

1 **Title:** Urban warming inverse contribution on risk of dengue transmission in the
2 southeastern North America

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20 **ABSTRACT**

21 1. Preventing diseases from becoming a problem where they are not is a common
22 ground for disease ecology. The expectation for vector-borne diseases,
23 especially those transmitted by mosquitos, is that warm and wet conditions

24 favor vector traits increasing transmission potential. The advent of urbanization
25 altering inner climate conditions hazards to increase mosquito's transmission
26 potential on "disease-free" cooler areas as a consequence of a warming urban
27 heat island (UHI) effect.

28 2. We assessed the realism of the anticipated dengue transmission potential into
29 the southern United States in a causal pathway with the ongoing UHI effect,
30 vectors' spatial distribution patterns, and exogenous environment; We also
31 measured the climatic niche similarity between both dengue vectors species.

32 3. Our path model revealed that the UHI effect presents negative or no relation
33 with dengue transmission potential. Instead, the surrounding non-urban
34 temperature was rather suitable for the expected mosquitos' transmission
35 potential.

36 4. Both dengue vectors' occurrence revealed to be more aggregated then expected
37 by chance. These mosquitos' density patterns were responsive to the warming
38 effect of UHI- especially *Aedes Aegypti*- but not a reliable predictor for the
39 anticipated dengue transmission potential pattern. The climatic niches of both
40 vectors are not equivalent. Although currently highly overlapped, there is a wide
41 space of their climatic niche still to be filled.

42 5. *Policy implications.* We highlight that the warming UHI effect on urban sites is
43 not congruent with the expected suitability for dengue transmission. Instead,
44 non-urban areas would be a better focus for dengue hazards into the southern
45 United States. Our study also highlights the need for including low scale
46 temperature on further mosquito-borne disease transmission models and track
47 vectors niche filling under anthropogenic changes.

48 **KEYWORDS:** disease potential, dengue, temperature suitability, mosquito,
49 macroecology of disease transmission, niche overlap, urban heat island effect (UHI),
50 vector capacity

51 **1. INTRODUCTION**

52 Vector-borne pathogens are characterized by their dependence on vectors, in
53 general arthropods (*e.g.*, mosquitoes), that feed on blood to proceed the infection cycle
54 (Gubler, 2002). Their resulting diseases represent one of the greatest challenges faced
55 by public health worldwide (World Health Organization, 2014). Some critical vector-
56 borne diseases, such as; dengue, chikungunya, and Zika, which were formerly restricted
57 to tropical and subtropical regions, have begun to spread into new parts of the world as
58 a consequence of accidental introductions of vectors and pathogens along with changes
59 in climate and habitat distributions (Gubler, 2001; Murray et al., 2015).

60 Despite the complex nature of vector-borne diseases transmission,
61 understanding main drivers of its geographic spread is crucial for monitoring potential
62 impacts on public health (World Health Organization, 2014). Vector transmission is
63 linked with traits such as the biting rate, life span, and inner incubation period albeit
64 also the abundance of vector species (Watts et al., 2018). Recently, studies have
65 considered the temperature role on vector traits to assess the environmental suitability
66 range for transmission capacity (*e.g.*, Brady et al., 2014; Ryan et al., 2019). This
67 geographical perspective highlights the potential of macroecological analyses on disease
68 ecology and public health strategies against the burden of disease transmission
69 (Stephens et al., 2016). In this sense, the usage of transmission potential spatial patterns
70 on causal structures with acknowledged exogenous drivers (*e.g.*, urban features), rise as

71 a promising research area to infer causal pathways on disease ecology, ultimately
72 orienting effective strategies on public health surveillance (Kraemer et al., 2019,
73 Mordecai et al., 2019).

74 Some of the most consequential vectors species, including *Aedes aegypti* and
75 *Aedes albopictus*, have lifestyles adapted to the ecology of urban settings and inner
76 climatic conditions have the potential to favor their vector traits (Arnfield, 2003; Gloria-
77 Soria et al., 2018). Urban sites might exhibit higher temperatures than surrounding, a
78 phenomenon called ‘Urban Heat Island’ (UHI), and changes in the global climate and
79 human population growth are expected to intensify the UHI conditions (Zhao et al.,
80 2014; Manoli et al., 2019). As ectotherms, mosquito behavior, abundance, fitness and
81 distribution patterns can be strongly affected by small changes in temperature
82 (Amarasekare & Savage, 2011; Huey et al., 2012). In cooler regions, relative to mosquito
83 species thermal optima, it is expected that species’ abundance might increase with UHI
84 effect, particularly at range margins of mosquito species (Ladeau et al., 2015; Kraemer
85 et al., 2019). In addition, even where mosquito species do not increase in abundance,
86 their vectorial capacity might increase with the UHI effects (Araujo et al., 2015; Murdock
87 et al., 2017). Conversely, UHI effects in areas already near the thermal maxima of a
88 mosquito species may lead to decreases in their vectorial capacity (Mordecai et al.,
89 2019). For instance, known upper thermal bounds for dengue transmission is 34.0 C° for
90 *Ae. aegypti* and 29.4 C° for *Ae. albopictus* (Ryan et al., 2019). However, even though UHI
91 effects might increase the potential for a disease outbreaks at the range margins of
92 vector mosquitoes, UHI effects have received little attention in the infectious disease
93 ecology (Misslin et al., 2016).

