

Comprehensive Profiling of Zika Virus Risk with Natural and Artificial Mitigating Strategies, United States

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Zika virus is transitioning to become a long-term public health challenge, and countries should remain informed of the risk for emergence. We developed a stochastic epidemiologic model to profile risk for Zika virus emergence, including trimester-specific fetal risk across time, in all 3,208 counties in the United States, including Puerto Rico. Validation against known transmission in North America demonstrated accuracy to predict epidemic dynamics and absolute case counts across scales ($R^2 = 0.98$). We found that, although sporadic single transmission events could occur in most US counties, outbreaks will likely be restricted to the Gulf Coast region and to late spring through autumn. Seasonal fluctuations in birth rates will confer natural population-level protection against early-trimester infections. Overall, outbreak control will be more effective and efficient than prevention, and vaccination will be most effective at >70% coverage. Our county-level risk profiles should serve as a critical resource for resource allocation.

Zika virus is a flavivirus spread by *Aedes* mosquitoes that for >60 years remained only an esoteric threat to human health (1). However, the recent Zika epidemic, which erupted in South America in 2015 and became the largest in history, brought the virus to prominence, particularly because infection has been linked to fetal microcephaly and other neurodevelopmental and neurologic sequelae (2).

Although no longer classified a global emergency by the World Health Organization (WHO), Zika virus emergence and transmission continues globally, and WHO warns that Zika virus is set to remain as a long-term public health challenge (3). Given the critical importance of preventing Zika virus infections, especially during pregnancy, transmission anywhere requires that nations remain vigilant and informed at local, state, and national levels to prevent and control introduction and onward transmission (4,5). This imperative is especially important for countries such as the United States that simultaneously harbor the *Aedes* vectors and maintain essentially entirely susceptible populations.

Numerous models for the potential emergence of Zika virus in the United States focus largely on the ecologic niche of *Aedes* mosquitoes (6–10). Projections that simultaneously consider vector dynamics and human demographics, including birth seasonality, to resolve both relative and absolute epidemic risk and potential control measures across space and time throughout the year are more limited.

Here we present a stochastic Zika virus compartment model that considers the overlap of vector dynamics and human demographics at the county level in the United States, including Puerto Rico. The model was used to profile the risk for Zika virus transmission, assuming an initial introduction into each county, including trimester-specific fetal exposures for each of the 3,208 counties and municipalities within the United States including Puerto Rico over time and under varying control measures. We tested 3 approaches to controlling Zika virus transmission and assessed their utility in preventing or abrogating Zika virus transmission. These approaches include reducing human–vector contact (i.e.,

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behavior modification and ubiquitous technologies such as air conditioning, screens, and long clothing); depleting adult vectors (i.e., mosquito fumigation programs); and vaccination, which, should a successful candidate vaccine come to market, might reduce individual and community risk for infection once herd-immunity thresholds are achieved (11).

Methods

We modeled county-level Zika virus transmission using a coupled 2-system stochastic human-mosquito differential equation compartment model (Appendix Figure 1, <https://wwwnc.cdc.gov/EID/article/26/4/18-1739-App1.pdf>). The human system was a susceptible-exposed-infected-recovered model and the mosquito system a susceptible-exposed-infected compartment model that incorporates vector and viral life-stage dynamics as functions of temperature throughout the year, as well as climate (temperature) and demographic data, including county- and municipality-level seasonality of births. More specifically, we coupled high-resolution *Aedes* vector risk maps (12) describing the ecologic extent of the major vectors of Zika virus, *Ae. aegypti* and *Ae. albopictus* mosquitoes, with dynamic temperature-dependent Zika virus and *Aedes* life-stage models, local climate data, and county-level demographic information, including population and monthly birth cohort data. We simulated Zika virus transmission given a single importation (index case) into each county across time and under varying control measures. We simulated stochastic trajectories by using an adaptation of the fundamental Gillespie stochastic simulation algorithm, an adaptive tau-leaping procedure (13) for continuous-time Markov processes, which we implemented by using the AdaptiveTau R package (13).

For each county and each scenario, we conducted ≥ 500 simulations and derived probability of initiation of a transmission chain from the index case, expected outbreak size when transmission occurs, and, by fitting nonlinear models to county-level monthly birth data, trimester-specific fetal Zika virus exposures. To remain relevant to local, state, and national entities, all 3,208 counties and municipalities were investigated independently, assuming only that an index case-patient arrives in the county, regardless of origin (i.e., spread from a neighboring county or an international import).

Model Parameters

We selected parameters from ecologic and epidemiologic literature (Appendix Table 1; Appendix Figure 1). Given the novelty of the Zika virus as a major

human pathogen, relatively limited information on its dynamic life-stage properties is available. Thus, properties relating to transmission and extrinsic incubation period were borrowed from the large body of literature on dengue virus dynamics, because dengue virus is a closely related but more completely studied mosquito-borne flavivirus that shares the same mosquito vector host system as Zika virus. Such a strategy is commonly used in modeling for emerging pathogens, including other Zika virus transmission models (7,14).

Trimester-Specific Pregnancies and Exposure Calculations

Infection with Zika virus is most concerning during pregnancy, where maternal infection has been linked to congenital birth defects, most notably microcephaly (15). These defects appear to be most strongly associated with Zika virus infection during the first and second trimesters (16,17). Therefore, we derived trimester-specific maternal-fetal exposures from county-level demographic data, including birth seasonality.

Throughout the year, the proportion of a population's births fluctuate in a predictable manner across calendar months. To estimate the numbers of children born per month, and thus calculate expected numbers of first-, second-, and third-trimester pregnancies per month, we used the number of births per month for each county over an 8-year period (2007–2014) based on US Census data. For each county, we fit generalized additive models to the monthly data to estimate the fraction of annual births per month for each county. We then coupled the county-level generalized additive model output, indicating the expected proportion of annual births in each calendar month, to annual birth numbers for each individual county to calculate monthly county-specific expected pregnancies.

From the monthly birth data for each county, we back-calculated the time of conception, assuming a 40-week gestation and a constant rate within a given month. On the basis of this calculation, we derived pregnancy cohorts, defined as the number of women becoming pregnant per month of the simulation, which allowed us to follow each cohort throughout their pregnancies and evaluate the number of pregnancies in their first, second, or third trimester during each month for each county or municipality. To calculate infections during pregnancy during the simulations, we derived the number of fetal exposures per week per trimester by drawing simultaneously from 3 binomial distributions each week, each

with the size equal to the number of first-, second-, or third-trimester pregnancies in the county during the week of interest, and with a probability equal to the proportion of the population infected during that week (Appendix). By drawing from a binomial distribution, we incorporated stochastic effects that influence the number of infections among gravid women, relative to the proportion infected across the population as a whole.

Model Validation

We compared models by comparing reported or published estimated incidence and case counts for known Zika that have arisen from local transmission in the United States including Puerto Rico against the respective simulated data. In addition, given similarities between Zika virus and dengue virus, such as common transmission vectors and dynamics (18), we compared reported or published estimated incidence and case counts for known dengue outbreaks that have arisen from local transmission in the contiguous United States against the respective simulated data. Validation data for Brownsville County, Texas, and Miami-Dade County, Florida, came from the Texas and Florida departments of health, respectively (19,20). Validation data for Monroe and Martin counties in Florida came from serosurvey data collected by the Florida department of health and the Centers for Disease Control and Prevention (CDC) (21,22).

Model validation for Puerto Rico used 2 resources to derive estimates of monthly and cumulative Zika virus incidence across Puerto Rico's 8 health regions. Official reported data from the Puerto Rico Ministry of Health (<http://www.salud.gov.pr/Estadisticas-Registros-y-Publicaciones/Pages/VigilanciadeZika>) provided information on the monthly dynamics (fractional abundance) of the epidemic for each health region, namely the proportion of cases per month in each of the 8 health regions. Separately, to obtain best estimates for total cumulative incidence, we used a recent and thorough report from CDC by Chevalier et al. (23), which analyzed blood donor screening data from April 3 through August 12, 2016, from the 2 largest blood banks in Puerto Rico to estimate overall epidemic size. The use of both resources used the strengths of both types of reports (accurate fractional abundance over time and in each health region, and accurate estimates of cumulative incidence) to derive best estimates for model validation (Appendix).

Results

Across the United States, when an infectious Zika virus-infected person was introduced during peak

Aedes abundance for each county (Appendix Figure 2), the model predicted at least minimal transmission (defined as ≥ 1 transmission event in $\geq 0.05\%$ of simulations) in 86% of US counties (Figure 1, panel A), essentially reflecting the limit of *Aedes* mosquito distribution (Appendix Figure 3). However, the probability of any transmission varied widely and was focused in the Southeast United States, Puerto Rico, and portions of Texas (Figure 1, panel A; Appendix Figures 4–6).

Once initiated, transmission chains were very limited. Of counties where the model indicated at least minimal transmission from index case-patients during peak vector abundance, 93% of transmission chains (interquartile range [IQR] 88%–98%) had median incidence (among simulations with transmission) of $< 1\%$ of the population (Figure 1, panel B), and 63% (IQR 48%–78%) of chains had final outbreak sizes of < 10 total cases (Figure 1, panel C; Appendix Figure 6). Where *Ae. aegypti* mosquitoes are scarce compared with *Ae. albopictus* mosquitoes (Appendix Figure 7, panel A), 95% of counties had median outbreaks of < 10 total cases (Appendix Figure 7, panel B), demonstrating that onward transmission is driven primarily by *Ae. aegypti* mosquitoes.

Along the Gulf Coast, outbreaks were more sustained. In Harris County, Texas, home to the Houston metropolitan area (population ≈ 4.8 million), the model predicted the largest epidemics in the 50 states, with a median epidemic size of 6,538 infections (IQR 1,846–17,440 infections) from an import during peak vector abundance. Although the entire Gulf Coast region is at risk for outbreaks, only 3 states contributed 97% of the top 100 counties with the largest simulated outbreaks: Florida (40%), Texas (35%), and Louisiana (22%). Mississippi contributed the other 3%.

According to our model, no counties within the 50 states sustained transmission beyond the first winter (Figure 1, panel D; Appendix Figure 8), although Miami-Dade and Broward counties in Florida sustained transmission as late as February in a fraction of simulations. Only Puerto Rico, Hawaii, and select counties, primarily in Florida and Texas, supported any transmission from the index cases occurring outside of the late spring through early autumn months (Appendix Figure 9, 10). Within the 50 states, only Miami-Dade County had evidence of transmission as early as February, and outbreaks there were limited in size (median 2 cases).

Our model showed final epidemic size was particularly sensitive to time of introduction (Appendix Figure 11), especially among counties most susceptible to transmission. Among the top 10% of counties

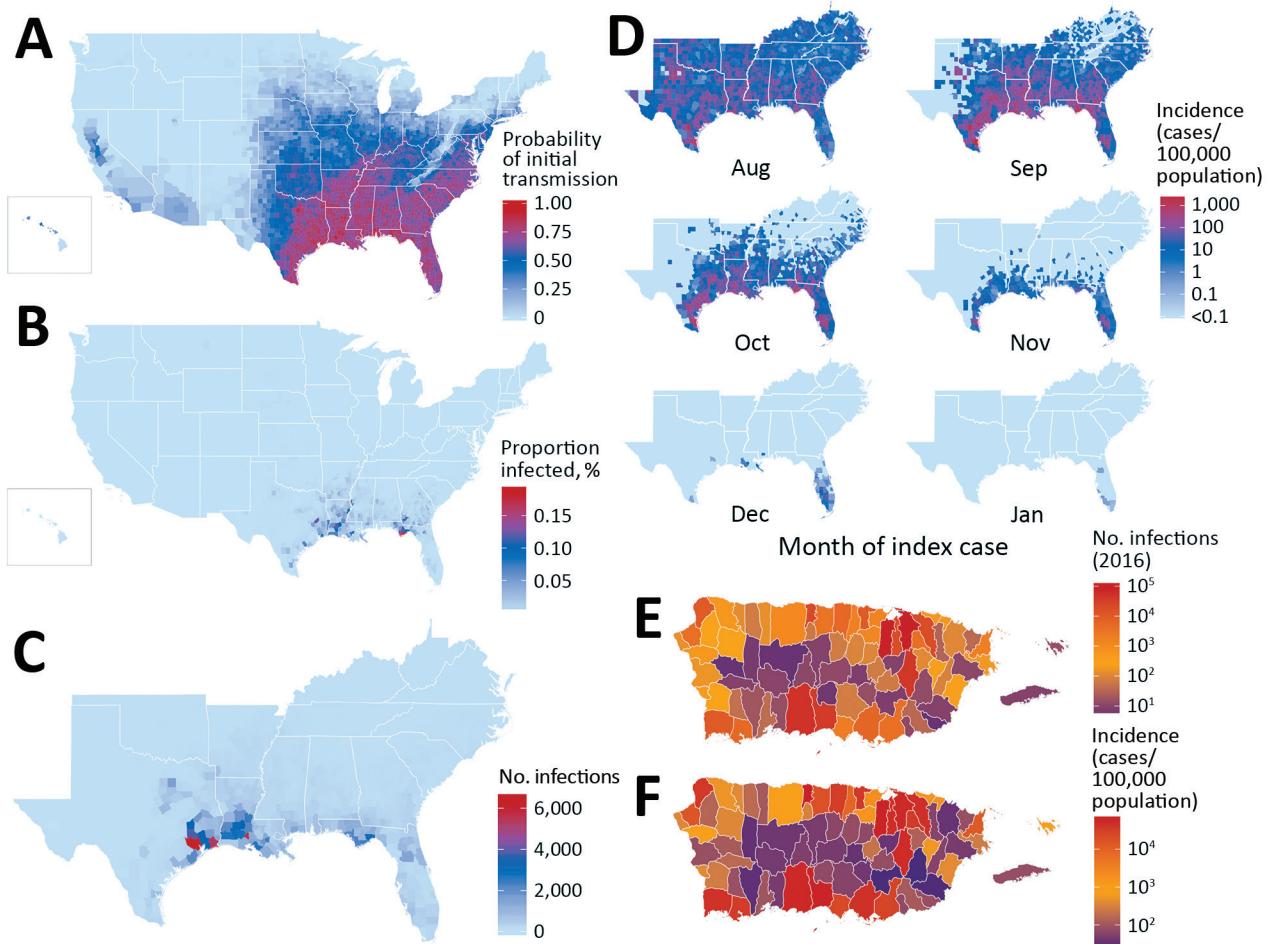


Figure 1. County-level Zika virus risk profiling, United States including Puerto Rico. A) Probability of initial transmission from an index case introduced during peak vector abundance, calculated as the proportion of simulations with ≥ 1 transmission event, for every county. B) Proportion of population infected. C) Total case counts for the southeastern United States (nationwide data depicted in Appendix Figure 6, <https://wwwnc.cdc.gov/EID/article/26/4/18-1739-App1.pdf>) when transmission does occur after index cases during peak abundance (median calculated among simulation with ≥ 1 transmission event). D) Monthly incidence and duration of outbreaks. Shown is the median monthly incidence of Zika virus infections from August index cases. E) Total number of simulated exposures in Puerto Rico ending December 31, 2016. F) Final epidemic size (incidence) at the end of simulations. For panels E and F, imports into each municipality corresponded temporally with initial cases reported in 2015 and 2016. All simulations assess counties and municipalities independently.

by predicted final epidemic size, the time of import that maximized incidence was ≈ 2 months earlier than that which maximized initial transmission (May vs. July; $p < 0.001$) (Appendix Figure 12, panels A, C), and final incidence was as much as 10-fold greater. This difference disappeared among the 80% of counties with the smallest predicted final epidemic size (Appendix Figure 12, panels B, D), where both metrics were maximized by imports during peak vector abundance, reflecting very limited transmission chains in most counties.

