The social and spatial ecology of dengue presence and burden during an outbreak in Guayaquil, Ecuador, 2012

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Abstract

Background: Dengue fever, a mosquito-borne viral disease, is an ongoing public health problem in Ecuador and throughout the tropics, yet we have a limited understanding of the disease transmission dynamics in these regions. The objective of this study was to characterize the spatial dynamics and social-ecological risk factors associated with a recent dengue outbreak in Guayaquil, Ecuador.

Methods*:* We examined georeferenced dengue cases (n = 4,248) and block-level census data variables to identify potential social-ecological variables associated with the presence and burden of dengue fever in Guayaquil in 2012. We applied LISA and Moran's I tests to analyze hotspots of dengue cases and used multimodel selection in R computing language to identify covariates associated with dengue incidence at the census zone level.

Results: Significant hotspots of dengue transmission were found near the North Central and Southern portions of Guayaquil. Significant risk factors for presence of dengue included poor housing conditions (e.g., poor condition of ceiling, floors, and walls), access to paved roads, and receipt of remittances. Counterintuitive positive correlations with dengue presence were observed with several municipal services such as garbage collection and access to piped water. Risk factors for increased burden of dengue included poor housing conditions, garbage collection, receipt of remittances, and sharing a property with more than one household. Social factors such as education and household demographics were negatively correlated with increased dengue burden.

Conclusions. Findings elucidate underlying differences with dengue presence and burden and indicate the potential to develop dengue vulnerability and risk maps to inform disease prevention and control, information that is also relevant for emerging epidemics of chikungunya and zika.

Keywords: Dengue fever, geography, risk, climate, spatial, temporal, Ecuador

Background

The public health sector in Latin America is facing the alarming situation of concurrent epidemics of dengue fever, chikungunya, and zika, febrile viral diseases transmitted by the mosquito vectors *Aedes aegypti* and *Aedes albopictus* [1–4]. Traditional surveillance and vector control efforts have been unable to halt these epidemics [5]. Macro-level social-ecological factors have facilitated the global spread, co-evolution and persistence of the dengue viruses and vectors, including growing urban populations, global movement, climate variability, insecticide resistance, and resource-limited vector control programs. It is necessary to study effects of these drivers at the local level to understand the complex dynamics and drivers of disease transmission, which vary from region to region, thus allowing decision makers to more effectively intervene, predict, and respond to disease outbreaks [5].

Spatial epidemiological risk maps provide important information to target focal vector control efforts in high-risk areas, potentially increasing the effectiveness of public health interventions [6,7]. Typically, historical epidemiological records are digitized to understand the spatial distribution of the burden of disease and the presence/absence of disease. Layers of social-ecological predictors (e.g., land use maps, socioeconomic census data) are incorporated to test the hypothesis that one or more predictors are associated with the presence /absence or burden of disease. This information allows decision makers to identify geographic areas to focus interventions (e.g., hotspots) and risk factors to target in integrated vector-control interventions (e.g., community health interventions for specific vulnerable populations). Spatial risk maps can also be integrated into disease early warning systems (EWS) to generate disease risk forecasts, such as seasonal risk maps. [8–11]. Previous studies indicate that associations between social-ecological risk factors and dengue transmission may vary by location and time, highlighting the need for local analyses of dengue risk [6,12–17].

Since 2000, DENV 1-4 have co-circulated in Ecuador, presenting the greatest burden of disease in the lowland tropical coastal region [18]. Guayaquil, Ecuador, the focus of this study, is the largest city in the country and the historical epicenter of dengue transmission in the country. The first cases of autochtonous chikungunya cases were reported in Ecuador at the end of 2014, resulting in a major epidemic in 2015, with over 33,000 cases reported. The first cases of zika were confirmed in Ecuador on January 7, 2016, and to date (25 Aug 2016) 2,076 suspected cases of zika have been reported by the Ministry of Health [3].

Climate is an important source of predictability for these diseases, mainly because both the viruses and the vectors are sensitive to temperature. For example, anomalously high surface temperatures produced by a combination of natural climate variability and climate change have been suggested to have played a role in the present zika epidemic [4].

The aim of this study was to characterize the spatial dynamics of cases and demographic risk factors associated with a recent dengue epidemic (2012) in the coastal city of Guayaquil, Ecuador. This study builds on prior studies in Machala, Ecuador, that demonstrated the role of social determinants in predicting dengue risk at the household and city-levels, and contributes to a broader effort to strengthen surveillance capacities in the region in partnership with the Ministry of Health and the National Institute of Meteorology and Hydrology (INAMHI) [16,17]. This study is intended to both provide the much needed local-level social-ecological context, and to demonstrate the differences arising in inference from presence and burden of cases in these analyses.

Methods

Study Area

Dengue fever is hyper-endemic in Guayaquil, Guayas Province, a tropical coastal port city (pop. 2,350,915) [19], as well as the largest city in Ecuador (Fig. 1). There is a pronounced seasonal peak in dengue transmission from February to May, which follows the onset of the hot rainy season (Fig. 2). In 2012 there were over 4,000 cases of dengue fever (and 79 DHF) reported in Guayas province, marking the biggest dengue outbreak to date [20]. In Guayaquil, there were 4,248 clinically reported cases of dengue fever in 2012, or a disease incidence of 18.07 dengue cases per 10,000 population per year compared to an average incidence of 4.99 dengue cases per 10,000 population per year for the period of 2000 to 2011 (Fig. 3) [22].

Data Sources

Epidemiological data (dengue case reports for 2012) and national census data (2010) were examined to identify potential social-ecological variables associated with the presence and burden of dengue fever during the 2012 outbreak in Guayaquil, Ecuador. Epidemiological data were provided by INAMHI through a collaborative project with the Ministry of Health that was sponsored by the Ecuadorian government [21]. No formal ethical review was required as the data used in this analysis were de-identified and aggregated to the census zone level, as described in the following.

Epidemiological data. For the analyses presented here, INAMHI provided a map of georeferenced dengue cases from Guayaquil in 2012 (n = 4,248), de-identified and aggregated to census zone polygons to protect the identify of individuals [22]. This map was generated from individual records of clinically suspected and confirmed cases of dengue fever and DHF (aggregated as total dengue fever) reported to a mandatory disease surveillance system operated by the Ministry of Health, and included 15.03% of total dengue cases confirmed by the Ministry of Health in Ecuador for 2012 (n= 16,544) [23]. Dengue cases included in this study were defined based on clinical diagnosis rather than laboratory confirmed cases due to the low rate of laboratory confirmation.

Social-ecological risk factors. We extracted individual and household-level data from the 2010 Ecuadorian National Census [19] to test the hypothesis that social-ecological variables were associated with the presence and burden of dengue (Table 1). We selected variables that have been previously described and used in similar epidemiological studies [17]. We created a normalized housing condition index (0 to 1, where 1 is the worst) by combining three housing variables: the condition of the roof, condition of the walls, and condition of the floors. Using individual and household census records, we recoded selected census variables and calculated parameters as the percent of households or percent of the population per census zone (n = 484).