94 Dengue is a neglected disease that has rapidly expanded geographically over the
95 last decades (Gubler, 2002; Ramos-Castañeda et al., 2017), and although *Ae. aegypti*
96 was historically considered the main responsible for dengue urban transmission, *Ae.*
97 *albopictus* has starred in recent major outbreak events (Lambrechts et al., 2010).
98 Despite of their differing invasion timing and native origins (Kaplan et al., 2010), both
99 vector species are currently listed among worst invasive organisms (Global Invasive
100 Species Database, IUCN). In a recent future, both species are expected to spread farther
101 north and south into temperate regions along with climate changes (Kraemer et al.,
102 2019). Besides, the ongoing co-occurrence and continuing spread of both vectors in
103 “dengue-free” areas, such as the southeastern North America, aggravates the
104 temperature suitability predictions of dengue transmission into these areas under
105 current and future climate conditions (Brady et al. 2014; Rosenberg et al., 2018; Messina
106 et al., 2019), given the lack of heard immunization (Johnson et al., 2017).

107 In the present work, we aim to evaluate the realism of the geographical pattern
108 on dengue transmission potential in the face of the urban heat island effect (UHI) and
109 existing vectors distribution in the southeastern United States. To achieve our goal, we
110 take two steps. Foremost, we build a correlative path structure (Fig. 1) to comprise the
111 weight of UHI effect and other urban features on observed dengue potential pattern;
112 and, as burden of dengue transmission largely reflects the distribution and density of
113 the mosquito vectors, we also consider both the effect of urban features in increasing
114 *Ae. aegypti* and *Ae. albopictus* clustering and the dengue transmission risk resulting from
115 their distribution pattern. Second, as the niche similarity between these important
116 mosquito vectors is unclear, we additionally use a niche overlap approach to compare
117 the climatic niches of both species assuming that, in spite of sharing similar geographical

118 spaces, they do not have equivalent niches, which would result in low overlap between
119 vectors niche and in current avoidance of dengue outbreak on the region.

120 2. MATERIALS AND METHODS

121 (a) Data

122 (i) *Vector species occurrence*

123 The *Ae. aegypti* (*Stegomyia aegypti*) and *Ae. albopictus* (*Stegomyia albopicta*)
124 occurrence was obtained from Kraemer et al. (2015) available at
125 <http://datadryad.org/resource/doi:10.5061/dryad.47v3c> and improved with last
126 published records (Johnson et al., 2017). This comprehensive dataset is a compilation of
127 occurrence point records over the last 57 years (1960 – 2017) documented in previous
128 studies– Kraemer et al., 2015; Hahn et al. 2016; 2017. To latter evaluate each specie
129 density in southeastern United States we selected the occurrence points located into
130 the region, ultimately comprising 1227 and 217 records of *Ae. albopictus* and *Ae.*
131 *aegypti*, respectively.

132 (ii) *Dengue transmission suitability*

133 To assess the geographic range of dengue transmission potential we used
134 Brady's *et al.* (2014) global consensus map of vector transmission suitability based on
135 temperature, from which we extracted the information within the southeastern United
136 States. This map is a result of a mechanistic model derived from experimental data that
137 assess vector traits of dengue transmission (*e.g.*, mosquito survival; extrinsic incubation
138 period [EIP]) based on temperature effect, separately for *Ae. aegypti* and *Ae. albopictus*,

139 and spatialized using a global temperature dataset with 1km resolution (see Brady *et al.*
140 (2014) for modeling approach details). Their output predicted areas where global
141 temperature support year-round dengue transmission given the presence of an infected
142 individual (*i.e.* the basic reproduction number, R_0) ranging from 0 to 1, for each vector
143 species, where within pixel values closest to 1 indicate a higher potential for the virus
144 transmission.