In Puerto Rico, simulated epidemics were more sustained and greater in magnitude. When index case-patients were introduced into each municipality to match timing of first reported cases in the

2016 epidemic (6), through 2016 our model detected 479,025 (IQR 310,365–662,257) total infections (Figure 1, panel E), representing a median incidence of 14% (IQR 9%–19%) of the population. The model also showed that San Juan (population 365,576) had the largest epidemics, which usually persisted for up to 3 years and infected 58% (IQR 52%–74%) of the population (Figure 1, panel F; Appendix Figure 13). These findings are consistent with previous Zika epidemics among island populations, where seropositivity reached 50%–70% (24,25). Across simulations, the total incidence on the island of Puerto Rico was 24% (IQR 19%–30%), suggesting that most infections had already occurred in 2016, when the index case was introduced. In addition, only 19%

(IQR 13%–23%) of the municipalities in the model sustained transmission through the first winter, whereas 14% and 3% sustained through the second and third winters, respectively.

Zika Virus Infections during Pregnancy

We found that natural seasonality in births results in waves of first- and second-trimester pregnancies that are out-of-phase with peak Zika virus infections in the model (Figure 2, panel A) and thus confers significant population-level protection against early-trimester exposures (Figures 2, panels B, C). Our model indicates that birth seasonality alone reduced risk for Zika virus exposure during first- (versus second- and third-) trimester exposures by 11% (relative risk 0.89 [95% CI 0.80–0.99]; $p = 0.012$).

Although counties in our model with the greatest numbers of fetal exposures generally tracked with epidemic size, distinct demographics led to deviations. In particular, Florida contributed 12% fewer counties to the top 100 counties, when ordered by rates of fetal exposures versus rates of total infections. Within the continental United States, Harris County, Texas, had the highest number of exposures during pregnancy (78 [IQR 20–183] exposures) after introduction of index cases during peak vector abundance (Figure 2, panel D; Appendix Figure 14). In Miami-Dade County, when simulated with a July index case introduction to match the 2016 outbreak (see also model validation below), we detected only 1 (IQR 0–3) fetal exposure from locally transmitted infections.

In Puerto Rico, when index cases were introduced into each municipality to match timing of initial cases reported in the current outbreak, through 2016 we detected 4,187 [IQR 2,733–5,760] infections during pregnancy (Figure 2, panel E), representing 10% (IQR 6%–13%) of all births. Throughout the entire simulated epidemic in Puerto Rico, the IQR for exposures in pregnancy was 5,800–9,100 (Figure 2, panel F).

Control Strategies

When human–vector contact rates were reduced from baseline in the model, the probability of initial transmission remained relatively insensitive, until contact was reduced by $\geq 70\%$, at which point initial transmission fell sharply (Figure 3, panels A, B). Incidence was exquisitely sensitive to reductions in contact, and fell log-linearly, with the magnitude of the slope proportional to the baseline incidence (Figure 3, panel C).

Depletion of adult *Aedes* mosquitoes through reductions in *Aedes* mosquito average lifespan in the model was effective at decreasing likelihood of initial transmission and epidemic size across all levels

of intervention, again with incidence more sensitive than initial transmission from the index case (Figure 3, panels D–F).

Vaccination was relatively more effective at preventing initiation of transmission than reducing incidence, particularly once vaccination coverage exceeded 70% (Figure 3, panels G–I). This finding is consistent with an R_0 for Zika virus of 3–4, based on the simple but robust formula for the vaccination coverage V required to achieve herd immunity: $V = 1 - 1 / R_0$ where R_0 is the basic reproductive number), in agreement with previous estimates (26,27).

Model Validation

We validated the model against known Zika outbreaks in the United States including Puerto Rico since late 2015, including Miami-Dade County (Florida), Brownsville County (Texas), and Puerto Rico, with separate tests across each of Puerto Rico's 8 health regions. Overall, the model accurately predicted the dynamics and absolute case counts for each site tested ($R^2 = 0.980$; $p < 0.001$; Figure 4, panel A). In Miami-Dade County, where Zika virus transmitted locally in 2016, the model estimated a total epidemic size of 185 (IQR 45–467) cases (Figure 4, panel B), in strong agreement with the 225 locally transmitted cases reported by the Florida Department of Health and the 214 reported by CDC (20,28,29). In Brownsville County, Texas, where local Zika virus transmission was detected during October–December 2016 and infected 6 persons (19), the model estimated a median of 4 cases (IQR 1–8).

Because much of the model is parameterized on the basis of existing biological data measured for dengue viruses, we also validated the model against known dengue outbreaks in Florida. In Monroe County, Florida, local dengue transmission was detected in September 2009. A serosurvey conducted in the surrounding areas of the locally acquired cases estimated an infection rate of 3%–5% among residents during July–September 2009, where 5% includes presumptive infections in addition to acute and recent infections. The model estimated a median proportion infected of 1.4% (IQR 0.07%–3.38%) (21,22). In Martin County, Florida, local dengue transmission was detected in August 2013 and resulted in 22 cases. By late September 2013, a serosurvey in the surrounding area of the reported cases estimated a total of 29 cases. Given an import in early August, the model estimates a median of 69 (IQR 11–236) cases; for September import, the estimate is 14 (IQR 3–33) cases (22,30). When index cases were introduced into each municipality in Puerto

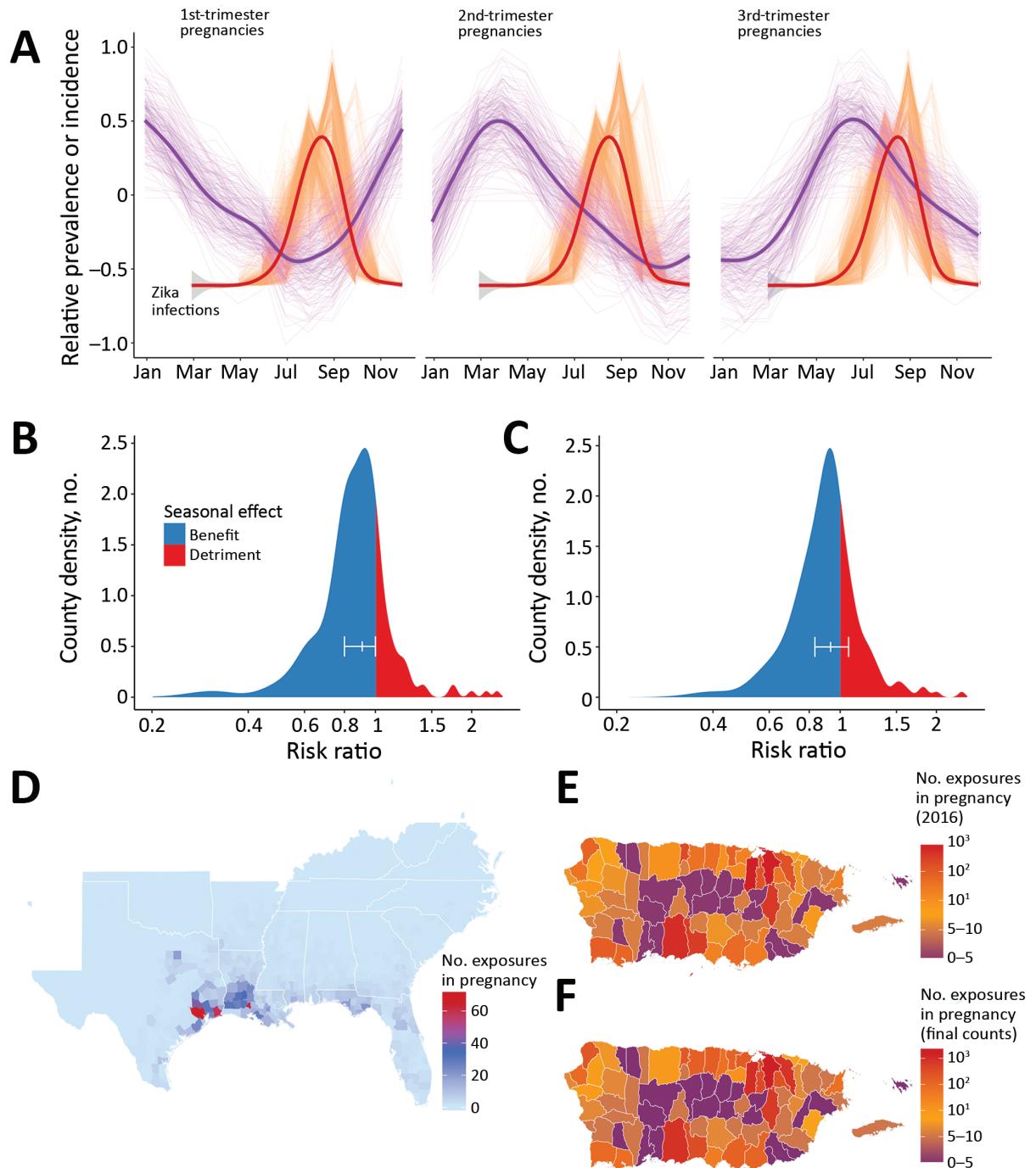


Figure 2. Zika virus infections during pregnancy and effects of natural birth dynamics, United States including Puerto Rico. A) Standardized prevalence of first-, second-, and third-trimester pregnancies throughout a year in the southeastern United States and Texas are plotted against the simulated and standardized Zika epidemic curves for each county and for every month of import. Thin purple lines indicate county-specific prevalence of pregnancy in each respective trimester, and thick purple lines show a generalized additive model fit. Thin orange lines indicate median outbreak per county, including distinct lines for each month of import during March–November. Thick orange line is a generalized additive model fit to the county-level data. B, C) Zika virus exposure risk ratio and 95% CI during (B) first (versus third) and (C) second (versus third) trimester of pregnancy, driven by the dynamics depicted in panel A (Appendix Table 2, <https://wwwnc.cdc.gov/EID/article/26/4/18-1739-App1.pdf>). D) Median number of infections (simulated) during pregnancy when index cases are imported during peak vector abundance. E, F) Median number of infections (simulated) during pregnancy for each municipality (E) in Puerto Rico in 2016 and (F) over the entire epidemic. Data in panels E and F include index cases that were introduced into each municipality to correspond with initial introductions reported in the current epidemic

Rico to correspond temporally with initial cases per health region reported by the Puerto Rico Ministry of Health (6), the model accurately predicted the monthly and cumulative case counts in Puerto Rico (325,000 infections vs. 314,209 simulated infections; Figure 4, panel C) and performed nearly as well for each of Puerto Rico's 8 health regions (Figure 4, panels D, E; Appendix Figure 15), each representing an independent validation set. Across the 10 independent sites that we were able to validate the model against, the actual (realized) incidence was within

the IQR of our simulations, and usually within a single-fold difference from the median simulation.

Discussion

Overall, our model predicts interventions would be more effective at preventing additional transmission initiated by the index case than reducing the probability of an outbreak taking place. Therefore, given limited resources, a reactive approach focused on infection control rather than complete prevention might prove most beneficial. However,

