https://doi.org/10.34172/hpp.2021.48> (2021).

80. Talbot, B. *et al.* Determinants of Aedes mosquito density as an indicator of arbovirus transmission risk in three sites affected by co-circulation of globally spreading arboviruses in Colombia. *Ecuador and Argentina. Parasites & Vectors***14**(1), 482. <https://doi.org/10.1186/s13071-021-04984-z> (2021).
81. Tang, B., Clark, J. S. & Gelfand, A. E. Modeling spatially biased citizen science effort through the eBird database. *Environmental and Ecological Statistics***28**(3), 609–630. <https://doi.org/10.1007/s10651-021-00508-1> (2021).
82. Tennekes, M. tmap: Thematic maps in R. *Journal of Statistical Software***84**(6), 1–39. <https://doi.org/10.18637/jss.v084.i06> (2018).
83. Tesla, B. *et al.* Temperature drives Zika virus transmission: Evidence from empirical and mathematical models. *Proceedings Biological Sciences***285**(1884), 20180795. <https://doi.org/10.1098/rspb.2018.0795> (2018).
84. Vehtari, A., Gelman, A. & Gabry, J. Practical bayesian model evaluation using leave-one-out cross-validation and waic. *Statistics and computing***27**, 1413–1432 (2017).
85. Venter, Z. S. *et al.* Environmental justice in a very green city: Spatial inequality in exposure to urban nature, air pollution and heat in Oslo, Norway. *Science of The Total Environment***858**, 160193. <https://doi.org/10.1016/j.scitotenv.2022.160193> (2023).
86. Wang, Y. *et al.* The effect of urbanization and climate change on the mosquito population in the pearl river delta region of china. *International journal of biometeorology***64**, 501–512 (2020).
87. Whiteman, A. *et al.* Aedes Mosquito Infestation in Socioeconomically Contrasting Neighborhoods of Panama City. *EcoHealth***16**(2), 210–221. <https://doi.org/10.1007/s10393-019-01417-3> (2019).
88. Whiteman, A. *et al.* Do socioeconomic factors drive aedes mosquito vectors and their arboviral diseases? A systematic review of dengue, chikungunya, yellow fever, and Zika Virus. *One Health***11**, 100188. <https://doi.org/10.1016/j.onehlt.2020.100188> (2020) <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7772681/>.
89. Whiteman, A. *et al.* Do socioeconomic factors drive Aedes mosquito vectors and their arboviral diseases? A systematic review of dengue, chikungunya, yellow fever, and Zika Virus. *One Health***11**, 100188. <https://doi.org/10.1016/j.onehlt.2020.100188> (2020).
90. WHO. A global brief on vector-borne diseases. Tech. rep., World Health Organization, DOI: WHO/DCO/WHD/2014.1. http://apps.who.int/iris/bitstream/10665/111008/1/WHO_DCO_WHD_2014.1_eng.pdf (2014).
91. WHO. Global Vector Control response 2017 -2030: An integrated approach for the control of vector borne diseases. http://www.who.int/vector-control/burden_vector-borne_diseases.pdf (2017).
92. WHO. Launch of the WHO Global Arbovirus Initiative. Tech. rep., WHO (2022).
93. Wick, H. ggplot2: Elegant Graphics for Data Analysis. Springer-Verlag New York, <https://ggplot2.tidyverse.org> (2016).
94. Wodtke, G. T. *et al.* Concentrated poverty, ambient air pollution, and child cognitive development. *Science Advances***8**(48), eadd0285. <https://doi.org/10.1126/sciadv.add0285> (2022).
95. Zwijnenburg, J., Bournot, S., Grahn, D., *et al.* Distribution of household income, consumption and saving in line with national accounts: Methodology and results from the 2020 collection round. Tech. rep., OECD (2021).

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Author contributions

A.P.P.: conceptualization, methodology, investigation, formal analysis, data curation, writing - original draft, review, and editing, visualization; F.B.: conceptualization, methodology, investigation, data curation, writing - original draft, review, and editing, supervision, project administration, funding acquisition; T.M.: investigation, data curation, writing - review and editing; I.S.C.: investigation, data curation, writing - review and editing; A.V.: investigation, data curation, writing - review and editing; J.R.B.P.: investigation, conceptualization, methodology, formal analysis, data curation, writing - original draft, review, and editing, visualization, funding acquisition, project administration, supervision.

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Declarations

Competing interests

The authors declare no competing interests.

Ethics approval

The use of Mosquito Alert for this research was approved by the Ethics Board of the Spanish National Research Council (CSIC) in the context of the Big Mosquito Bytes project (approval number 001/2019), and it was also given a favorable Data Protection Impact Assessment (DPIA) by an independent assessor on 17 July 2020 (Protocol number C-12.633) for the processing of personal data in accordance with the Regulation (EU) 2016/679 on the protection of natural persons with regard to processing of personal data and on the free movement of such data (GDPR).

Consent to participate

All Mosquito Alert participants provide informed consent prior to registering or providing any data. (Participation is not possible without first providing this consent and no data is collected from anyone who does not provide it.)

Additional information

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1038/s41598-024-73416-6>.

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