Climate data. INAMHI provided rainfall and 2-meter temperature station data at monthly scale for the period 1981-2012. The long-term means were computed for both variables, and monthly values for the year 2012 were compared with those climatological values (Fig. 2). A complementary analysis was performed to understand the behavior of these two variables during 2012, using sea-surface temperature fields from both the Pacific and the Atlantic Oceans (ERSST version 4, [24], and vertically integrated moisture fluxes computed using the NCEP-NCAR Reanalysis Project version 2 [25].

Statistical Analyses

Spatial analyses. We applied Moran's I with inverse distance weighting (ArcMap 10.3.1) to disease rates derived from epidemiological dengue case and population census data to test the hypothesis that dengue cases were non-randomly distributed in space. Moran's I is a global measure of spatial autocorrelation, that provides an index of dispersion from -1 to +1, where -1 is dispersed, 0 is random, and +1 is clustered. We identified the locations of significant dengue hot and cold spots using Anselin Local Moran's I with inverse distance weighting (ArcMap 10.3.1). The Local Moran's I is a local measure of spatial association (LISA) [26] and identifies significant clusters (hot or cold spots) and outliers (e.g., nonrandom groups of neighborhoods with above or below the expected dengue prevalence). Previous studies have used global Moran's I and LISA statistics to test the spatial distribution of dengue transmission [27], including in Ecuador [6], allowing for comparison between studies.

Social-ecological risk factors. Individual and household level census data were examined to identify potential social-ecological variables associated with the presence and burden of dengue fever, including population density, human demographic characteristics, and housing condition (Table 1). We hypothesized that the presence or absence of dengue and the severity of the outbreak were associated with one or more of these factors. Each factor was presented as a suite of census variables, representing testable variable ensemble hypotheses in a model selection framework.

Two model searches were performed using 'glmulti', an R package for multimodel selection [28]. The first search was to determine which census factors were influencing the presence or absence of dengue in Guayaquil, specifying a logistic modeling distribution in a Generalized Linear Model (GLM) framework (GLM, family=binomial, link=logit). The second model search examined which census factors were influencing outbreak severity, defined as the localized concentration of dengue, by using dengue case counts per census zone offset by local population as the dependent variable (GLM, family=negative binomial). Model searches were run until convergence using glmulti's genetic algorithm (GA) [28]. Generated models were tested and ranked based on Akaike's Information Criterion (AIC) corrected for small sample size (AICc).

$$AIC = 2k - 2\ln(L)$$

$$AICc = AIC + \frac{2k(k+1)}{n-k-1}$$

Where k is the number of parameters in the model, n is the sample size, and L is the maximized likelihood function for the model. The top ranked model for each search was compared to its respective global model, which included all proposed variables as model parameters [29]. Parameter estimates and 95% confidence intervals (CI) were calculated for variables in the top ranked model from each search. Variance inflation factors (VIF) were calculated to assess multi-collinearity and model dispersion.

Results

Spatial dynamics. Dengue incidence in census zones ranged from 0 cases (n = 88 zones) to 160 cases per 10,000 population (n = 1 zone) (Fig. 4). Dengue cases during the epidemic were significantly clustered (Moran's I = 0.066, $p < 0.05$). Findings from the LISA analysis indicated that there were significant dengue hotspots (n = 30 high-high census zones) in the North Central and Southern areas of the city, and a smaller number of significant outliers (n = 3 high-low neighborhood, n = 7 low-high neighborhoods) ($p < 0.05$, Fig. 4).

Social-ecological risk factors. The most important risk factors associated with the presence of cases of dengue fever were poor housing conditions (e.g., poor structural condition of the floor, roof, and walls) and the proportion of households that received remittances. Other significant risk factors positively associated with the presence of dengue included greater access to municipal services (sewerage, piped water, garbage collection), fewer households that drink tap water, and lower proportion of Afro-Ecuadorians in the local population (Table 2). Ten additional models were found within 2 AICc units of the top model (Supplemental Table 1).

Poor housing condition was also the most important risk factor associated with the severity of localized dengue outbreaks in Guayaquil. Other factors positively associated with the number of dengue cases per census zone included lower proportion of heads of household with postsecondary and primary education, lower proportion of Afro-Ecuadorians in the population, lower proportion of household members under 15 years of age, older age of the heads of household, greater access to municipal garbage collection, a greater proportion of housing structures with more than one household, and a greater proportion of families receiving remittances (Table 3). Twenty-nine additional models were found within 2 AICc units of the top model (Supplemental Table 2).

Results from the VIF analysis showed that 17 of the 23 tested variables had VIF scores under 10, indicating a fair degree of collinearity among certain predictors within census categories (e.g. measures of education and household age structure showed some correlation) Collinear variables were included in the multimodel searches as the main concern with inflated VIF scores is large error terms, not the coefficient estimates. Collinear variable suites were shown to be significant in many top models even with conservative model search criteria in place.

Climate analysis. The 2012 outbreak occurred toward the end of a weak La Niña event (2011/2012), with a peak of reported dengue cases around March, just after the precipitation peak of February brought anomalously high rainfall (approximately twice as much as the typical values for Guayaquil), and concurrent with an increase in temperatures from below-normal to normal seasonal values (Fig. 2). Although identified as a weak La Niña due to the behavior of the sea-surface temperature anomalies in the Equatorial Pacific (see Supplemental Figure 1, “climate”a,c,d), anomalously high moisture fluxes continuously arrived to coastal Ecuador from the Pacific during January and March (see Supplemental Figure “climate”b,d,e), providing suitable conditions for the above-normal rainfall amounts observed during the season in Guayaquil.

Discussion

Since the 1980s, febrile illnesses transmitted by *Aedes aegypti* and *Aedes albopictus* (dengue fever, chikungunya, zika fever) have been increasing in incidence and distribution despite ongoing vector control interventions [2,10,30]. Targeted interventions and new surveillance strategies are urgently needed to halt the spread of these diseases. The results of this study highlight the need to differentiate between disease burden and presence when developing risk maps, providing an important contribution to our understanding of the spatial dynamics of dengue transmission. This study also provides an important local-level characterization of transmission dynamics, which are complicated by the non-stationary relationships among apparent dengue infection, climate, vector, and virus strain dynamics [31–33]; and the geographic and temporal variation in the social-ecological conditions that influence risk [12–15].

In this study, we found that city neighborhoods with certain social-ecological conditions were more likely to report dengue cases during the 2012 outbreak in Guayaquil. Dengue cases were clustered in neighborhood-level transmission hotspots near the North Central and Southern portions of the city during the outbreak. The most important risk factors for both presence and increased burden of dengue outbreak included poor housing condition and the proportion of households receiving remittances.

This study contributes to ongoing efforts by INAMHI and the Ministry of Health of Ecuador to develop a dengue prediction models, early warning systems, and other climate services in coastal Ecuador. The results of this study will inform the development of dengue vulnerability maps and data-driven dengue seasonal forecasts that provide the Ministry of Health with information to target high-risk regions, allowing for more efficient use of scarce resources [8].