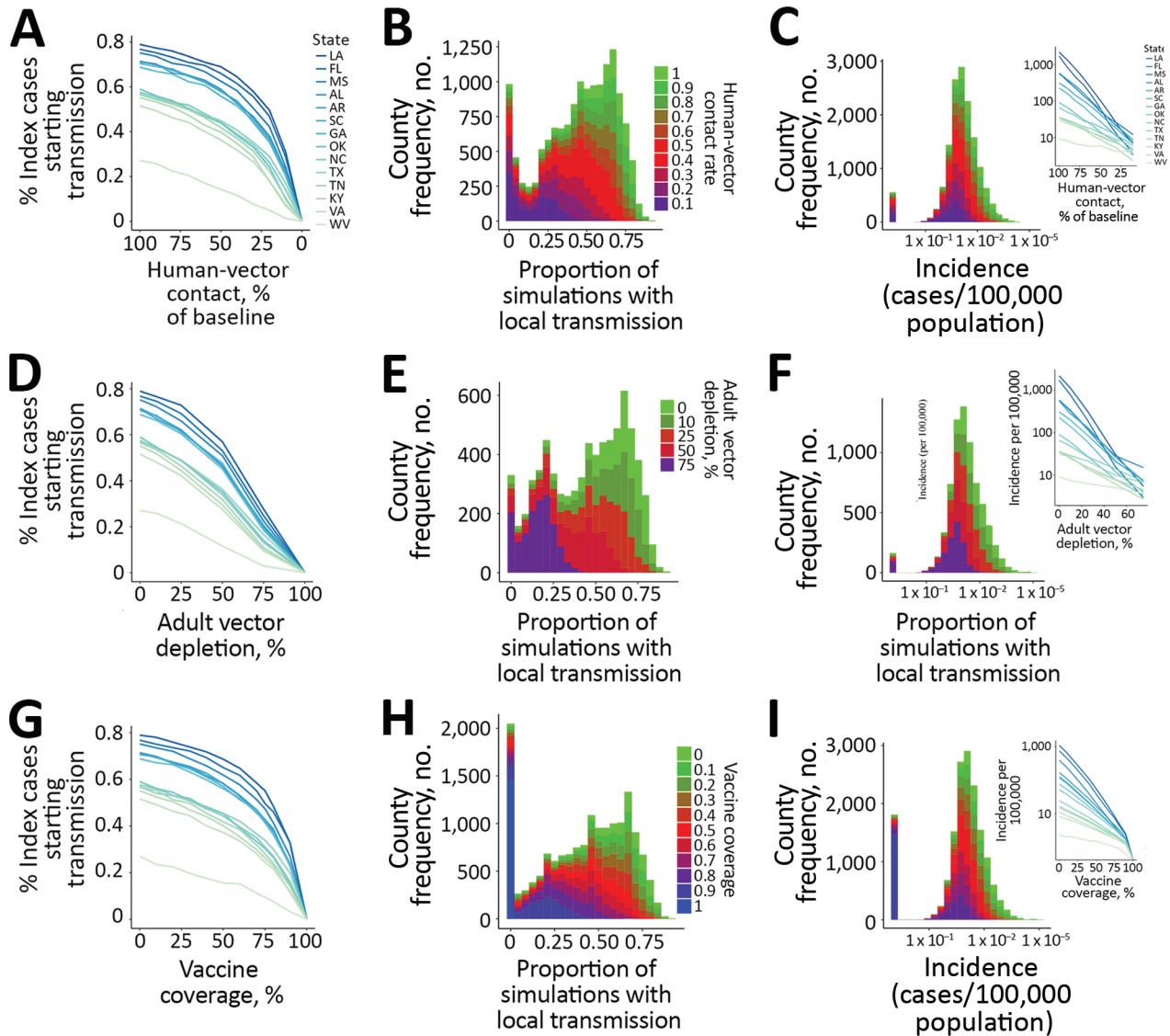
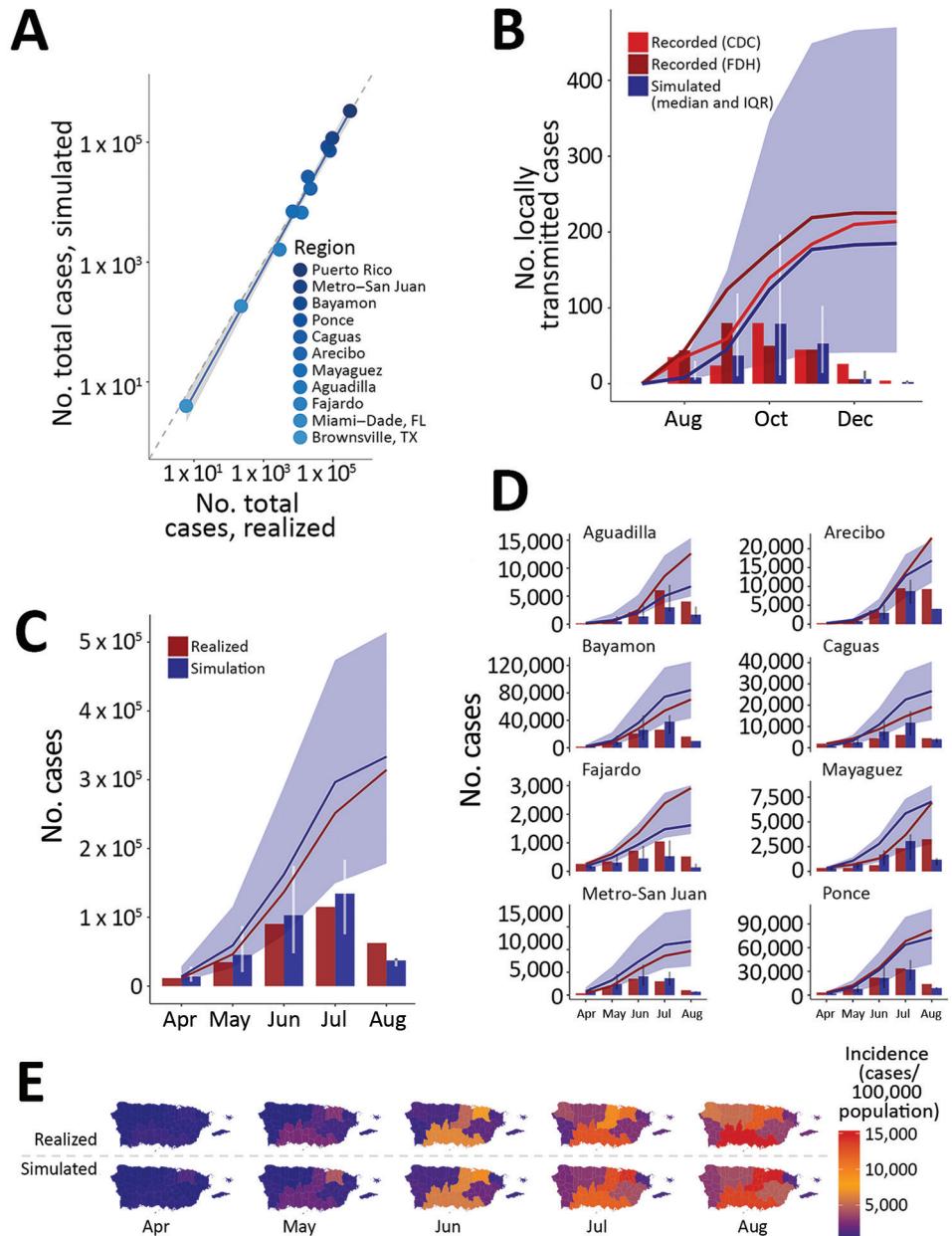


Figure 3. Zika prevention and control strategies, United States. For each county in the United States including Puerto Rico, classes of prevention or control strategies were assessed, including (A–C) reductions in human–vector contact, (D–F) adult vector depletion, and (G–I) vaccination. A, D, G) Proportion of index cases initiating ≥ 1 transmission event versus extent of each intervention. Each line represents the statewide average across each of the constituent county's median simulations. B, E, H) Histograms depicting number of counties versus probability of permitting ≥ 1 transmission event from the index case, color coded by the level of each respective intervention. C, F, I) Histogram showing the number of counties versus incidence across levels of respective intervention (color coding as in panels B, E, and H). Insets in panels C, F, and I show incidence (on a log-linear scale) versus extent of each respective interventions.

Figure 4. Model validation for Zika virus infection cases reported or estimated and simulated for outbreaks, United States including Puerto Rico, 2016. A) Total cases (median simulated) versus total cases reported or estimated (realized) for each of the regions are plotted as a scatter plot. Dotted line indicates 1:1 relationship. B–D) Monthly and cumulative simulated cases are plotted against reported or estimated cases for (B) Miami–Dade County, Florida, (C) Puerto Rico, and (D) each of the 8 health regions of Puerto Rico. Dark blue columns and line in panel B show monthly and cumulative case counts for the median simulated outbreak (among simulations with ≥ 1 transmission event) and shaded region shows the interquartile range. Red columns and red solid lines indicate the respective monthly and cumulative cases recorded or estimated, as noted. Data in panels C and D are as in B, but summed over the constituent municipalities (i.e., the dark blue line in panel C shows the sum of the cumulative case counts for each municipality in Puerto Rico). For panels C and D, validation data were available only for April–August 12, and thus realized and simulated case counts represent only cases measured or predicted within this period. E) Cumulative cases realized (upper panel) and simulated (lower panel) for each health region of Puerto Rico during April–August 2016. Validation data were available only for April–August 12, and thus realized and simulated case counts represent only cases measured or predicted within this period. CDC, Centers for Disease Control and Prevention; FDH, Florida Department of Health; IQR, interquartile range.



for those counties with highest overall invasion potential (Appendix Figure 16), early strategies aimed at preventing any transmission might be warranted, especially areas with high rates of potential imported cases (e.g., southeastern US cities with international airports). A vaccination coverage $>70\%$ would be most effective in preventing future outbreaks in these high-risk areas. However, pockets of unvaccinated persons are associated with elevated risk for

infectious disease outbreaks (31). Therefore, this threshold might vary given a nonhomogeneous spatial distribution of vaccination coverage. In addition, these counties might serve as optimal US settings for Zika vaccine efficacy trials.

Zika outbreaks are likely to be highly restricted by both time and space, limited within the 50 US states almost exclusively to the summer months and the Gulf Coast region, where the *Ae. aegypti*

mosquito vector is most abundant. Although our model predicts many counties within the United States could support ≥ 1 transmission event from an index case, nearly all transmission outside of this region was extremely limited. Therefore, outside of the southeastern United States, a detected transmission event from an imported case will most likely represent only a sporadic occurrence, with minimal onward transmission even in the absence of local control efforts. These transmission patterns are consistent with previous local transmission patterns of other mosquito-borne flaviviruses in the United States, such as chikungunya and dengue, and with other model estimates (9,32).

Our model also shows that few municipalities in Puerto Rico sustained transmission through the first winter, with even less transmission sustained through the second and third winters. This finding suggests that sustained transmission throughout Puerto Rico requires continued case exports from municipalities with uninterrupted transmission. These findings are also consistent with CDC's reported Zika virus disease trends among travelers for 2016 and 2017, which show a decrease in the number of reported cases, from 4,205 cases in 2016 to only 331 cases in 2017 (32).

We also found that the natural seasonality in human births will likely serve to reduce population risk for early-trimester infections, which alone should serve to abrogate the number of fetal exposures resulting in neurologic complications. In addition, planned seasonal conception (based on birth seasonality and local Zika virus transmission data) is a viable intervention to pursue while maternal Zika virus vaccine and risk profiles, as they relate to gestational age, are being developed (33,34). Our model showed that in Puerto Rico, most fetal exposures occurred within the first year of the epidemic, suggesting that most fetal exposures have already occurred in 2016. Previous estimates by Ellington et al. (29) using Zika case data projected that $\approx 7,800$ exposures in pregnancy would occur through 2016. Of note, that study anticipated an overall population incidence of 25% through 2016, whereas more recent estimates (23) place the actual incidence closer to 15%–20%. Thus, Ellington et al. might have overestimated actual fetal exposures by 20%–40%, which, when corrected for the updated incidence, places our model estimate well in line with theirs.

Some limitations to the proposed model might influence county level risk profiles for Zika virus transmission. For areas with a high level of travel-associated imports of Zika virus cases, such as

cities with cruise ship ports and large airports, the associated risk might be an underestimate because our model does not consider multiple imports of infectious persons (35). In addition, certain parameters (e.g., incubation period and period of infectiousness of Zika virus infection) and transmission pathways (e.g., sexual transmission of Zika virus) are not fully understood and might contribute to elevated risk for Zika epidemics (36,37).

Zika virus transmission is expected to persist as a long-term public health challenge, and the United States remains an entirely susceptible population, with risk for transmission. As long as Zika virus circulates anywhere, the continued importation into the United States remains a potential risk. Our comprehensive profiling efforts should serve a critical need for decision making across all levels of government regarding efficient use of local, state, and national resources aimed at preventing and controlling Zika virus transmission and should provide critical information to inform future vaccination efforts.

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Comprehensive Profiling of Zika Virus Risk with Natural and Artificial Mitigating Strategies, United States

Appendix

Materials and Methods

Model Overview

The SEIR-SEI human-vector model (Appendix Figure 1) is based on the Ross-Macdonald set of simplifying assumptions, namely that following a latent period, a pathogen is passed from an infected mosquito to a susceptible vertebrate host and from an infected vertebrate host to a susceptible mosquito during blood feeding (1,2). Once recovered from infection, immunity is considered absolute and not waning. Zika virus transmission between human and vector populations is dependent on: the number of mosquitos per human per day, the number of blood meals on humans per mosquito per day and the probability of transmission from an infectious mosquito to a susceptible human, and vice versa. Our model expands upon the basic Ross Macdonald model by integrating both *Aedes aegypti* and *Aedes albopictus* vectors, and their separate temperature dependent life-stage dynamics. Of note, by explicitly modeling vector life-stage and feeding as functions of temperature, the mosquito-human interaction rates change dynamically over the course of simulations (e.g., the number of mosquitos per human will differ markedly between summer and winter months). As well the extrinsic incubation period (EIP) is temperature dependent and modeled as a temperature dependent function. Thus our model incorporates a dynamic description of virus-vector-host interactions, parameterized from the best available information in the literature, described below, enabling simulations to extend over multiple years, while avoiding common limiting assumptions such as constant human:mosquito rates across time throughout the year. On the other hand, given the novelty of the Zika virus as a major human pathogen, there is relatively limited information on its dynamic life-stage properties. Thus, a limitation of the current study is that numerous properties relating to

transmission and EIP are borrowed from the large body of literature surrounding dengue virus dynamics, as it is a closely related but more completely studied mosquito-borne flavivirus that shares the same mosquito vector host system. Such a strategy for closely related viruses is common for emerging pathogens, and has been successfully employed for other Zika virus transmission models (3,4).

Spatial Properties

To best inform at the county-level (and by extension also inform at state and national levels), our aim was to describe the potential for Zika virus transmission within each county and municipality independently. Simulations thus assume that an index case arrives in that county, regardless of whether the case arrives from a neighboring county or via a traveler from a distant country. The current investigation therefore provides information on potential for Zika virus transmission in a given county in a manner that is source agnostic, and thus equally useful for a county sharing a border with a nearby county with an ongoing epidemic, or a county likely to receive travelers coming from Zika infected regions.

Model Parameters

Mosquito-Human Interactions per Day (m)

For each county, a maximum number of mosquitos-human interactions per day ($\lambda = m_{\max}$) during peak vector abundance was calculated using high resolution (5km x 5km) maps detailing the global spatial distribution of *Aedes aegypti* and *Aedes albopictus* (5). In brief, these maps, produced by Kraemer et al. were developed by coupling the largest contemporary database of known geographic occurrence of both *Aedes aegypti* and *Aedes albopictus* ($n = 19,930$ individual observations) with pertinent environmental layers (temperature, precipitation, vegetation and urbanization) to derive what are widely considered the best available data on the spatial distributions of *Aedes aegypti* and *Aedes albopictus* occurrence probabilities. Additionally, these global maps, which are freely available for download (<http://goo.gl/Zl2P7J>) agree with the estimated range of *Aedes aegypti* and *Aedes albopictus* in the U.S. as put forth by the U.S. Centers for Disease Control and Prevention (6,7). Using these high resolution *Aedes* occurrence probability maps, we calculated mean probability of occurrence of *Ae. aegypti* and *Ae. albopictus* for each county or municipality using border data retrieved from the Global Administrative Areas or GADM database, freely available at <http://www.gadm.org>, and easily

accessible in R using the `getData()` function of the Raster package (8). The mean occurrence probability for each county was converted to vector abundance as described by Perkins, et al. (3). In brief, by assuming that mosquito abundance is distributed as a Poisson random variable, Perkins et al. nicely point out that the expected abundance of mosquitos (λ) in a given location (i) can be calculated from the probability of a mosquito (P_M) at the i^{th} location as $P_{M_i} = 1 - \exp(-\lambda_i)$. Thus, the expected peak abundance of mosquitos available per person per day (λ) can be calculated as $\lambda = -\ln(1 - P_M)$, and λ is thus taken to approximate the maximum mean daily number of mosquitos available per person. Importantly, because the probability of occurrence maps were generated to reflect the extent of the geographic distribution of *Ae. aegypti* and *Ae. albopictus*, as mentioned above, λ is considered to reflect the maximum expected number of mosquitos per person, or the number of mosquitos available per person during peak vector abundance. λ therefore represents an upper bound of m , the maximum average number of mosquitos per person per day (calculated separately for each *Aedes* vector) throughout the year.

For each county, simulations were initiated at time of peak vector abundance (see below and Appendix Figure 2) and as simulations progressed, mosquitos available per human changed dynamically. For each simulation, λ was used to initialize the mosquito populations (T_{M_0}) such that: $T_{M_0} = \lambda T_H$, where T_H represents the total human population in the respective county. Simulations were thus initiated during the month of the year in each county when vector abundance was expected to be greatest (see below). Once initialized however, vector populations were modeled explicitly via a series of stochastic ordinary differential equations (ODE) and thus human-mosquito interactions changed dynamically. At peak mosquito abundance (i.e. $\frac{T_M}{T_H} = \lambda$), the rate of mosquito bites per person per day (m) was given by $m = \frac{T_M}{T_H} \tau \alpha = \lambda \tau \alpha$, Where τ represents the mean number of daily blood meals taken by each respective *Aedes* vector, and α the proportion of blood meals taken on humans. To account for fluctuating mosquito vector dynamics, which occur over orders of magnitude between summer and winter, the mosquito-human bite rate (m) was constantly updated at every time-step to account for changes in the individual *Aedes* mosquito populations, as well as the number of blood meals taken per day, which is dependent on the duration of the gonotrophic cycle.