145 *(iii) Meteorology and land use*

146 To test the effect of urban differential temperature on dengue transmission
147 suitability we used the UHI dataset from 'NASA Socioeconomic Data and Applications
148 Center' (SEDAC, 2016), available at [http://sedac.ciesin.columbia.edu/data/set/sdei-](http://sedac.ciesin.columbia.edu/data/set/sdei-global-uhi-2013/data-download)
149 [global-uhi-2013/data-download](http://sedac.ciesin.columbia.edu/data/set/sdei-global-uhi-2013/data-download). The UHI data comprises the estimate of summer
150 daytime maximum and nighttime minimum surface temperature within urban extent
151 and surrounding non-urban areas (buffer of 10 km), and the difference between them,
152 in Celsius degrees. Here we used both daytime and nighttime temperatures, once vector
153 activity is referred to be even superior at nighttime than it is in daylight (Stoddard *et al.*,
154 2009). The global GeoTIFF is in the resolution of 30 arc-seconds (~1Km), on which we
155 made a subset based on southeastern United States area.

156 To account for the influence of other urban-modified features on vectors density
157 and dengue transmission we obtained the data referent to precipitation and wind speed
158 from NASA Langley Research Center (LaRC) POWER Project, available at
159 <https://power.larc.nasa.gov/data-access-viewer/>. Both variables represent the average
160 annual information in a 0.5° global grid. The wind speed data is scaled on 2 meters
161 elevation, accounting for the limited space of mosquito's activity (Reisen *et al.*, 2003;

162 Guerra et al., 2014). The land-cover features, known to increase mosquito vectors
163 density due to anthropogenic changes favoring species associated with urban areas
164 (Beaulieu et al., 2019), were obtained in 1-km resolution (Tuanmu & Jetz, 2014). The
165 data account for 7 land-cover classes (*i.e.*, Evergreen/Deciduous Needleleaf Trees,
166 Deciduous Broadleaf Trees, Mixed/Other Trees, Herbaceous vegetation, Cultivated and
167 Managed Vegetation, Regularly Flooded Vegetation and Urban/Built-up) chosen based
168 on their matter on vector settlement and ultimate dengue transmission (Guerra et al.,
169 2014).

170 Finally, to build and later compare both vector species niche we delimited the
171 niche boundaries using bioclimatic variables, which are widely accepted given its
172 robustness to represent seasonal trends and physiological constrains of species (Lobo
173 et al., 2010). In this sense, we used all 19 bioclimatic variables from WorldClim dataset
174 on the resolution of 30 arc-seconds, available at <http://www.worldclim.org/>.

175 **(b) Analysis**

176 *(i) Density estimation*

177 For the estimation of vector density across southeastern U.S., we used the point
178 pattern approach based on species occurrence data. Firstly, to account for bias in point
179 density estimation, we applied the rarefaction curve, commonly used to quantify bias in
180 presence counting measures (Gotelli & Colwell, 2001), with the R package *iNEXT* (Hsieh
181 et al., 2019). Then, we used the R package *spatstat* (Baddeley et al., 2015), where we
182 performed a near neighbor analyses (ANN) between vector occurrence records and
183 compared with a commonly used null model based on the distribution of simulated ANN
184 values given the Complete Spatial Random (CSR) point process (Wiegand & Moloney,

185 2004; Baddeley et al., 2014). To generate a vector density raster, we used the Kernel
186 density estimation to interpolate around each point, for which we established the
187 bandwidth value of 0.5 to give weight to distant points contribution on density
188 estimation using the R package *KernSmooth* (Wand, 2015).

189 *(ii) Path model*

190 To recover the underlying direct and indirect causal mechanisms between UHI
191 and other features on dengue transmission suitability on the southeastern United States
192 (Fig. 1) we used the structural equation modeling (SEM) approach with the R package
193 *lavaan* (Rosseel, 2012). Usually, the SEM model is applied to mediate causal
194 assumptions, which assumes that the presumed explanatory variables can influence an
195 outcome directly and indirectly through other variables (Fan et al., 2016). However, SEM
196 does not account for spatial information and the autocorrelation that frequently arise
197 when dealing with spatially explicit structures, which ultimately inflates the type I error
198 given the lack of independence between observations across space (Legendre &
199 Legendre, 1998).

200 Aiming to consider the spatial autocorrelation and provide unbiased regression
201 coefficients we used eigenvector-based spatial filters, which consist on extracting the
202 eigenvectors of a distance matrix describing the spatial structure of the data and adding
203 them as additional predictors into the SEM model (Griffith, 2003). First, we extracted
204 the geographical coordinates along southeastern U.S. to build a distance matrix, which
205 was truncated at the distance of 300 km based on a previous evaluation of the Moran's
206 I correlogram. Then, the truncated matrix was submitted to a principal coordinate
207 analyses (PCO) and its resultant eigenvectors were selected as predictors based on

208 significance of each partial regression coefficients (following Borcard & Legendre, 2002).
209 For the spatial filter approach, we used the R packages *letsR* (Vilela & Villalobos, 2015)
210 and *ecodist* (Goslee et al., 2007).