Spatial dynamics

During the 2012 outbreak, dengue transmission was focused in hotspots in the North Central and Southern areas of the city, where land use is a mix of densely populated urban neighborhoods, industrial lots, and parks. Although they have access to basic services, previous work suggests that communities in the urban periphery in coastal Ecuador have limited social organization and interaction with local authorities [5]. Vector control in these areas consists of larvicidal products distributed by public health workers, but these products must be applied by individual households. Although there has been no formal evaluation of public mosquito abatement, health workers have indicated that homeowners do not use provided larvicides (M Borbor-Cordova, *pers comm.*). It should be noted that these census data do not capture the quality of the access to services, for example, the frequency of interruptions in the piped water supply or the frequency of garbage collection, which have a direct effect on mosquito breeding sites. Many previous studies that used spatial clustering statistics also found evidence of significant clustering of dengue transmission across the urban landscape [12,34–36] A previous study in Guayaquil, Ecuador, also identified neighborhood-level dengue hot and coldspots, and found that the location of hotspots shifted over a 5-year period, highlighting the importance of continued spatial surveillance [6,7]. Longitudinal dengue field studies in Thailand found evidence of fine-scale spatial and temporal clustering of dengue virus serotypes and transmission at the school and household levels [37,38]. Focal transmission patterns may be associated with the limited flight range of the *Ae. aegypti* mosquito. Human movement patterns may also play a role in determining spatial transmission dynamics in urban environments, as demonstrated by recent studies of dengue in Peru [39,40]. We suggest that a combination of linked vector flight range, combined with intra-urban human movement, may lead to moderate hotspot patterns, while enabling broad spread of dengue.

Open access tools are especially important in resource-limited settings, and analysis packages targeted to dengue are becoming available [41]. Web-based GIS tools have been developed for global dengue surveillance, such as the CDC's DengueMap, and for local dengue surveillance research projects [51,52]. National-level dengue GIS initiatives have been developed in countries such as Mexico, where Ministry of Health practitioners and software developers jointly designed the software platform. This technology would help public health decision makers to assess intervention programs and allocate resources more efficiently, and ultimately providing the foundation for an operational dengue EWS.

Social-ecological risk factors

We found that poor housing condition was the most important risk factor for dengue transmission, influencing both the presence of dengue cases and the localized burden of the outbreak. Dengue was more likely to be present in a census zone when housing structures (i.e. roofs, walls, and floors) were in poor condition, access to paved roads was limited, and the proportion of houses receiving remittances was high. The risk factors for higher dengue burden were poor housing condition, proportion of houses receiving remittances, and the number of dwellings housing more than one family. These results suggest that accessibility of households to mosquitoes via structural deficiencies, as well as the overall socioeconomic status of neighborhoods, played a role in the 2012 outbreak (Fig. 6). Although the link between poverty and dengue transmission is not well characterized, the relationship between poor housing structure and arbovirus transmission has been well documented [42–45]. Following the economic crisis in the late 1990s, many Ecuadorians immigrated to the U.S., Spain, and other countries in Europe for work, resulting in fragmented households and communities. The role of immigration in urban dengue control and prevention should be explored further [46–48].

When modeling for the presence of dengue, all top models included access to core municipal services such as garbage collection, sewage, access to piped water, and number of houses drinking tap water as positive predictors of dengue cases (Table 2, Supplement 1). Municipal garbage collection was also positively correlated with dengue burden in all top models (Table 3, Supplement 2). Previous studies in smaller communities have observed positive correlations between lack of services and dengue transmission, as poor sanitation and water storing habits in urban areas are well-documented for providing habitat for larval *Aedes* mosquitoes [16,17]. Although municipal services are known to reduce the amount of larval mosquito habitat, there is some evidence to suggest that heavily urbanized areas, like Guayaquil, provide ample habitat regardless of service availability [42]. Municipal services in Guayaquil are spatially heterogeneous, but in general services are more widely available in densely populated areas of the city (Fig. 5). However, it is important to note that access to service does not necessarily serve as an indicator for quality or frequency of services. Several studies have identified the interaction between local *Aedes* production and human population density as a key factor in triggering dengue outbreak events [12,49–51]. The observed counterintuitive findings may indicate that although access to service should reduce the amount of available habitat for larval mosquitoes, human population density and quality of service may play a larger role in urban transmission of dengue.

Several demographic characteristics were found to be negatively correlated with dengue burden, i.e. age structure of households and access to primary and secondary education. Education, specifically knowledge about dengue, has been shown to influence the prevention practices of households and elimination of mosquito breeding sites [52]. Previous work in Machala, Ecuador, also revealed that household-level risk factors and perceptions of dengue risks vary with social and economic structures between communities [5]. The proportion of Afro-Ecuadorians per census zone was associated with both lower dengue presence and burden, indicating the possibility of cultural and racial differences influencing localized transmission, or disproportionate case reporting.

Our findings support previous findings of household risk factors for *Ae. aegypti* rather than dengue cases in Machala, where it was found that poor housing condition and access to piped water inside the home were positively associated with the presence of *Ae. aegypti* pupae [16]. Interestingly, the same risk factors in this study and the prior study emerged despite differences in rainfall (i.e., the field study was conducted 1 year after the epidemic, during a drier than average year) and differences in spatial scale (i.e., household versus neighborhood level). These studies suggest that high risk households could be identified and targeted using a locally adapted rapid survey of housing conditions, similar to the Premise Condition Index, an aggregate index measuring house condition, patio condition, and patio shade, which has been validated in other countries [53,54]. In addition, the housing condition index and the combined housing condition-water access variables that we developed for this study should be explored and validated as dengue predictors in future studies in this region.

The model selection framework used in this study is an effective strategy for exploratory studies to capture a large number of complex social-ecological processes. In contrast to traditional frequentist statistical approaches, a model selection approach enabled us to test multiple hypotheses simultaneously and identify potentially important variables for inclusion, not limited to significant variables determined by arbitrary p values. Information theoretic or likelihood modeling approaches allow the modeler, who has *a priori* knowledge of the system, to make explicit informed decisions about which variables to include in testing in the model, and explore multiple compatible hypotheses rather than being limited to testing and excluding individual competing hypotheses. Additionally, the genetic algorithm (GA) in the R package 'glmulti', which explores subsets of all possible models, is a more robust model selection procedure than stepwise regression techniques, which can lead to biased estimates [28].

Guayaquil is a large, heterogeneous urban area, and there may be reporting bias of dengue cases especially in less populated areas with reduced access to medical care. However, reporting bias may not be as profound in Guayaquil as in other less-developed coastal cities in Ecuador. While the number of reported dengue cases was highest in densely populated census zones, cases were consistently reported throughout most of the city (Figure 3). Previous studies have shown that there is spatial and temporal variation in dengue hotspots within Guayaquil [6,7]. With multiple years of data at finer timescales, we could evaluate whether dengue transmission at the beginning of the dengue season or at the beginning of an epidemic is more likely to begin in neighborhoods with similar characteristics, to assess whether there are persistent high-risk, hotspot communities that trigger outbreaks. The analyses were limited by a lack of laboratory confirmation for cases or information about the immune status or nutritional/health status of the population. Efforts are ongoing to improve dengue diagnostic infrastructure in the region and to reduce the time lag between epidemiological reporting and vector control interventions.

Climate analysis

Rainfall excess in 2012 produced moisture-saturated soils, formation of ponds of different sizes, water accumulation in a variety of container, and other suitable conditions for vector proliferation. The transition to higher temperatures between February (rainfall maximum) and March is hypothesized here to have also contributed to the outbreak; for an analysis of similar conditions for a dengue outbreak in Machala [15]. We note that the fact that it was not a strong La Niña positively contributed to the occurrence of the dengue epidemic that year, as that case tends to be associated with a higher number of rainfall extreme events in the region, and thus more runoff and a harder environment for mosquito breeding.