Temperature Dependent Functions

For the temperature dependent parameters (described in the following sections), we obtained empiric data reported in the literature across ranges of temperatures, based on relevant papers that studied each individual parameter of interest across the range of relevant temperatures, and fit very simple models (splines, simple linear, simple exponential, etc.) to each set of temperature dependent empiric data. These models were sufficient to capture the parameter of interest's empiric data across temperature gradients for each mosquito *aegypti* and *albopictus* where relevant. Once parameterized, for model runs, the simple models were then embedded into simple functions, usually of the form “getZZZperTemp(T = ..., mosquito = c(“aegypti,” “albopictus”)) where ZZZ refers to, for example, EIP or duration of the gonotrophic cycle at the respective temperature, etc. See code script “2 Create aedes FXNs” for details on individual models describing the empiric parameters over temperature ranges.

Duration of the Gonotrophic Cycle

Duration of the gonotrophic cycle as a function of temperature ($g(T)$) for each *Aedes* vector species was parameterized from Brady et al. (9) In their report, the authors used a large and comprehensive dataset comprised of 54 unique studies of *Aedes aegypti* and *Aedes albopictus* gonotrophic cycles across temperatures to fit a robust enzyme kinetics model to estimate the duration of *Aedes aegypti* and *Aedes albopictus* gonotrophic cycles across temperatures. We used these estimates to parameterize the duration of the gonotrophic cycle at each temperature as simulations moved through time. For average temperatures below those estimated by Brady et al. ($<15^{\circ}\text{C}$) the expected duration of the gonotrophic cycle greatly exceed the expected lifespan of an adult *Aedes* mosquito by an order of magnitude or more, and thus the duration of the gonotrophic cycle at low temperatures was both not reliably estimated nor important in any of our measured outcomes (data not shown), primarily because mosquito abundance was negligible when average temperatures were low. To allow the model to run, we set gonotrophic cycle duration at these cold temperatures arbitrarily to 100 days. No counties within the U.S. or Puerto Rico had mean high temperatures that exceeded those reported by Brady et al.

Extrinsic Incubation Period (EIP)

Chan et al. (10) identified 8 unique studies comprising 146 distinct observations of the extrinsic incubation period to estimate EIP across temperatures. Briefly, the authors used censored time-to-event analyses, and Markov Chain Monte Carlo (MCMC) simulations to compare fits from multiple parametric distributions (Exponential, Weibull, Gamma and Log-normal). Among the fits, Chan et al. found that the log-normal distribution provided the best fit to model EIP as a function of temperature, and we used this fit to parameterize EIP in our model. Although this study was performed only in *Aedes aegypti* mosquitos, Brady et al. (9) too addressed EIP and found no important differences in the EIP between the two *Aedes* vectors and, additionally, their estimated EIP durations across temperatures were in strong agreement with Chan et al. We parameterized our model to match Chan's results, primarily because they incorporated a wider temperature range than the Brady 2014 analysis. Of note, owing to a paucity of data on EIP for Zika virus, EIP here is estimated based on the closely related Dengue virus, a limitation of this study. Given the difficulty of measuring EIP, especially in field conditions, coupled with the novelty of the Zika virus epidemic, reliable data to describe the EIP of Zika virus is not yet available and thus measured Dengue virus properties (owing to its close phylogenetic proximity to Zika virus), provides us with our best available estimates for numerous Zika virus properties, a strategy that has been successfully used by others (3,4). We packaged the log-normal fit provided by Chan et al. into a simple function in R with a single argument (temperature) to be called dynamically, at every time step, for incorporation of continuously updated temperature dependent EIP during simulations.

Aedes lifespan (vA)

Using a robust dataset consisting of 410 unique experiments, including 351 laboratory experiments and 59 mark-release-recapture field experiments observing *Aedes aegypti* and *Aedes albopictus* survival, Brady et al. developed survival distributions across a continuous temperature spectrum from 0 to 40°Celsius (9). Using these survival distributions for each *Aedes* vector type, we defined temperature specific durations of adult *Aedes* survival as the median duration estimated at each temperature between 0 and 40 C (for temperatures below 0°C, duration of survival was set to zero). The expected lifespan distributions across all temperatures, at 0.1-degree increments can be freely downloaded for both *Aedes aegypti* and *Ae. albopictus* at the following URLs.

Model of adult *Aedes albopictus* (<http://dx.doi.org/10.6084/m9.figshare.865035>).

Model of adult *Aedes aegypti* (<http://dx.doi.org/10.6084/m9.figshare.865034>).

Blood Meals per Mosquito per Day (τ)

Blood meals per mosquito per day (τ) was defined as the number of expected feeding events that a mosquito takes per day; calculated as the number of feeds, including interrupted feeding patterns per gonotrophic cycle: two and four for *Ae. Aegypti* and *Ae. Albopictus*, respectively (9,11–14), divided by the duration (days) of the gonotrophic cycle.

Clutch Size, Egg, Pupal, and Larval Viability across Temperature

Aedes albopictus

Using captured *Ae. albopictus* mosquitos housed at 8 different temperatures between 5°C and 40°C, Delatte et al. (15) monitored the numbers of eggs laid, and their development and viability over 10–19 repetitions per temperature to estimate duration to hatch and egg viability. Delatte et al. also describe larval duration and viability by housing, feeding and monitoring at least ten larvae at each temperature, and repeated this over 8 experiments. The authors then applied various statistical models (see original work (15) for complete description) to best approximate temperature dependent functions for durations of egg and larval/pupal development and egg and larval/pupal viability. Additionally, they captured the proportion eggs male versus female at each temperature (9,15). We incorporated these parameters – clutch size or number of eggs laid per gonotrophic cycle (used to calculate ϵ , the mean eggs laid daily per adult female mosquito, as clutch size/duration of the gonotrophic cycle), egg survival (v_e), egg and larval development times (D_e , D_{LV}), larval survival (v_{LV}), and proportion eggs female at each temperature into our model by packaging their output into simple functions to enable updated parameters at each time step, based on current temperature in the simulation. Data available for number of eggs and egg survival was limited to temperatures at or above 20°C. However, we found that our simulations were insensitive to differences in number of eggs laid below these temperatures, as gonotrophic cycle duration greatly exceeds predicted lifespan of the adult *Aedes albopictus* mosquito at low temperatures and because larvae generally fail to develop at temperatures below 10 or 15°C. Additionally, because male mosquitos do not contribute to the spread of Zika virus, we took the number of eggs laid to be the fraction expected to be female at

each temperature, which ranged from 41% to 66% (9,15). The above temperature dependent patterns of *Ae. albopictus* development are in agreement with others (16), although we did note that egg viability was shifted up $\approx 10\%$ in the studies by Dickerson et al. This is most likely because the baseline number of eggs for viability calculations in that study were taken to be only embryonated eggs, while Delatte and others used a denominator consistent with all laid eggs. To incorporate the best-fit model of larval development by temperature (also by Delatte et al.) into our model, we captured the output data from their resulting best-fit curve and packaged it into a simple R function for rapid retrieval and updating of larval development time during simulations. The inverse of the fit represents the duration of larval development, in days, across temperatures.

Aedes Aegypti

Carrington et al. reared captured *Aedes aegypti* mosquitos across temperatures from 16°C to 37°C to determine various *Aedes aegypti* life history traits, including clutch size (number of eggs laid), as well as larval development time and larval survival (ϵ , D_e , v_{LV}) (17). Among numerous metrics, the authors measured: duration from first blood meal to the first day eggs were observed (gonotrophic cycle duration), number of eggs laid, time to pupation (larval development time) and larval survival. Because proportion of females at each temperature were not available for *Ae. aegypti*, we took proportion of female eggs at each temperature to be the same as the proportions described by Delatte et al. for *Ae. albopictus*, described above (15).

For egg viability and egg and larval development rates across temperatures for *Aedes aegypti*, we referred to a comprehensive review and analysis by Eisen et al. (18) that analyzed impact of temperature on various developmental and life stage characteristics of *Aedes aegypti* mosquitos. They included all studies (earliest in 1901) that observed at least 100 eggs or 25 larvae and only those that observed hatching rates from eggs kept in water, as would be the case in field conditions.

Courette et al. (19) performed a thorough meta-analysis of 49 unique studies, each directed at understanding the relationships between many biotic and abiotic factors likely to contribute to *Aedes aegypti* development. They found temperature to be the primary influencer of *Aedes albopictus* and *Aedes aegypti* development, and reported larval development time across a range of temperatures from 15 to 37°C. Of note, the larval development rate determined by Courette et al. matches the findings by Eisen et al. (18) Similar to methods mentioned above, we

packaged the respective outputs of these works into simple R functions for dynamic temperature dependent retrieval of each parameter during simulations. For durations of egg and larvae/pupae development, we took the inverse of the daily reported rates.

Data

Monthly Temperature Data

Monthly temperature data was retrieved from WorldClim – Global Climate Data (<http://worldclim.org>), a climate data repository for ecologic modeling and global information systems. The monthly temperature data was retrieved at a resolution of 2.5 arc minutes (grids of ≈ 4.6 km edges) and mean monthly temperatures for each county or municipality were calculated using border data retrieved from the Global Administrative Areas or GADM database, freely available at <http://www.gadm.org>, and easily accessible in R using the `getData()` function of the Raster package (8).

County Population Data

Population data per county was collected from the U.S. census bureau at (<http://www.factfinder.census.gov/>).

Monthly Birth Rates

Throughout the year, the proportion of a population's births fluctuate in a predictable manner across calendar months. To estimate the numbers of children born per month, and thus calculate expected numbers of first, second and third trimester pregnancies per month, the numbers of births per month were collected for each county over a span of 8 years, from 2007 to 2014 from the U.S. Census database. For each county, generalized additive models (GAM's) were fit to the monthly data to model expected proportions of annual births per month per county. For counties with populations fewer than 50,000, stochastic effects masked clear seasonality of human birth rates. Therefore, for those counties with populations below 50,000, the proportion of annual births in each month were pooled within a given state (excluding counties with populations above 50,000) and GAMs were fit to the pooled statewide data. The county-level (for counties $\geq 50,000$) or statewide (counties $< 50,000$) GAM output, indicating the expected proportion of annual births in each calendar month, was then coupled to annual birth numbers for each individual county to calculate monthly county-specific expected pregnancies.

Trimester-Specific Pregnancies and Exposure Calculations

From the monthly birth data for each county, we calculated the number of pregnancies in their first, second or third trimester during each month for each county or municipality. To achieve this, we assumed that within a given month, births were uniformly distributed and that each trimester is 13.33-weeks long, for a 40-week gestation. Therefore, for example, among January births, we assume that all of those pregnancies delivering in January were in their third trimester in January (up until delivery), as well as in December and November, and that half were in their third trimester in October (those with deliveries in the first half of January), and half were in their second trimester in October (those with deliveries in the second half of January). We iterated this routine for each trimester and month for each county to derive numbers of pregnancies in each trimester across all months.

To calculate infections during pregnancy during the simulations, we assumed that pregnancies were among women who remained well-mixed within the population. Given the large numbers of simulations, for efficiency, rather than including numerous compartments for women in each trimester of their pregnancy into our SEIR model, using the assumption of homogenous mixing, we derived the number of fetal exposures per trimester per week for each simulation by drawing from a binomial distribution, with the size equal to the number of first, or second, or third trimester pregnancies in the county, during the week of interest, and with a probability equal to the proportion of the population infected during that week. Therefore, for example, to calculate number of first trimester pregnancies infected during week 36 in a given county, q , in R we coded: `rbinom(n = 1, size = n_tri1_wk36_q, prob = prop_Inf_wk36_q)`, where $n_tri1_wk36_q$ is the number of first trimester pregnancies expected in week 36 for county q , and $prop_Inf_wk36_q$ is the proportion of the county (q) population infected during that week. By drawing from a binomial distribution, we incorporate stochastic effects that influence the number of infections among gravid women, relative to the proportion infected across the population as a whole.

Model

The model is a stochastic SEIR / SEI model with an additional two equations to describe mosquito egg, larval/pupal, and adult development for simulating mosquito populations as functions of temperature throughout the year in each county. The model is defined as follows (Appendix Figure 1 and equations below).

SEIR Model (Human)

$$\begin{aligned}\frac{dS_H}{dt} &= -m\beta_H \left(\frac{I_M}{T_M}\right) S_H \\ \frac{dE_H}{dt} &= m\beta_H \left(\frac{I_M}{T_M}\right) S_H - E_H\delta^{-1} \\ \frac{dI_H}{dt} &= E_H\theta\delta^{-1} - \gamma^{-1} \\ \frac{dR_H}{dt} &= \gamma^{-1} \\ \frac{dR_{H2}}{dt} &= E_H(1 - \theta) \cdot \delta^{-1}\end{aligned}$$

Mosquito Development

$$\begin{aligned}\frac{dEgg}{dt} &= \varepsilon T_M - \left(\frac{1 - v_E}{D_E} + D_E^{-1}\right) Egg \\ \frac{dLV}{dt} &= Egg \cdot D_E^{-1} - \left(\frac{1 - v_{LV}}{D_{LV}} + D_{LV}^{-1}\right) LV\end{aligned}$$

SEI Model (Mosquitos)

$$\begin{aligned}\frac{dS_M}{dt} &= \frac{LV}{D_{LV}} - \left(\tau\alpha\beta_M \frac{I_H}{T_H} + D_A^{-1}\right) S_M \\ \frac{dE_M}{dt} &= \left(\tau\alpha\beta_M \frac{I_H}{T_H}\right) S_M - E_M(EIP^{-1} + D_A^{-1}) \\ \frac{dI_M}{dt} &= \frac{E_M}{EIP} - \frac{I_M}{D_A}\end{aligned}$$

Where S_H , E_H , I_H , R_H , R_{Hs} indicate compartments for the susceptible, exposed, infectious, recovered following infectious period, and recovered following non-infectious period, respectively. Additionally, S_M , E_M , I_M , LV and Egg indicate population compartments for susceptible, exposed and infectious mosquitos, as well as larvae and egg populations. Definitions for each of the variables and rate parameters are presented in Appendix Table 1.

Simulations

Simulations were run using an adaptation of the Gillespie Stochastic Simulation Algorithm (SSA), adaptive tau-leaping algorithm on a continuous time scale. Tau-leaping was initially described by Gillespie (20). Briefly, tau-leaping procedures achieve efficient implementations of the SSA by relaxing the requirement to model every change (step) in the system – a hugely resource consuming process – by using a Poisson approximation to take “leaps” over fast (stable) steps, while well approximating the stochastic behavior that would be expected over the duration (τ) of the leap. A limitation of tau-leaping however is that the leap size must be pre-specified. When the system is stiff and, by definition predictable, such as during the exponential growth phase of an epidemic, relatively large leaps can be taken because the Poisson approximation is sufficient to approximate the behavior of the system. In fact, under stiff (stable) conditions, with very fast steps and large populations, the tau leaping method limits to the explicit Euler method. However, when the system is nonstiff, and a particular single event can have profound effects on the simulation, i.e., a “critical reaction,” such as following introduction of an index case to a community or, more generally, when an extinction of a compartment is possible, the leap sizes must be much smaller. Therefore, if critical reactions are possible, the leap sizes must be reduced, eventually approximating the fundamental Gillespie SSA such that no more than a single critical reaction can take place during a given time-step or leap, also ensuring a population cannot become negative. Because epidemic behavior shifts from nonstiff systems (for example just following introduction of an index case, when extinction of an infectious disease in a community is likely, or when mosquito populations become very low in winter months) to very stiff systems (for example once an epidemic takes off in a susceptible population) declaring a prespecified leap size will either risk missing critical reactions when τ is large but the system is nonstiff, or will be highly inefficient if τ is small but the system is stiff. The adaptive tau-leaping procedure solves this problem by monitoring the stiffness of the system and determines τ by automatically switching between explicit (best for nonstiff systems) and implicit (best for stiff systems) tau selection formulas to determine tau size compatible for the leap conditions at each step. The details of tau selection, including switching between implicit- and explicit-tau selection over the course of a simulation is outside of the scope of this description, and we refer to initial work by Cao, Gillespie and Petzold (21).

Simulation Initialization

Initial mosquito abundance per person was given by λ , the maximum mosquito:human ratio described in previous sections and every simulation was initialized at the time of peak vector abundance. For each simulation however, a ‘settling’ period of at least 1 year was incorporated to allow mosquito population dynamics to be driven by their temperature functions, rather than purely by their initialized values. This was important to allow for simulations with index cases introduced at any time of the year, not just at peak vector abundance (initialization). Additionally, this served as a check on the utilization of the high resolution *Aedes* risk maps. For example, if the risk maps suggested a high density of *Aedes aegypti* mosquitoes in a particular area where temperature constraints should limit mosquito survival, the dynamic temperature dependent *Aedes* life-stage model would serve to temper the *Aedes* population, 1 year later, down from the initial estimated maximum value, to a value dictated more by the temperature and life-stage dynamics. However, we did not detect settings where peak mosquito populations in the year or two after initiation were highly discrepant from the initializing population – further confirming the detailed work by Kraemer et al in their initial development of the mosquito population risk maps.

To determine the start-month for each county’s simulations (i.e., the month of peak *Aedes* abundance when $T_M/T_H = \lambda$ for each county) we ran 36-month simulations for every county and municipality and recorded calendar month when vector abundance was maximized during each year of the simulations. The calendar month recorded to have highest average mosquito population was taken to be the start month of all further simulations for each respective county (this was important to determine because mosquito populations were initialized by their maximum abundance). Nevertheless, sensitivity analysis of the starting month demonstrated no effect of the particular starting month on outcomes, owing to the winter bottleneck during the minimum 1-year ‘settling’ period (these results not shown). This was further confirmed by checking that the month of peak *Aedes* abundance was consistent from year one to year three. Additionally, our findings of month of peak vector abundance are in agreement with results described by Monaghan et al. (22,23) (Appendix Figure 17) and in a recent report by Grubaugh et al. (24)

For each simulation and each vector, *Aedes* abundance was initialized by λ mosquitoes available per person, and the simulation was allowed to progress for at least a full year to allow

mosquito dynamics to be driven by their respective temperature dependent functions, as described above, before a single infected individual (index case) was input into a fully susceptible population at a time specified by the simulation of interest, as described in the main text.

Duration

For each simulation, epidemics were initiated by a single index case and were allowed to progress either until 4 consecutive months passed without any new infections, or for a maximum 60 months.

Design and Analysis

For all of the simulations described in the main text, at least 500 simulations were run for each county or municipality and for each scenario, requiring 1.6 million simulations for a full evaluation of single scenario (for example, a June index case in the setting of 10% vaccination is one scenario). We explored running as many as 1000 simulations per county, however results were generally robust, with minimal added information gained beyond even 200 simulations. Thus, 500 simulations were chosen owing to the already long run times per simulation (3.3 seconds). For the primary results discussed in the manuscript, for a given scenario and county, if 200 simulations passed with no transmission, simulations were halted. In total, over 50 million index cases were simulated for the described results. For each simulation, individual time steps were summarized and stored as daily, weekly or monthly summaries for all events of interest. Summary statistics discussed in the text were calculated from daily summaries (Appendix Table 2).

Computational Environment

All simulations were performed in R installed on Amazon Web Services® elastic cloud (EC2®) instances. Given the large number of full simulations (>50 million index cases and each simulation averaging 3.3 seconds depending on the compute instance), simulations were run in parallel over 160 cores and spread across multiple virtual machine instances. For raw model output and more model information, please see the following data repository:

https://github.com/lberylguterman/Zika_ViroImmuno/tree/gh-pages#zika_viroimmuno

Model Comparison

Although the official reporting of confirmed case counts (like all reporting of lab-confirmed cases) under-reports true incidence (i.e., many asymptomatic and symptomatic cases are never laboratory confirmed) the monthly data provided by the Ministry of Health offers an accurate assessment of the monthly fractional abundance of cases, and their relative distribution across the 8 health regions. Of note, this required an assumption that reporting rates were generally consistent across the 8 health regions, which we verified by comparing the overall contribution of positive cases per health region as reported by the Ministry of Health against the fraction of positive blood donor units that originated in each health region, as also reported by Chevalier et al. Indeed, the two matched closely with the exception of the health region of Ponce, which appeared to have a lower overall contribution of blood donor specimens than would be expected based on population size (i.e., Ponce contributed only 7% of all blood donation samples analyzed, which is considerably lower than the Ponce's overall population contribution to the Puerto Rican population, and, given the high Zika virus incidence in Ponce reported by the Ministry of Health, likely represents a reduced relative number of blood donations collected or analyzed from Ponce). Nevertheless, the similarities in the two reports, which are based on primarily orthogonal datasets suggests that the use of the Ministry of Health data to derive fractional abundance per health region is appropriate for development of a validation dataset.

We therefore coupled the monthly fractional abundance to the estimated case counts by Chevalier et al. to derive monthly incidence and case counts between April and August 12th, 2016, which was the duration over which the blood donor screening data was reported.

We used the final monthly incidence estimates from Chevalier et al, assuming a PCR detectable viremic duration of 14 days (which is the detectable duration suggested by U.S. FDA approved Zika virus assays). Note that in their manuscript, Chevalier et al provide estimates across a range of assumed durations of PCR detectable viremia – which is distinct from infectious duration. To derive monthly estimates, we took the product of the cumulative case counts on August 12th for each health region, and the fractional monthly incidence for each health region recorded from the Ministry of Health.

Model output for each county/municipality and month of index case, including county name, state, probability of transmission from the index case, median final incidence and

interquartile range, median exposures during each trimester: 1, 2 or 3. For every county or municipality there is an entry for each month of introduction of the index case, January through December. Medians are calculated across only simulations with at least a single transmission event.

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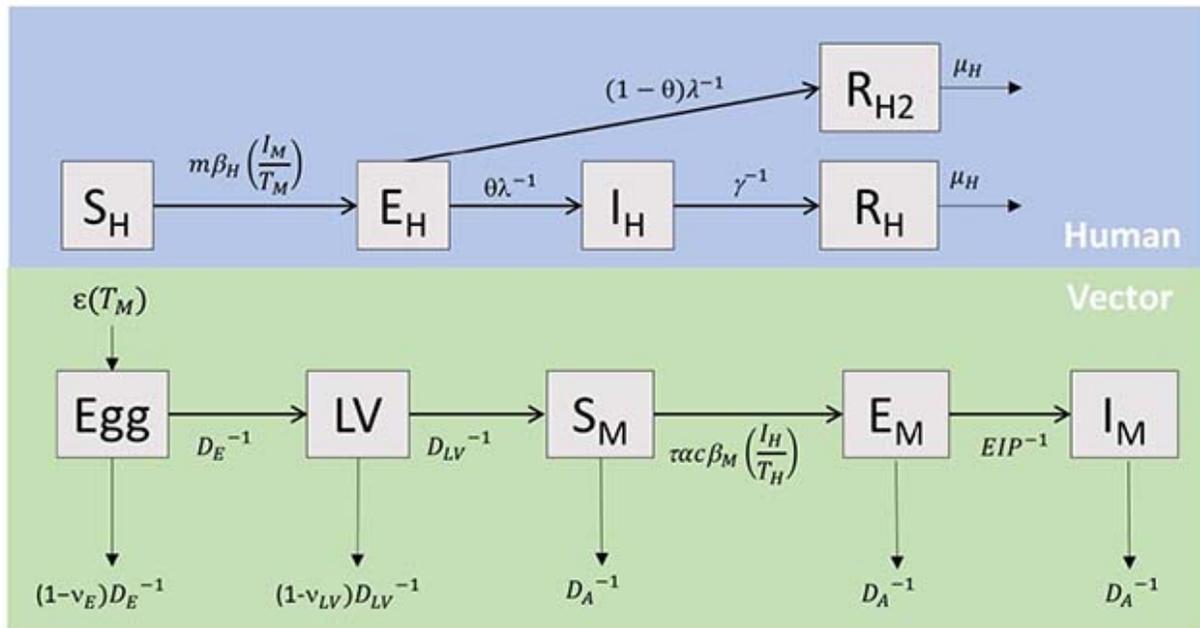
Appendix Table 1. Model parameter description and estimates

Parameter	Value	Modeled separately per <i>Aedes</i> vector
Mosquito infection and development parameters		
m : number of mosquito-human interactions (bites) per day	$f(T_M, T_H, T, \alpha, \tau, \lambda)$ see methods above	Yes
g : gonotrophic cycle (days)	$f(T)$ see methods	Yes
τ : blood meals per day per mosquito	$f(g(T))$; see methods	Yes
α : proportion of blood meals on humans	<i>Aedes aegypti</i> : 0.75 (25) <i>Aedes albopictus</i> : 0.4 (25)	Yes
β_M : probability that a bite of an infected human will infect the mosquito	0.75 (26,27)	No
EIP: extrinsic incubation period	$f(T)$ See methods above	Yes
D_A : adult <i>Aedes</i> lifespan	$f(T)$ See methods above	Yes
ϵ : mean (female) eggs laid per day per mosquito	$f(T)$	Yes

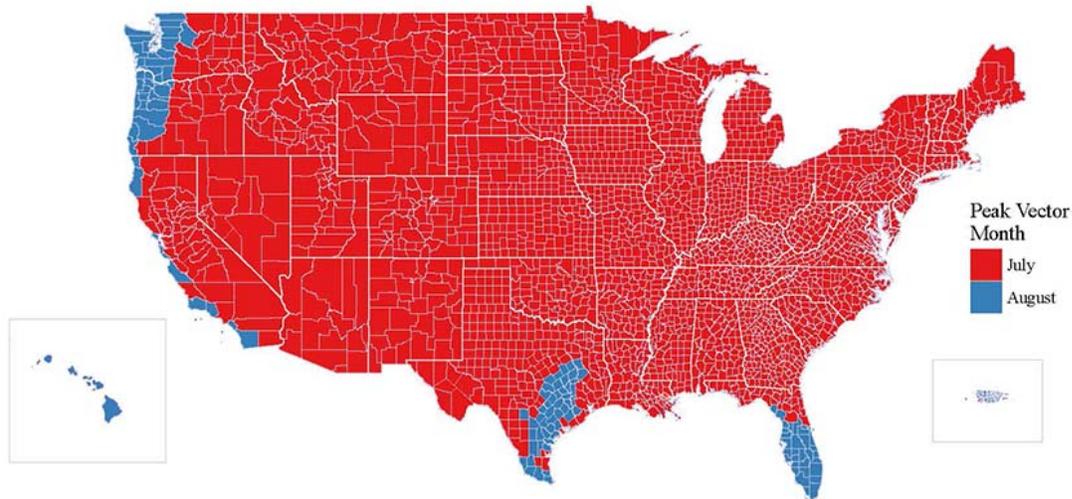
Parameter	Value	Modeled separately per <i>Aedes</i> vector
	See methods above	
v_E : egg viability	$f(T)$	Yes
	See methods above	
D_E : duration to egg hatch	$f(T)$	Yes
	See methods above	
v_{LV} : larvae/pupae viability	$f(T)$	Yes
	See methods above	
D_{LV} : duration from egg hatch to adult stage (larvae and pupae development duration)	$f(T)$	Yes
	See methods above	
Human infection parameters		
δ : average viral incubation period in humans (days)	6 (27,28)	No
γ : average duration of infectious period in humans (days)	6 (27,28)	No
θ : probability that a human who enters the exposed class will become infectious (regardless of symptomatic vs. asymptomatic state)	0.8 (Assumes a fraction of exposed individuals will not become symptomatic nor infectious (distinct from just asymptomatic). Very little information on this parameter, though sensitivity analysis demonstrated results are relatively insensitive.)	No
β_H : probability a bite of an infected mosquito will expose a human	0.75 (26,27)	No

Appendix Table 2. Model summary statistics

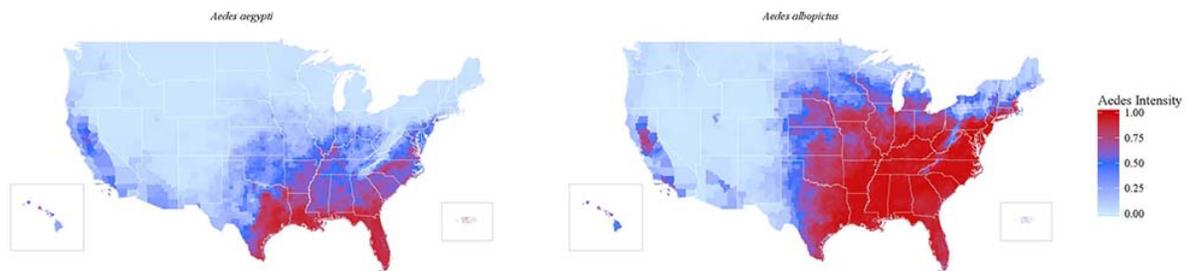
Summary statistic	Description	Figure (numerals) and panels (letters)
Initial transmission probability	The probability that an index case will result in at least a single transmission event. In other words, the fraction of simulations with at least with local transmission event.	1A, 3A, 3B, 3D, 3E, 3G, 3H
Minimal transmission	The idea of defining a county as having 'minimal transmission' is to be highly sensitive to detect places where transmission is possible (even if very unlikely). A county where 'minimal transmission' is achieved is defined as a county that had at least 1 local transmission event occur in at least 0.5% of simulations. Within a given simulation, minimal transmission was considered to be a single local transmission event.	
Proportion infected	Among those simulations where minimal transmission from index cases is achieved, the median proportion of the population infected.	1B
Infections	Among those simulations where minimal transmission from index cases is achieved, the median number infected.	1C, 1E
Incidence per 100,000	Among those simulations where minimal transmission from index cases is achieved, the median number infected per 100,000 population.	1D, 3C, 3F, 3I
Standardized prevalence (per trimester)	Among counties in the southeastern United States and Texas, county-specific prevalence of pregnancy for each respective trimester per month (see Trimester-specific pregnancies and exposure calculations) was standardized for plotting qualitative dynamics on a single scale by scaling to a mean prevalence across months of zero and standard deviation of one.	2A
Standardized incidence	Among those simulations where minimal transmission from index cases is achieved, monthly incidence was standardized for plotting qualitative dynamics on a single scale by scaling to a mean incidence across months of zero and standard deviation of one.	2A
Exposure risk ratios	The relative risk of exposure to Zika virus during the first (Figure 2, panel B) or second trimester (Figure 2, panel C) of pregnancy compared to the risk of Zika virus exposure during the third trimester of pregnancy, using data in Figure 2, panel A. This was calculated by first isolating all simulations per county with at least a minimum number of infections during pregnancy. For each simulation in each county, the total number of infections per trimester was calculated (described in the methods) and divided by the total number of pregnancies to obtain a trimester specific ZKV exposure incidence per simulation. For each county, the median trimester specific ZKV exposure incidence was calculated and the risk ratio per county was taken as the median (across simulations) trimester 1 (Figure 2, panel B) or trimester 2 (Figure 2, panel C) exposure incidence divided by the median trimester 3 exposure incidence. The distribution of these county specific risk ratios are then shown in Figures 2, panel B, C. For this analysis, to detect a seasonal signal from the stochasticity, simulations included were those with at least 25 infections during pregnancy.	2B, 2C
Median number of (simulated) infections during pregnancy	Among those simulations where minimal transmission from index cases is achieved in the southeastern United States, Texas (Figure 2, panel D) and Puerto Rico (Figure 2, panel E, F), the median number infected during pregnancy (see Trimester-specific pregnancies and exposure calculations for more details).	2D, 2E, 2F