Conclusions

Our findings highlight the importance of incorporating spatial and social-ecological information with georeferenced and clinically validated epidemiological data in a dengue surveillance system. We found spatial clustering of dengue cases within Guayaquil, and demonstrated that the presence and burden of dengue varied between census zones with social-ecological factors.

Abbreviations

AIC, Akaike's Information Criterion; AICc, Akaike's Information Criterion corrected for small sample size; CDC, Centers for Disease Control; CI, confidence intervals; DENV, dengue virus; DHF, dengue hemorrhagic fever; EWS, early warning systems; GA, genetic algorithm; GIS, geographic information system; GLM, Generalized Linear Model; INAMHI, National Institute of Meteorology and Hydrology; LISA, local indicators of spatial association; NCEP-NCAR, National Center for Environmental Protection – National Center for Atmospheric Research; VIF, variance inflation factors

Declarations

Ethics Approval: No formal ethical review was required as the data provided from INAMHI used in this analysis were de-identified and aggregated to the census zone level as described in the methodology.

Data Availability: The data that support the findings of this study were made available through the Ecuadorian Ministry of Health and INAMHI, but restrictions apply to the availability of these data which were used in partnership for the current study. As such these data are not publicly available. Data are however available from the authors upon reasonable request and with permission of INAHMI.

Competing interests: The authors declare that they have no competing interests.

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Authors’ contributions: AMSI, AGM, MJB, and RM conceived of the investigation. KR compiled the data used in analyses. AMSI, AGM, CAL, and SJR conducted analyses and drafted the manuscript. All co-authors assisted with interpretation of the data, providing feedback for this manuscript. All authors read and approved the final manuscript.

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Figures and Tables

Figure 1. The study site, Guayaquil, is located within Guayas province in coastal Ecuador.

Figure 2. Climate trends in Guayaquil, Ecuador. The bold line shows the average temperature and rainfall from 2000 – 2012 in comparison with monthly average temperature for 2012 (dashed line). The red bars show monthly totals of confirmed dengue cases from 2012.

Figure 3. Total number of clinically diagnosed cases of dengue fever in Guayaquil, Ecuador (2000 – 2012) (A). Cases during the 2012 outbreak were reported throughout the city's census zones (B).

Figure 4. LISA analysis for the 2012 Guayaquil outbreak. Cases of dengue were significantly clustered in the North Central and Southern areas of the city.

Figure 5. Population density (people per km^2) of census zones in Guayaquil (A) shown against the proportion of homes lacking municipal garbage collection (B), lacking municipal sewage (C), and lacking piped water (D). Although dengue cases were reported in both densely and sparsely populated census zones, dengue hot spots were more associated with higher density zones (Fig. 3), and the proportion of homes that lack basic municipal services tends to be higher in zones with lower population density. This may account for the counterintuitive model estimates associated with lack of these services (Tables 2 & 3).

Figure 6. Conceptual diagrams highlighting the census variable suites that significantly affected dengue presence (A) and dengue burden (B) in Guayaquil, Ecuador during the 2012 outbreak.

Table 1. Socio-ecological parameters tested in logistic regression and negative binomial model searches to respectively predict presence of dengue and severity of outbreak.

Table 2. Top logistic regression model used in determining which social-ecological factors are important to dengue presence.

Table 3. Top negative binomial model used in determining which social-ecological factors are important to dengue burden.

Supplemental Figure 1. Sea-surface temperature anomalies (contours (°C)) and surface-level winds (vectors (m/s)) (panels a, c, e); vertically-integrated moisture flux anomalies (g/kg m/s) over Ecuador (panels b,d,f), during January, February and March 2012 (top, middle and bottom rows, respectively). Red dot indicates location of Guayaquil.

Supplemental Table 1. All logistic regression models for presence or absence of dengue cases ≤ 2 AICc units.

Supplemental Table 2. All negative binomial regression models for burden of dengue cases ≤ 2 AICc units.