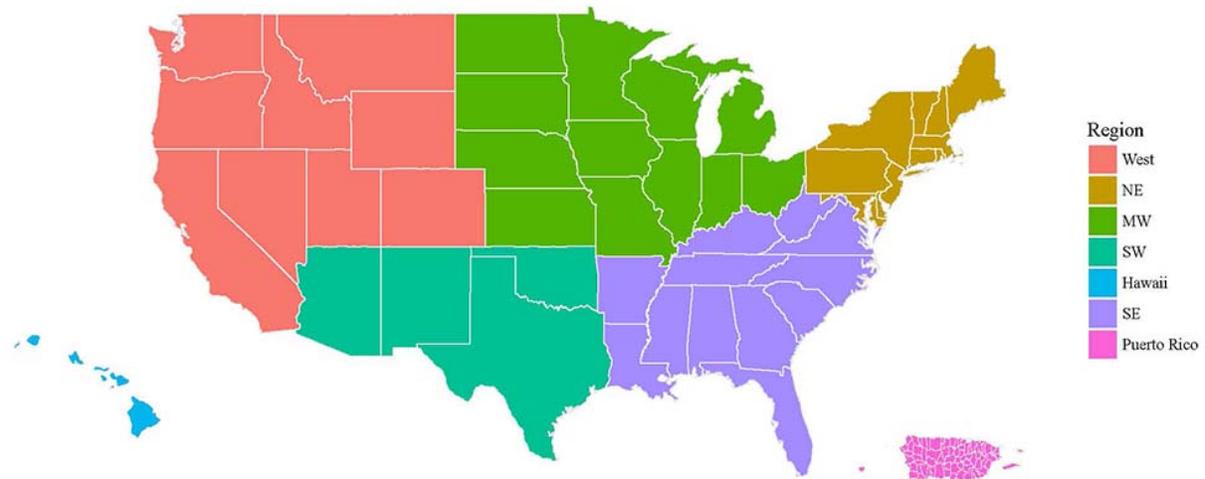
Appendix Figure 1. Compartment diagram of Zika virus transmission model. See methods for model description and definitions.



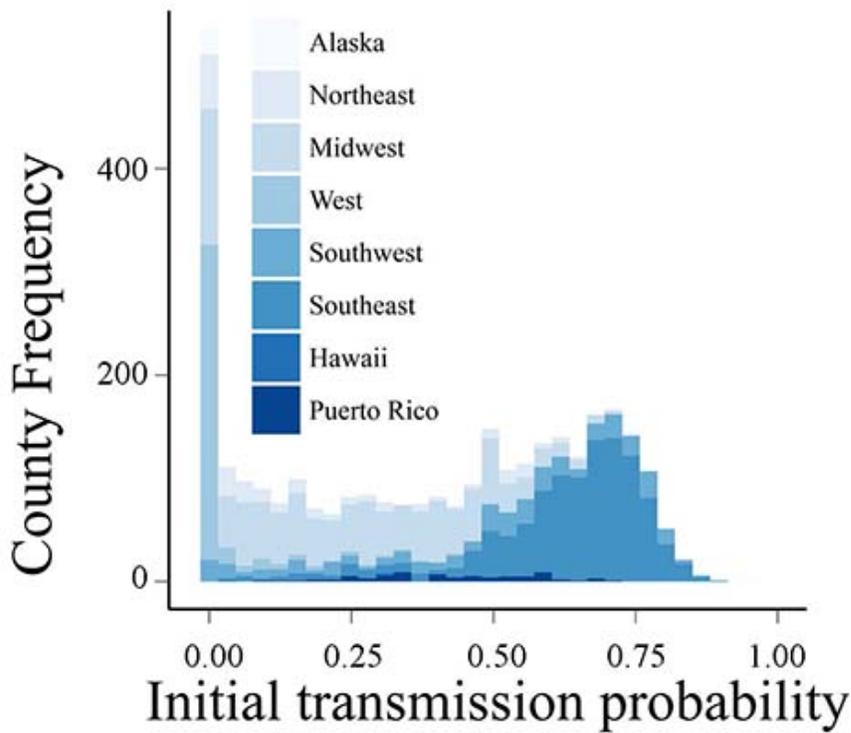
Appendix Figure 2. Month of Peak Vector Abundance. For every county in the United States, we followed *Aedes aegypti* and *Aedes albopictus* abundance in our simulations over 3 years following initialization across April - September. Although the actual abundance and fractional abundance over time differed markedly across counties and states, the peak abundance for each county was most often noted in July, with certain counties in Florida, Texas and along the west coast reaching peak abundance in August. Of note, for those counties where vectors were unable to be maintained (i.e. northern states), we initialized simulations as described in the methods for each month between April and September and calculated average mosquito abundance per month for the first year.



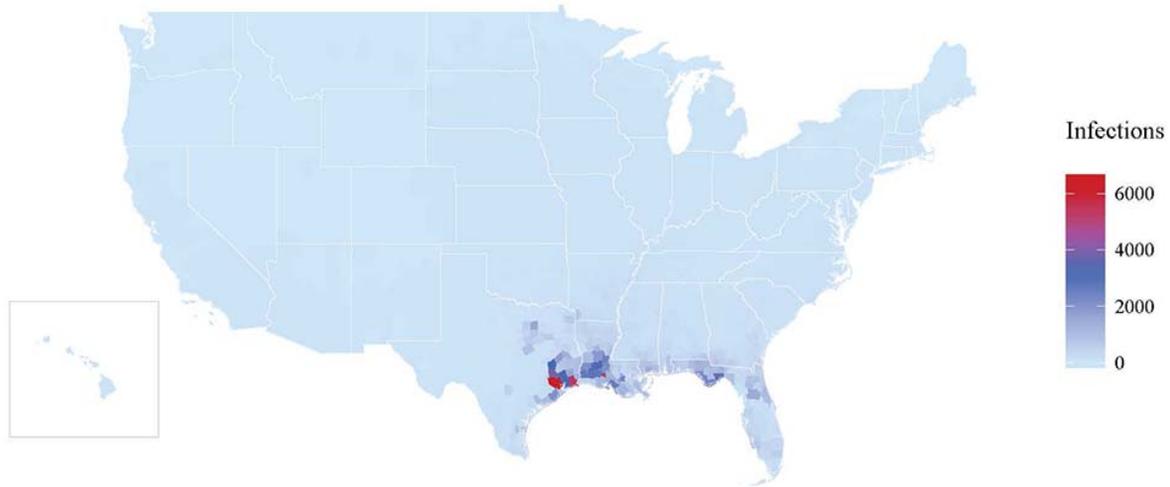
Appendix Figure 3. Predicted intensity of (A) *Aedes aegypti* and (B) *Aedes albopictus* mosquitos (developed and described from Kraemer et al. eLife. 2015;4:e08347 and adapted here per county).



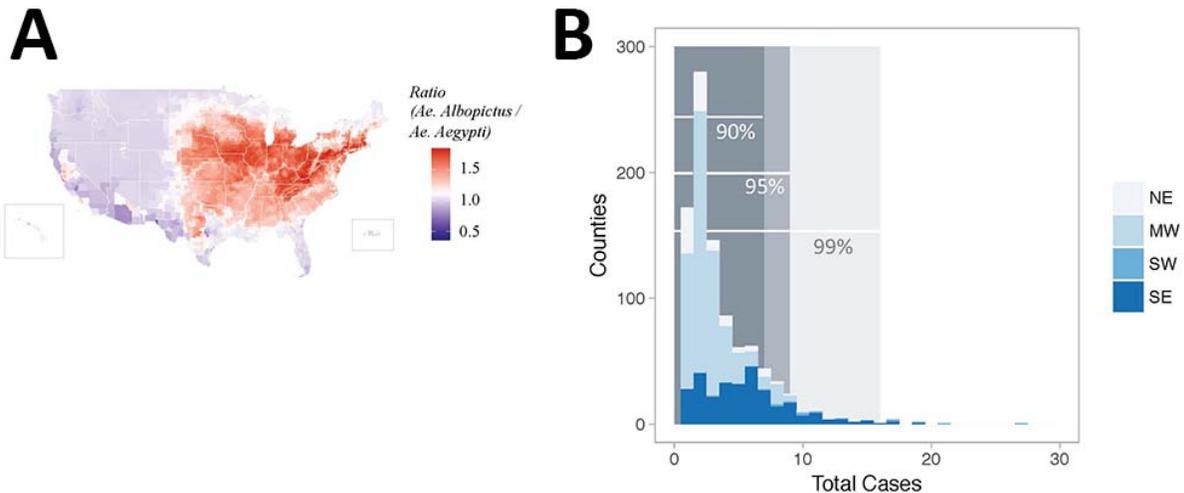
Appendix Figure 4. Regions of the United States. NE = Northeast; MW = Midwest; SW = Southwest; SE = Southeast.



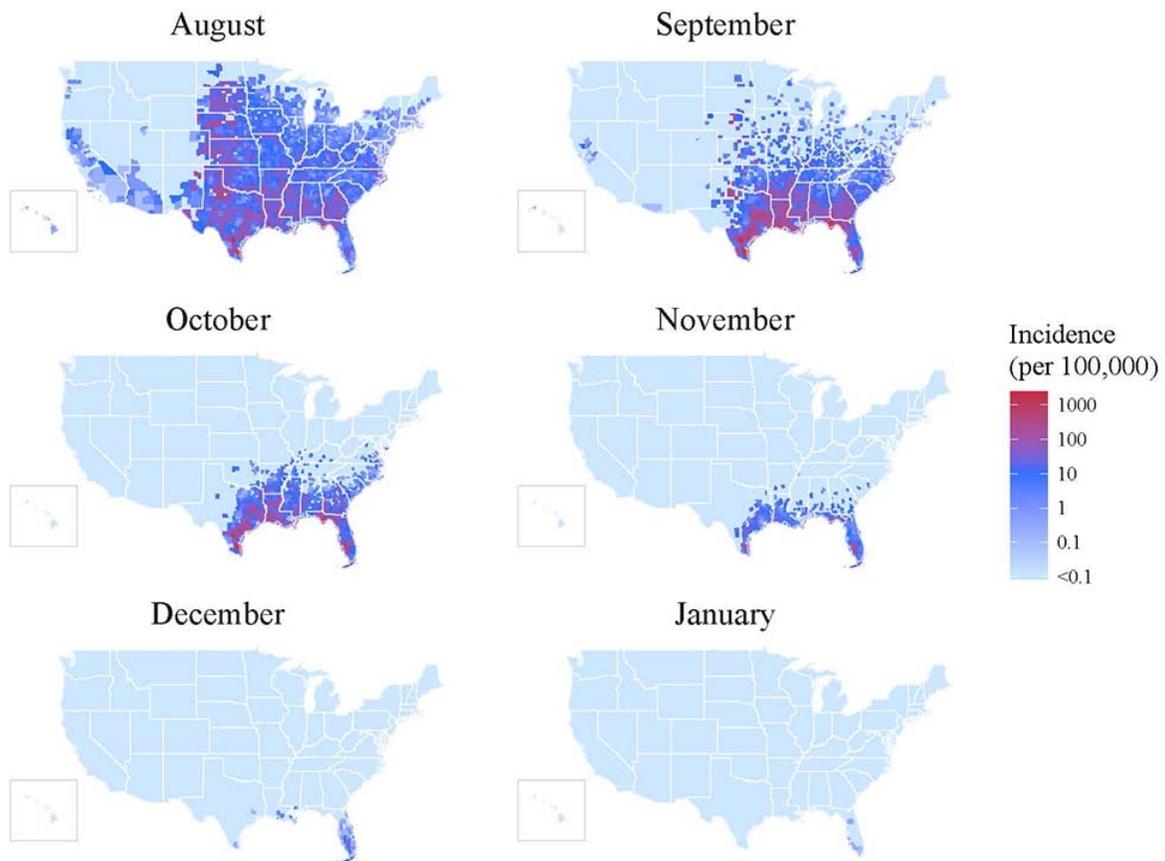
Appendix Figure 5. Probability of initial transmission from an index case introduced during peak vector abundance, calculated as the proportion of simulations with at least a single transmission event, for every county aggregated by region (see Appendix Figure 4 for regions) and displayed as a histogram with county frequency versus probability of transmission from the index case.



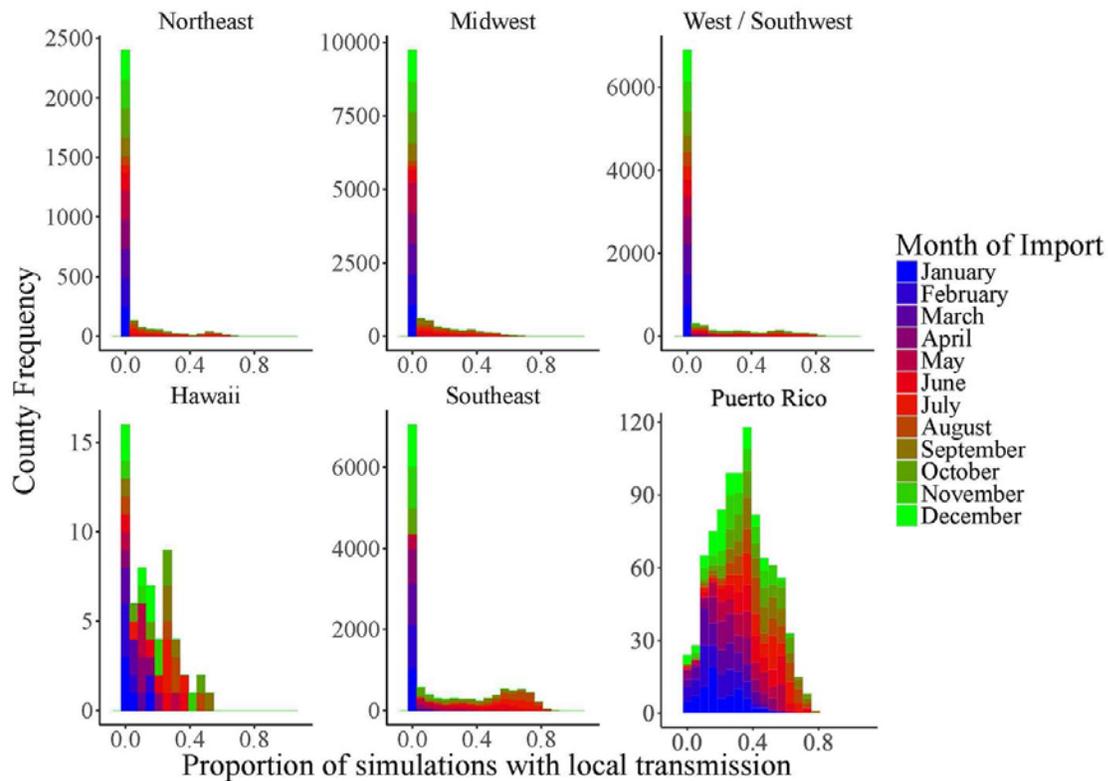
Appendix Figure 6. Total number of infections across the US states. Total number of infections (median across simulations) per county when an index case is imported during peak vector abundance in each respective county.