467 **Figure 1.**

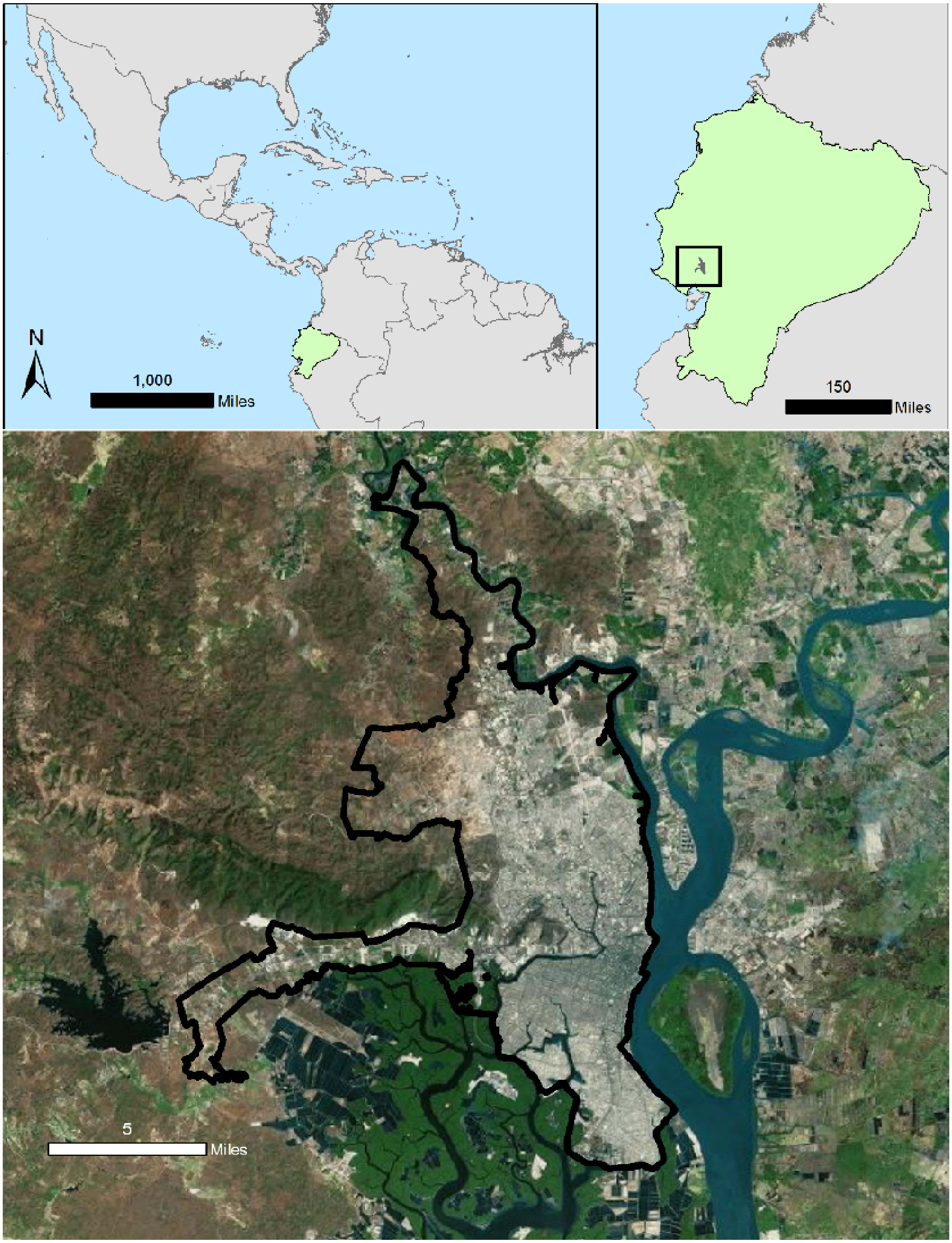

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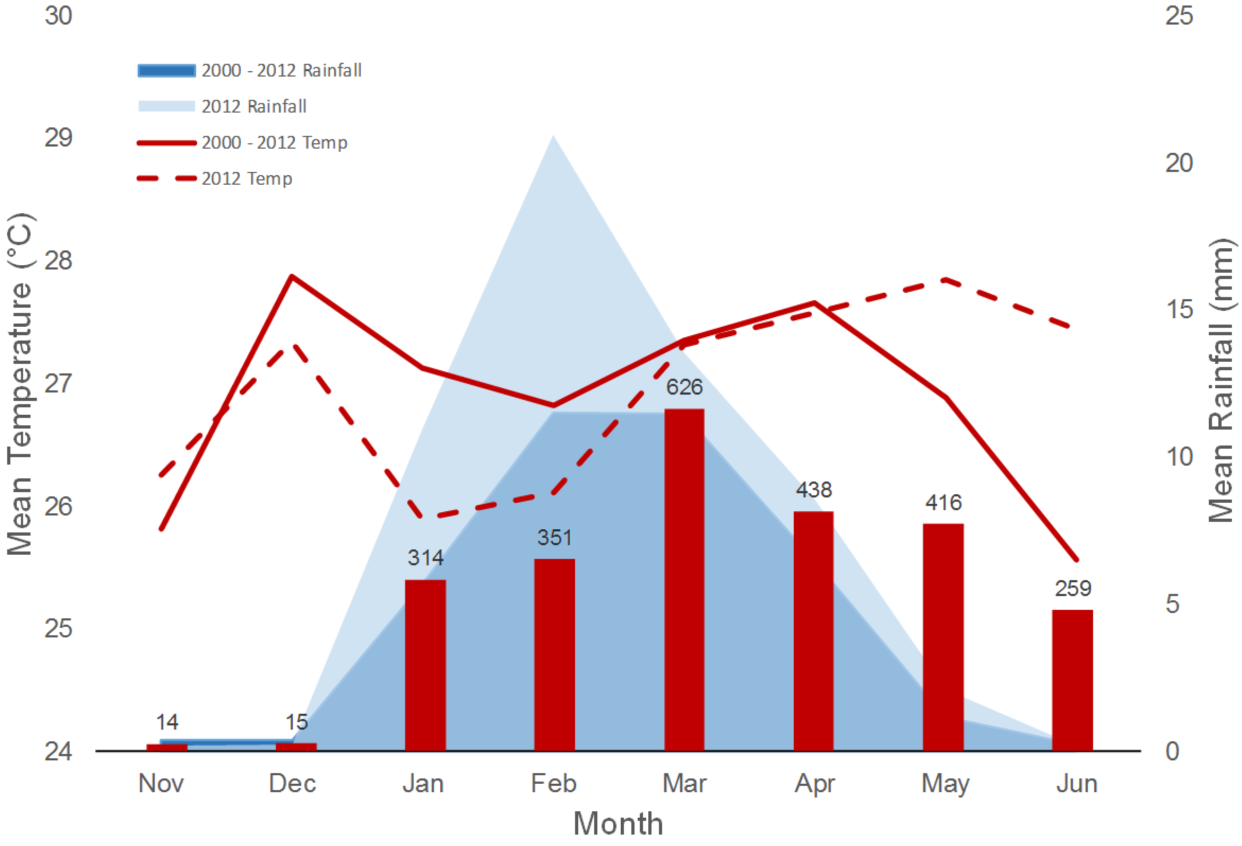
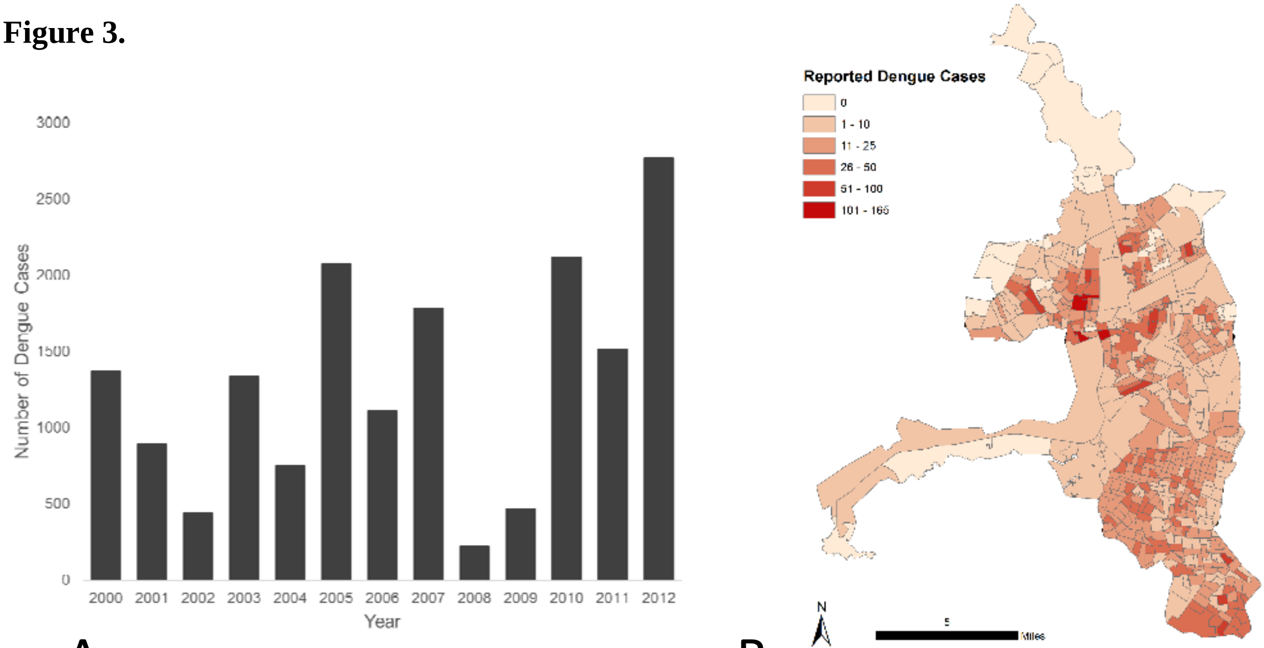
Figure 2.



2000 - 2012 Rainfall
2012 Rainfall
2000 - 2012 Temp
2012 Temp
Mean Temperature (°C)
30
29
28
27
26
25
24
Mean Rainfall (mm)
25
20
15
10
5
0
14
15
314
351
626
438
416
259
Nov
Dec
Jan
Feb
Mar
Apr
May
Jun
Month

Figure 3.