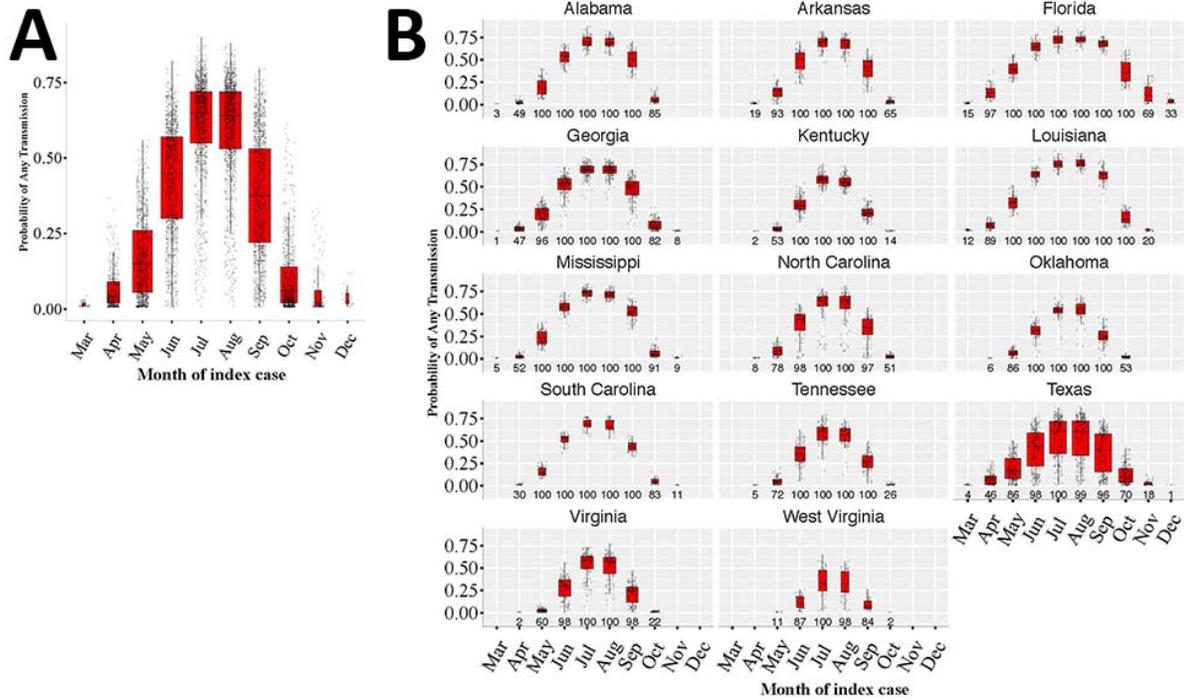
Appendix Figure 7. Total case counts where *Aedes albopictus* : *Aedes aegypti* ratio >1.5. (A) Map showing the ratio of relative *Aedes albopictus* intensity to relative *Aedes aegypti* intensity (intensities taken from Kraemer et al. (eLife 2015) as described in methods and shown in Appendix Figure 3). (B) Histogram shows that of these counties (those with a ratio >1.5), 90% (dark grey shading), 95% (medium grey), and 99% (light grey shading) have median final case counts of ≤ 7 , ≤ 9 and ≤ 16 total cases, respectively. Fewer than 1% of these counties had greater than 20 total median cases.



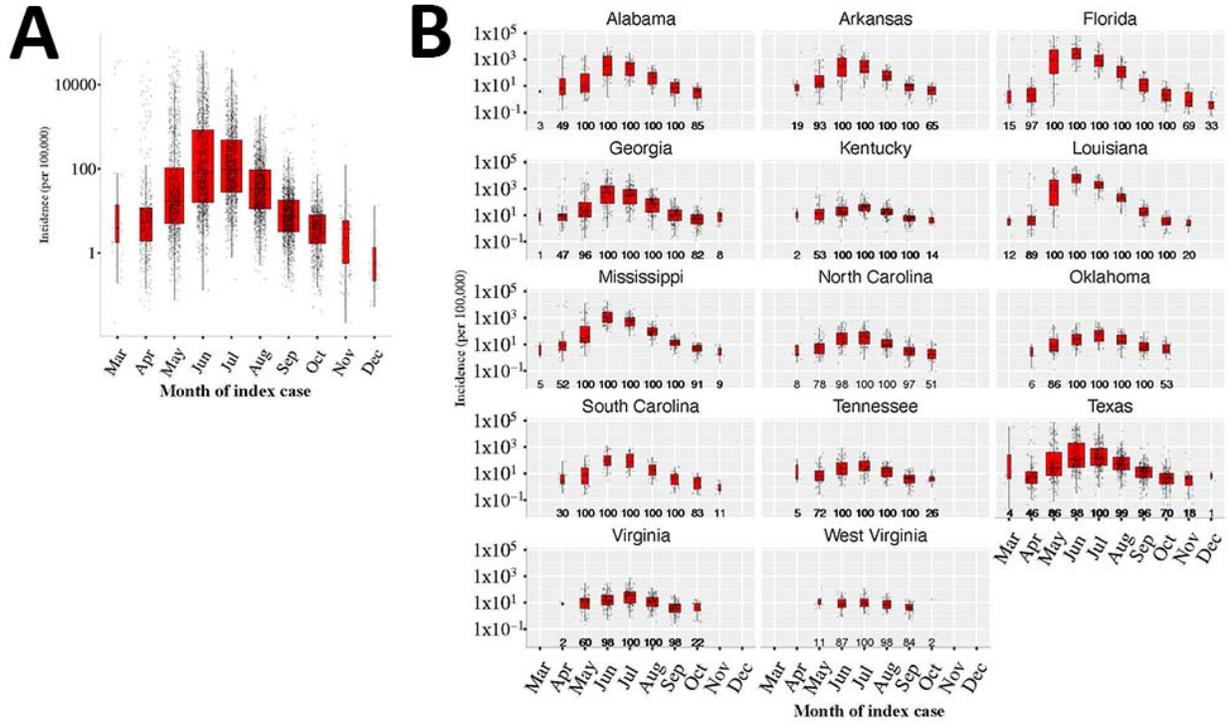
Appendix Figure 8. Monthly incidence of infections in each county following an August index case. Monthly incidence per county when an index case successfully imports into each respective county during the month of August. Incidence reported is the median incidence among simulations with at least a single transmission event.



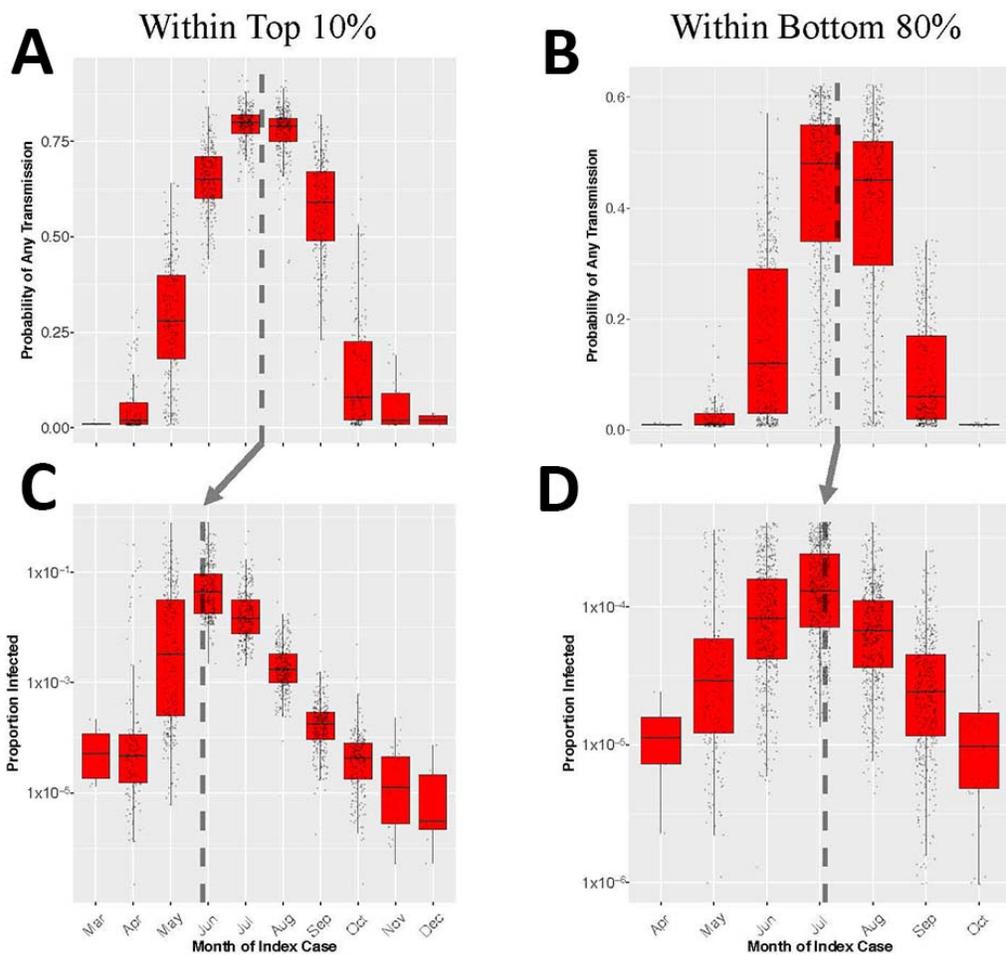
Appendix Figure 9. Probability of transmission from index cases imported across every month. Histogram showing the frequency of counties versus the probability of any transmission from the index case (calculated as the proportion of simulations for which a given county records any transmission) across different months of import. For each of the 3208 counties and municipalities, 200-500 simulations were run for every month of import. January index cases consistently recorded the lowest probability of any transmission, across all regions of the United States and Puerto Rico, while July and August consistently ranked highest for proportion of simulations resulting in any transmission away from the index case. Puerto Rico was the only region that reported initiation of transmission following index cases in every month. Note. Alaska is not reported because it never reported a single transmission event. See Appendix Figure 10 for more detailed results for counties in the southeastern United States.



Appendix Figure 10. Probability of initial transmission vs. month of import in the Southeastern United States. Probability of transmission from the index case is plotted for (A) all of the counties in the Southeastern United States and Texas and (B) each of the states individually. Each dot represents a county. Red shading indicates the interquartile range. Counties that fail to achieve at least minimal transmission (i.e. at least a single transmission event in at least 0.05% of simulations) are not plotted, and the width of IQR boxes represents the proportion of total counties included for a given month. Specifically, the width is scaled down from the baseline width in July (the only month with 100% of counties represented) by a factor equal to square root of the number of counties included. In B, the values in each column represent the proportion of counties from the respective state that achieved at least minimal transmission (i.e. the proportion of counties plotted) for a given month of import of the index case.

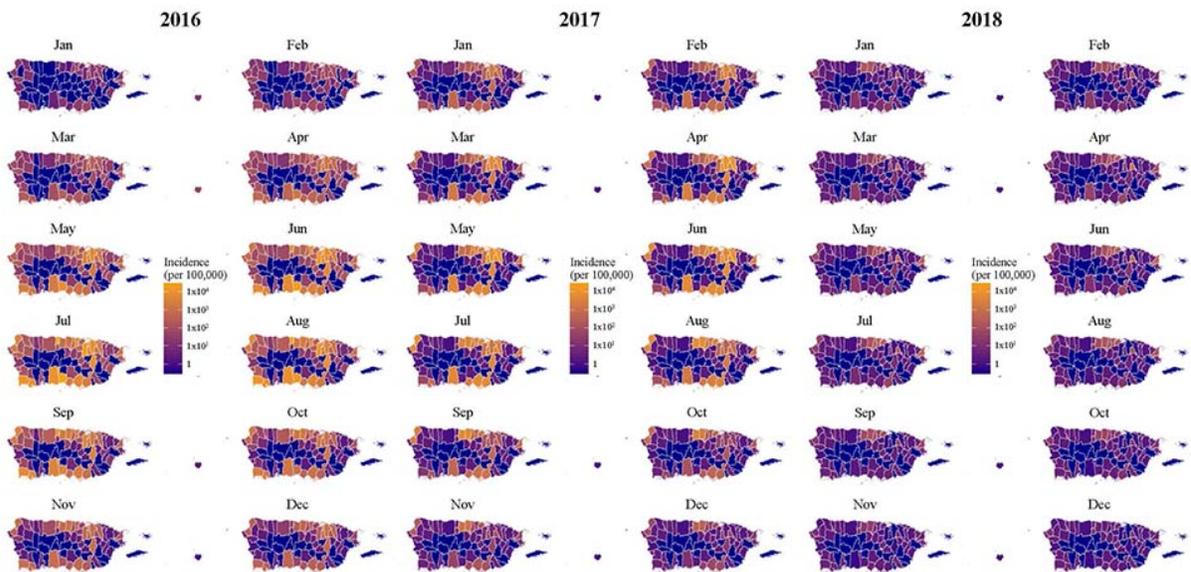


Appendix Figure 11. Incidence vs. month of import in the Southeastern United States. Incidence (median across all simulations with any transmission) of infection is plotted against month of index case for (A) all of the counties in the Southeastern United States and Texas and (B) each of the states individually. Each dot represents a county. Red shading indicates the interquartile range. Counties that fail to achieve at least minimal transmission (i.e. at least a single transmission event in at least 0.05% of simulations) are not plotted, and the width of IQR boxes represents the proportion of total counties included for a given month (as described for Appendix Figure 8). In B, the values in each column represent the proportion of counties from the respective state that achieved at least minimal transmission and are thus plotted for a given month of import. Months with no values and thus no points had no counties that achieved at least minimal transmission.