3000
2500
2000
1500
1000
500
0
Number of Dengue Cases
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
Year
Reported Dengue Cases
0
1 - 10
11 - 25
26 - 50
51 - 100
101 - 165
N
5
Miles

A. B.

Figure 4.

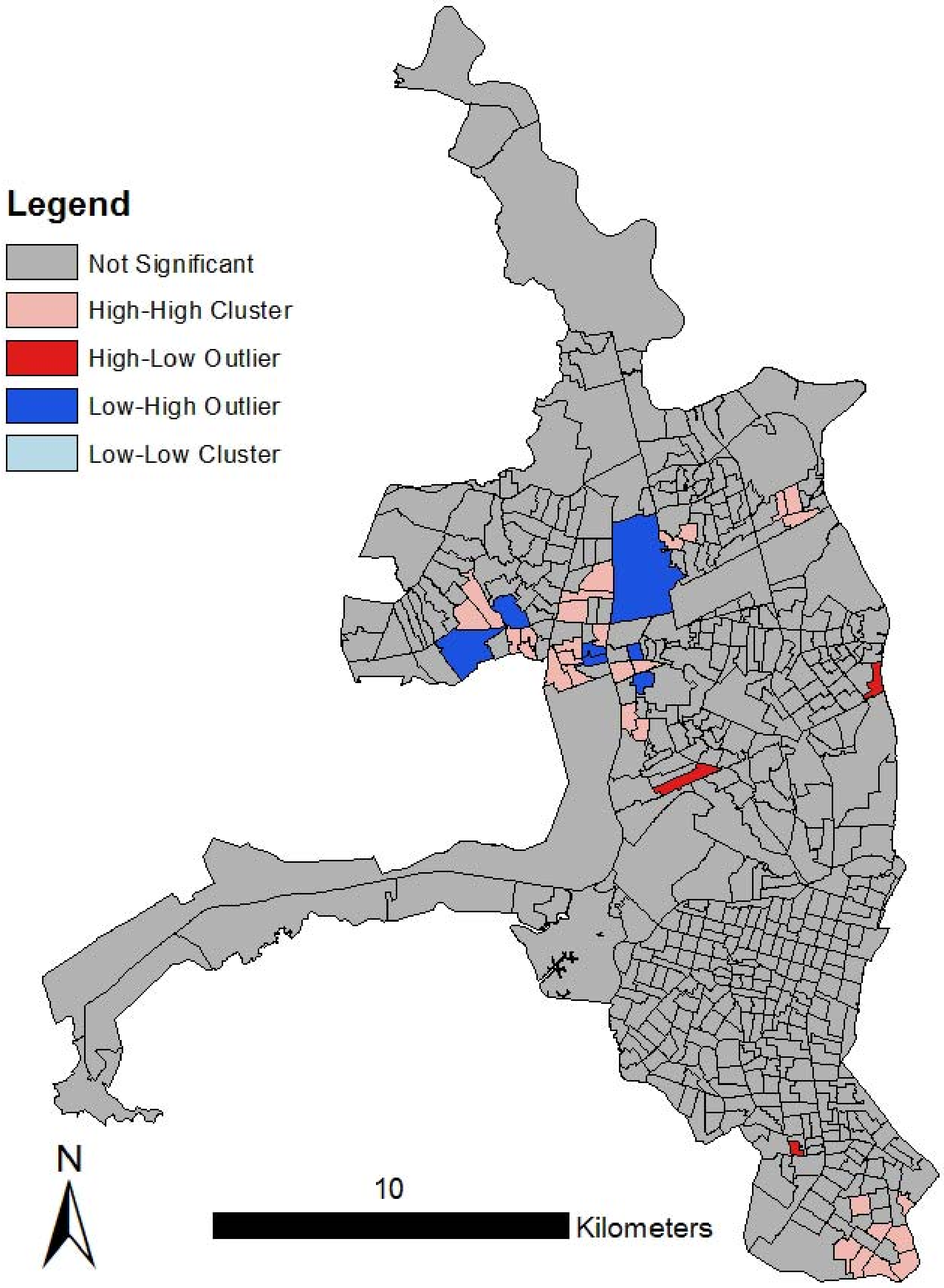

Legend
Not Significant
High-High Cluster
High-Low Outlier
Low-High Outlier
Low-Low Cluster
N
10
Kilometers

Figure 5.