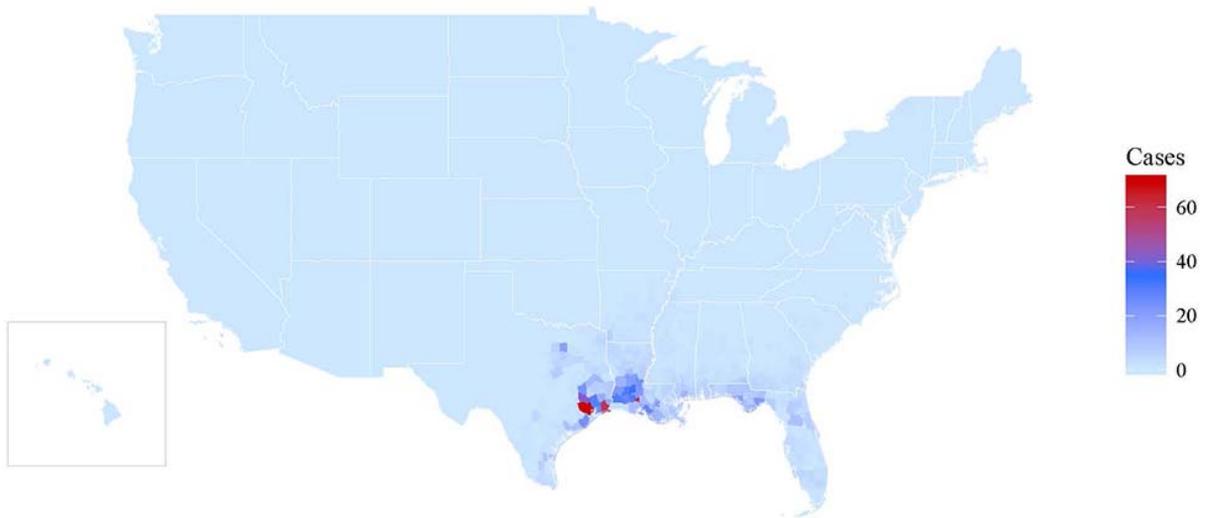


Appendix Figure 12. Probability of any Transmission from the Index case, or proportion infected, versus month of import. (A and B) Probability of at least a single transmission event from the index case (i.e. proportion of simulations with any transmission) versus month of the index case (i.e. month of import) for counties that are within the (A) top 10% or (B) bottom 80% of counties by proportion of simulations with any transmission. For each county, simulations are run separately for each month of import and, for each month of import, the probability of any transmission (i.e. proportion of simulations with at least a single transmission event from the index case) is calculated. For each county, the highest calculated probability (from across the months of import) is then used to bin counties into the top 10% or bottom 80% of counties by probability of achieving any transmission. Once binned, their probabilities of achieving any transmission are then plotted against month of Import, as shown. County-month combinations with zero simulations achieving any transmission are not plotted (as described in Fig S9). (C and D) Proportion of the county population infected, versus month of index case for counties that are within the (C) top 10% or (D) bottom 80% of counties by proportion of population infected. For each county, simulations are run separately for each month of import and, for each month of import, the median proportion of the population infected (among simulations with at least a single transmission event) is calculated. For each

county, the highest median proportion infected (from across the months of import) is then used to bin specific counties into the top 10% or bottom 80% of counties by proportion infected. Once binned, the median proportions infected are plotted for each distinct month of Import, as shown. County-month combinations with no infections are not plotted. The dotted lines represent the mean time of import that achieves the maximum transmission from the index case (A & B) or incidence (C & D). Notable is the difference in the month that maximizes incidence versus the month that maximizes probability of transmission, and that this difference is primarily apparent in the top 10% of counties for each respective metric, but not the bottom 80%, suggesting that among the bottom 80%, transmission chains are not limited by onset of winter, but rather likely die out within a short time-frame, regardless of month of import, and thus overall incidence is driven primarily by mosquito density at time of import.

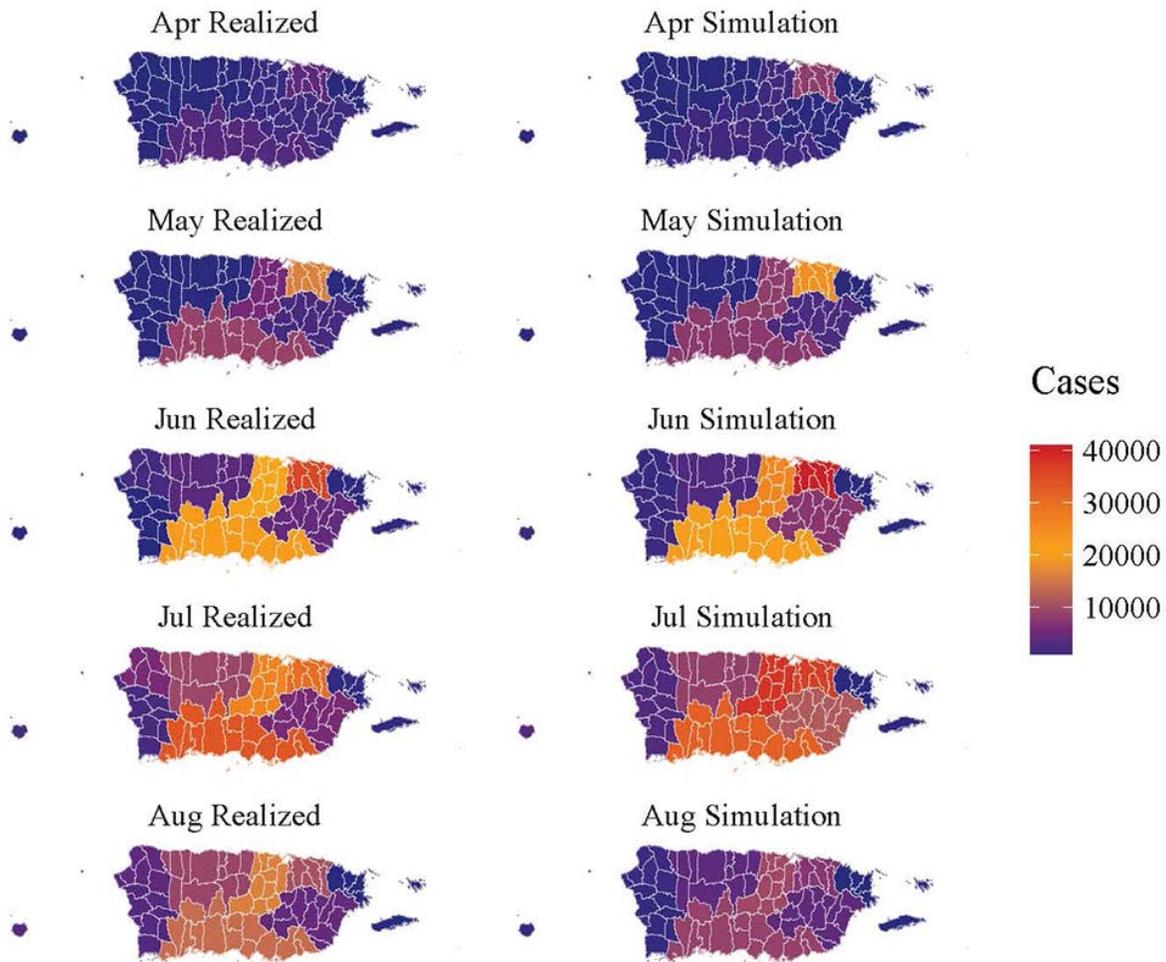


Appendix Figure 13. Monthly incidence of infections throughout Puerto Rico, in the absence of reintroductions. Incidence per month per municipality when index cases were introduced in late 2015 or early 2016 to match timing of initial cases reported in the current epidemic in Puerto Rico. Data shown, and that reported in the text, is absent of reintroductions. Therefore, once an outbreak takes off (cases >10), no reintroductions occur. In the absence of reintroductions here, most municipalities fail to sustain transmission through the winter, suggesting that sustained transmission will be driven by reintroduction events from municipalities where transmission persists uninterrupted, in particular the metropolitan centers of San Juan, Bayamón, Caguas and Ponce. Beyond the first year, these estimates likely underestimate the true state-wide incidence because reintroduction events are expected to be common due to human movement.

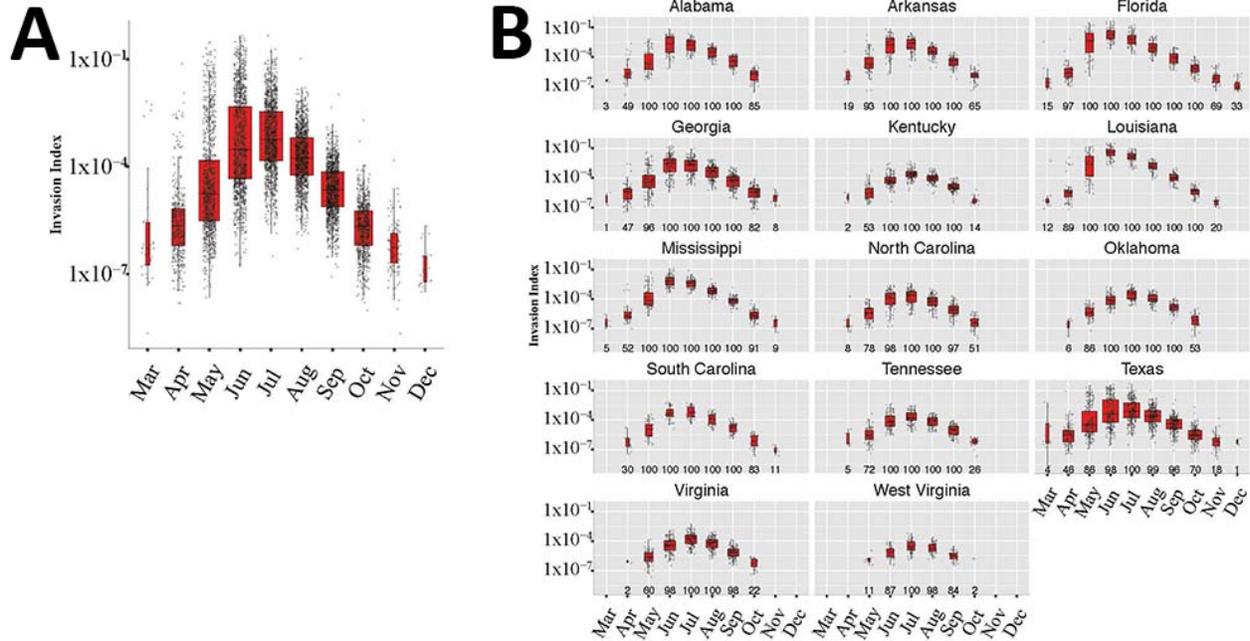


Appendix Figure 14. Zika infections during pregnancy. Total (median) number of zika infections among pregnant women following index cases imported when vectors are at peak abundance.

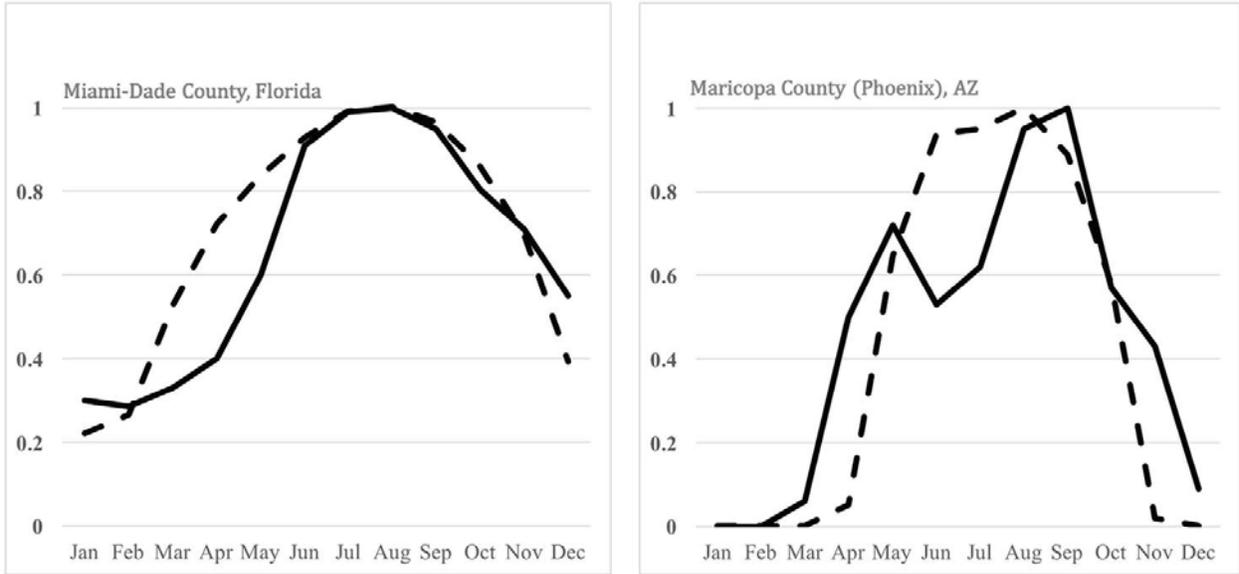
Monthly Cases per Health Region



Appendix Figure 15. Monthly numbers of infections per health region realized and simulated. In the left column. Monthly numbers of Zika exposures per health region were estimated from a combination of blood donor screening data estimates (available from April through August 12th, 2016) and surveillance data freely available from the Puerto Rican Ministry of Health (as described in methods). In the right column, simulated monthly numbers of exposures were tallied over the same duration (April – August 12th) from the median simulations for each municipality. As described in the methods and main text, simulations in each municipality were initiated (i.e. index case introduced) to align temporally with initial reported cases in each health municipality, reported and freely available by the Puerto Rican Ministry of Health. Although in our analyses reintroduction events were not generally introduced into any counties, for these particular validation studies, if a particular municipality in Puerto Rico failed to elicit at least 10 infections before the outbreak died-off, a second, or at a maximum a third reintroduction event (i.e. index case) was allowed.



Appendix Figure 16. Invasion Index vs. month of import in the Southeastern United States and Texas. The overall Invasion Index is a composite derived, for each county and each scenario (i.e. month of index case) from the product of the probability that any transmission will occur (Appendix Figure 10) and the median incidence (as the proportion of the population infected; Appendix Figure 11) when transmission does occur. It is therefore neither a measure of the probability of any transmission from the index case, nor the expected incidence, but rather represents an attempt to capture these two important metrics in a single metric to describe an overall or absolute risk for a given location. Whereas, on average, May imports led to the largest epidemics (Appendix Figure 10) and July imports were often most likely to result in transmission (Appendix Figure 9), June imports maximize the overall ‘invasion index’. Each dot represents a county. Red shading indicates the interquartile range. Counties that fail to achieve at least minimal transmission (i.e. at least a single transmission event in at least 0.05% of simulations) are not plotted, and the width of IQR boxes represents the proportion of total counties included for a given month (as described for Appendix Figure 9)



Appendix Figure 17. Example mosquito population dynamics for Miami-Dade County. In agreement with *Aedes aegypti* populations reported by Grubaugh et al (Nature 2017), *Aedes aegypti* increase above their winter baseline in March/April, peak in June – August and finally retreat to low levels again in November/December.