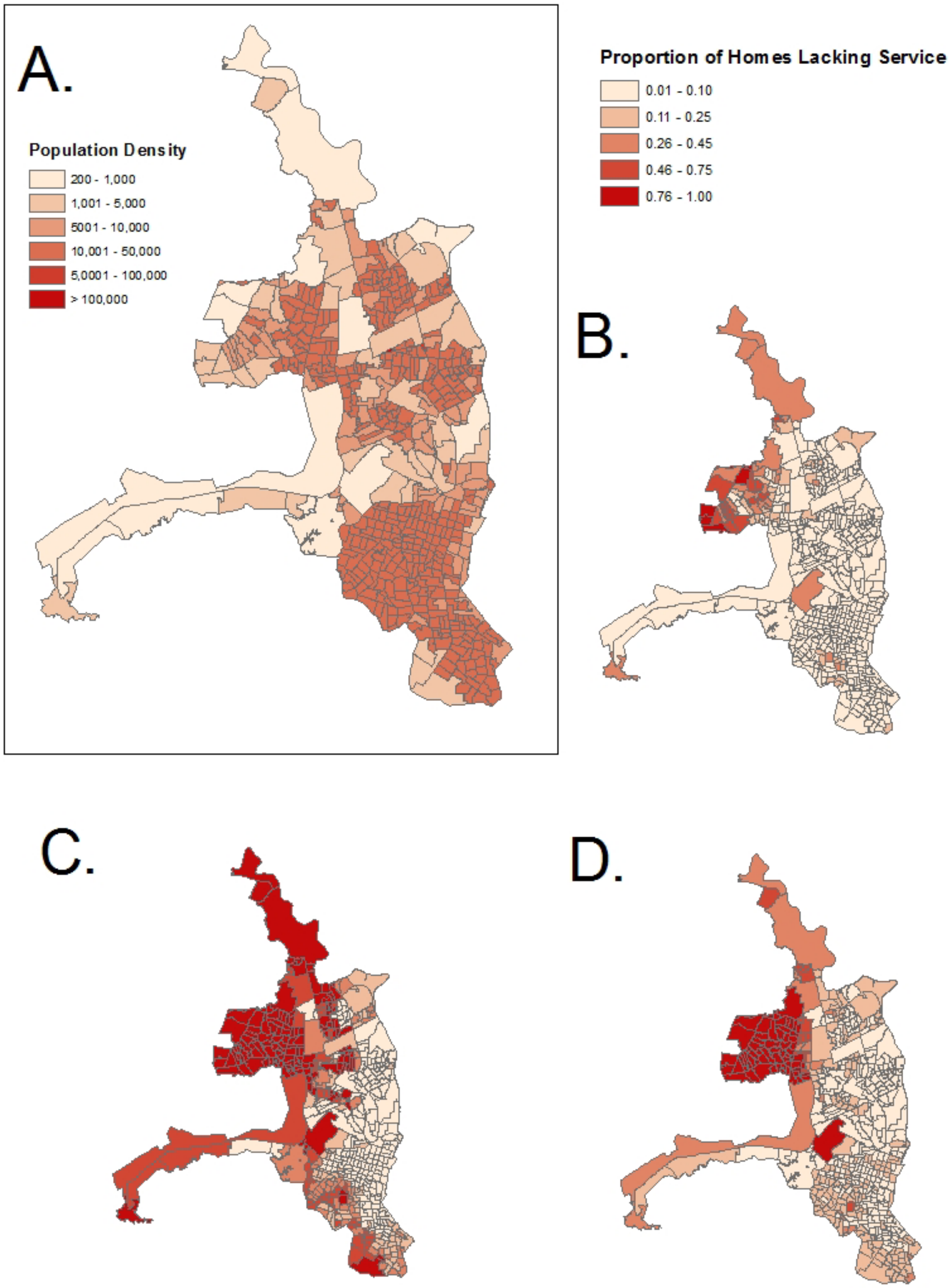

A.
Population Density
200 - 1,000
1,001 - 5,000
5001 - 10,000
10,001 - 50,000
5,0001 - 100,000
> 100,000
Proportion of Homes Lacking Service
0.01 - 0.10
0.11 - 0.25
0.26 - 0.45
0.46 - 0.75
0.76 - 1.00
B.
C.
D.

Figure 6.

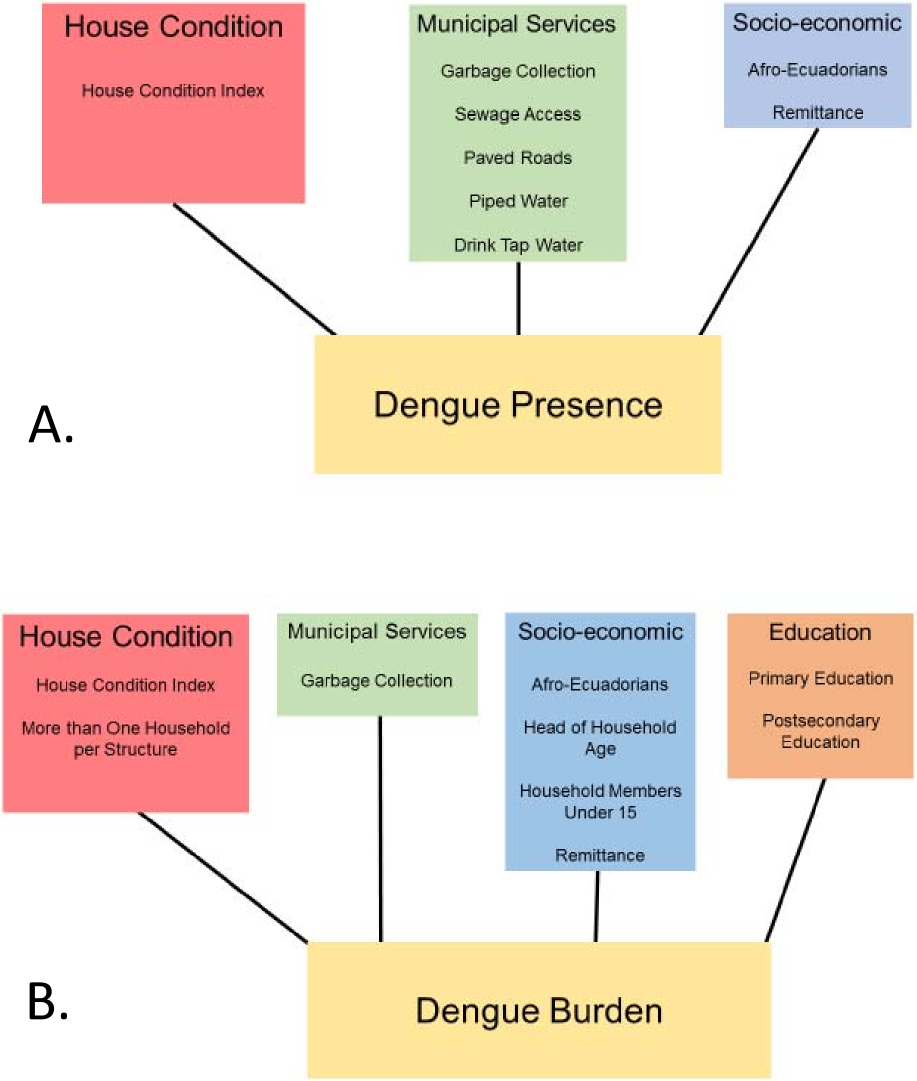

House Condition
House Condition Index
Municipal Services
Garbage Collection
Sewage Access
Paved Roads
Piped Water
Drink Tap Water
Socio-economic
Afro-Ecuadorians
Remittance
Dengue Presence
A.
House Condition
House Condition Index
More than One Household per Structure
Municipal Services
Garbage Collection
Socio-economic
Afro-Ecuadorians
Head of Household Age
Household Members Under 15
Remittance
Education
Primary Education
Postsecondary Education
Dengue Burden
B.

Table 1. Socio-ecological parameters tested in logistic regression and negative binomial model searches to respectively predict presence of dengue and severity of outbreak.

Parameter	Mean	SD
Housing conditions		
House condition index (HCI), 0 to 1, where 1 is poor condition	0.27	0.12
More than four people per bedroom	16.78 %	0.08
People per household	3.88	0.34
Municipal garbage collection	93.06 %	0.15
People in household drink tap water	76.85 %	0.09
Piped water inside home	77.03 %	0.31
Municipal sewage	62.52 %	0.39
Access to paved roads	80.06 %	0.25
More than one household per structure	1.90 %	0.01
Unoccupied households	16.08 %	0.56
Rental homes	1.55%	0.17
Demographics		
Receive remittances	8.85 %	0.04
People emigrate for work	1.88 %	0.01
Mean age of the head of the household (years)	45.69	4.54
Mean household age (years)	29.36	4.29
Proportion of household under 15 years of age	28.34 %	0.06
Proportion of household under 5 years of age	9.31 %	0.03
Head of the household has primary education or less	30.94 %	0.15
Head of household has secondary education	31.73 %	0.07
Head of household has post-secondary education	25.77 %	0.21
Afro-Ecuadorian	10.13 %	0.07
Head of the household is unemployed	26.84 %	0.06
Head of the household is a woman	33.29 %	0.04

Table 2. Top logistic regression model

Model	**Estimate**	**95% CI**	**SE**	**AICc**	**P-Value**
Intercept	3.84	0.54 – 7.25	1.71	369.85	0.03
House condition	24.55	17.62 – 32.11	3.69		< 0.001
Proportion of Afro-Ecuadorians	-9.69	-15.72 – -3.76	3.04		0.001
Municipal garbage collection	4.70	2.27– 7.37	1.29		< 0.001
Piped water	3.50	1.38 –5.72	1.10		0.002
Municipal sewage	2.04	0.44 – 3.62	0.81		0.012
Access by paved roads	-3.36	-6.36 – -0.54	1.48		0.023
Drink tap water	-10.74	-16.53 – -5.28	2.86		< 0.001
Remittance	23.20	10.83 – 36.15	6.44		< 0.001

Table 3. Top negative binomial model.

Model	Estimate	95% CI	SE	AICc	P-Value
Intercept	1.04	-4.09 – 6.25	2.54	2920.67	0.682
House condition	10.95	6.77 – 15.13	2.09		< 0.001
Postsecondary education	-2.53	-4.72 – -0.34	1.07		0.018
Primary education	-5.11	-8.52 – -1.71	1.62		0.002
Proportion of Afro-Ecuadorians	-4.23	-6.43 – -1.94	1.25		< 0.001
Proportion of household members under 15	-9.02	-15.58 – -2.50	3.46		0.009
Head of household age	-0.12	-0.19 – -0.05	0.03		< 0.001
Municipal garbage collection	2.82	1.77 – 3.87	0.61		< 0.001
More than 1 household per structure	7.57	-4.66 – 20.03	6.26		0.227
Remittance	4.76	-1.27 – 10.87	3.07		0.121

Supplementary Table 1

Model	AICc	Wt
x ~ 1 + afro + housecond + no_garbage + no_piped + no_sewage + no_pave + remit + drinktap	369.85	0.11
x ~ 1 + afro + unocc + housecond + no_garbage + no_piped + no_sewage + no_pave + remit + drinktap	370.97	0.06
x ~ 1 + afro + pplperhh + housecond + no_garbage + no_piped + no_sewage + no_pave + remit + drinktap	371.07	0.06
x ~ 1 + afro + fourpplbedrm + housecond + no_garbage + no_piped + no_sewage + no_pave + remit + drinktap	371.10	0.06
x ~ 1 + afro + housecond + no_garbage + no_piped + no_sewage + no_pave + gt1hh + remit + drinktap	371.13	0.06
x ~ 1 + afro + housecond + no_garbage + no_piped + no_sewage + no_pave + remit + drinktap + rental	371.39	0.05
x ~ 1 + prim + afro + housecond + no_garbage + no_piped + no_sewage + no_pave + remit + drinktap	371.61	0.04
x ~ 1 + afro + housecond + no_garbage + no_piped + no_sewage + no_pave + remit + emigr + drinktap	371.68	0.04
x ~ 1 + afro + womhead + housecond + no_garbage + no_piped + no_sewage + no_pave + remit + drinktap	371.70	0.04
x ~ 1 + afro + unemploy + housecond + no_garbage + no_piped + no_sewage + no_pave + remit + drinktap	371.73	0.04
x ~ 1 + sec + afro + housecond + no_garbage + no_piped + no_sewage + no_pave + remit + drinktap	371.82	0.04

Supplementary Table 2

Model	**AICc**	**Wt**
x ~ 1 + postsec + prim + afro + under15 + headhh_age + housecond + no_garbage + gt1hh + remit	2920.67	0.03
x ~ 1 + postsec + prim + afro + under15 + headhh_age + housecond + no_garbage + no_sewage + gt1hh + remit	2920.71	0.03
x ~ 1 + postsec + prim + afro + under15 + headhh_age + housecond + no_garbage + no_sewage + gt1hh + remit + drinktap + rental	2920.76	0.03
x ~ 1 + postsec + prim + afro + under15 + headhh_age + housecond + no_garbage + gt1hh + remit + drinktap + rental	2921.05	0.03
x ~ 1 + postsec + prim + afro + under15 + headhh_age + womhead + housecond + no_garbage + no_sewage + gt1hh + remit	2921.16	0.03
x ~ 1 + postsec + prim + afro + under15 + headhh_age + housecond + no_garbage + no_sewage + gt1hh + remit + rental	2921.18	0.03
x ~ 1 + postsec + prim + afro + under15 + headhh_age + womhead + housecond + no_garbage + gt1hh + remit	2921.20	0.03
x ~ 1 + postsec + prim + afro + under15 + headhh_age + fourpplbedrm + housecond + no_garbage + no_sewage + gt1hh + remit	2921.20	0.03
x ~ 1 + postsec + prim + afro + under15 + headhh_age + housecond + no_garbage + no_piped + no_sewage + gt1hh + remit + rental	2921.48	0.02
x ~ 1 + postsec + prim + afro + under15 + headhh_age + housecond + no_garbage + gt1hh + remit + drinktap	2921.52	0.02
x ~ 1 + postsec + prim + afro + under15 + hh_age + headhh_age + housecond + no_garbage + no_sewage + gt1hh + remit + drinktap + rental	2921.60	0.02
x ~ 1 + postsec + prim + afro + under15 + headhh_age + fourpplbedrm + housecond + no_garbage + gt1hh + remit	2921.65	0.02
x ~ 1 + postsec + prim + afro + under15 + hh_age + headhh_age + housecond + no_garbage + gt1hh + remit	2921.66	0.02
x ~ 1 + postsec + prim + afro + under15 + headhh_age + womhead + housecond + no_garbage + no_sewage + gt1hh + remit + drinktap + rental	2921.77	0.02
x ~ 1 + postsec + prim + afro + under15 + headhh_age + housecond + no_garbage + gt1hh + remit + rental	2921.97	0.02
x ~ 1 + postsec + prim + afro + under15 + headhh_age + fourpplbedrm + housecond + no_garbage + no_sewage + gt1hh + remit + drinktap + rental	2921.97	0.02
x ~ 1 + postsec + prim + afro + under15 + headhh_age + housecond + no_garbage + no_piped + no_sewage + gt1hh + remit + drinktap + rental	2922.00	0.02
x ~ 1 + postsec + prim + afro + under15 + under1 + headhh_age + housecond + no_garbage + no_sewage + gt1hh + remit + drinktap + rental	2922.05	0.02
x ~ 1 + postsec + prim + afro + under15 + headhh_age + housecond + no_garbage + no_sewage + gt1hh + remit + drinktap	2922.05	0.02
x ~ 1 + postsec + prim + afro + under15 + under1 + headhh_age + housecond + no_garbage + gt1hh + remit	2922.09	0.02
x ~ 1 + postsec + sec + prim + afro + under15 + headhh_age + housecond + no_garbage + gt1hh + remit	2922.11	0.02
x ~ 1 + postsec + prim + afro + under15 + under1 + headhh_age + housecond + no_garbage + no_sewage + gt1hh + remit	2922.13	0.02

x ~ 1 + postsec + sec + prim + afro + under15 + headhh_age + housecond + no_garbage + no_sewage + gt1hh + remit	2922.24	0.02
x ~ 1 + postsec + prim + afro + under15 + headhh_age + housecond + no_garbage + no_piped + gt1hh + remit	2922.26	0.02
x ~ 1 + postsec + prim + afro + under15 + headhh_age + pplperhh + housecond + no_garbage + no_sewage + gt1hh + remit + drinktap + rental	2922.44	0.01
x ~ 1 + postsec + prim + afro + under15 + headhh_age + housecond + no_garbage + no_pave + gt1hh + remit	2922.47	0.01
x ~ 1 + postsec + prim + afro + under15 + headhh_age + housecond + no_garbage + no_sewage + gt1hh	2922.47	0.01
x ~ 1 + postsec + prim + afro + under15 + headhh_age + fourpplbedrm + housecond + no_garbage + gt1hh + remit + drinktap + rental	2922.53	0.01
x ~ 1 + postsec + prim + afro + under15 + headhh_age + womhead + housecond + no_garbage + no_sewage + gt1hh + remit + drinktap	2922.56	0.01
x ~ 1 + postsec + prim + afro + under15 + headhh_age + pplperhh + housecond + no_garbage + gt1hh + remit	2922.63	0.01