211 (iii) Niche overlap

212 In order to estimate the overlap between dengue vectors niches and test the
213 hypothesis of niche non-equivalence we used the framework proposed by Broennimann
214 et al. (2012). The method assesses niche overlap by calibrating a principal component
215 analysis on the environmental space (PCA-env) and use kernel density smoothing to
216 correct potential sampling bias (Broennimann et al., 2012). We used the R package
217 *ecospat* (Di Cola et al., 2017) to pull the bioclimatic information, according to the species
218 occurrence, and create a background environmental space to perform the PCA. Thus,
219 the 1st and 2nd output axes were used to create a 100 x 100 occurrence density grid
220 representing each specie niche. The estimated niches was overlapped and the degree
221 of intersection was assessed using Schoener's D metric (following Warren et al. 2008)–
222 which ranges between 1 (*i.e.*, complete overlap) and 0 (*i.e.*, no overlap) –and compared
223 with 100 random simulated overlap index distribution to test for niche equivalence and
224 niche similarity.

225 3. RESULTS

226 (a) Density estimation

227 The test for vector occurrence point pattern clustering/dispersion on the
228 southeastern region of United States showed that, when compared with a null
229 distribution of average distance among geographic points, the distance between
230 occurrence points density, for both *Ae. albopictus* and *Ae. aegypti*, are greater than

231 expected. Even though, *Ae. aegypti* density pattern revealed higher concentration into
232 Florida and Louisiana, while *Ae. albopictus* showed a more diffused occurrence density,
233 with higher weight into the northern portion of southeastern U.S. like Virginia (Fig. 4).

234 **(b) Path model**

235 The SEM revealed that the combined influence of diurnal and nocturnal UHI,
236 wind speed, precipitation and land-use- including spatial filters - explained respectively
237 49% and 54% of the variance on *Ae. aegypti* and *Ae. albopictus* density (Fig. 2). In
238 addition, the interaction between vectors occurrence density, UHI and further
239 predictors explained 92% and 90% of variation on dengue transmission suitability
240 respectively by *Ae. aegypti* and *Ae. albopictus* into the southeastern U.S. (Fig. 2). The
241 addition of spatial filters on SEM structure to take in account the unknown endogenous
242 and exogenous influence shaping dengue transmission suitability pattern, improved the
243 model fit based on Akaike information criterion (AIC) and r square. The inclusion of 20
244 spatial filters on *Ae. aegypti* path model adjusted the AIC from 15356.419 to 11631.864
245 and the R² from 0.5 to 0.9, and the 30 spatial filters included on *Ae. albopictus* model
246 adjusted the AIC from 15655.011 to 11845.485 and the R² from 0.34 to 0.9 (Table 1).

247 The resulting SEM causal path indicated that daytime UHI (Fig. S1) is negatively
248 correlated with dengue transmission suitability ($\beta = -0.03$; sites with a greater UHI effect
249 are less suitable for transmission by vectors) but positive with the density of both
250 vectors ($\beta = 0.05$; 0.02 ; sites with a greater UHI effect have more of both mosquito
251 species), although the effect on the density pattern of *Ae. albopictus* is not significant.
252 In contrast to the effect of daytime UHI, the UHI effect during nighttime (Fig. S1) was
253 not significantly correlated with dengue transmission suitability in the southeastern U.S.

254 Interestingly, the density of both vector species was negatively correlated with
255 nighttime UHI ($\beta = -0.04$) (Fig. 2; Table 1), such that the effect of daytime UHI and
256 nighttime UHI were in the opposite directions for the mosquito species agglomeration
257 pattern. Precipitation was strongly positively correlated with the density of both vectors
258 ($\beta = 0.31$; 0.23), while its effect in dengue transmission suitability was not significant.
259 The SEM path output also indicated that wind speed has a high negative effect on the
260 density of both vector species ($\beta = -0.19$; -0.07), however it showed a positive
261 association with dengue transmission suitability by *Ae. aegypti* ($\beta = 0.07$) and *Ae.*
262 *albopictus* ($\beta = 0.013$). The effect of land-use over dengue predictors was indirect via its
263 influence on UHI ($\beta = 0.07$; 0.05). Moreover, the occurrence density of the two vectors
264 was not correlated with dengue transmission suitability in the southeastern U.S. (Fig. 2;
265 Table 1).

266 (c) Niche overlap

267 Schoener's D niche overlap index revealed a high level of overlap between *Ae.*
268 *albopictus* and *Ae. aegypti* niches (Fig. 3). The niche similarity test showed that niche
269 overlap comparisons between one randomly distributed over the unchanged other (1 -
270 > 2) and vice versa (2 -> 1) had a Schoener's D of 0.44, thus distant from a completely
271 unrelated scenario (*i.e.*, $D = 0$). The vector species niches are represented by the 1st axes
272 of the PCA-env, that is associated with temperature-related bioclimatic variables, and
273 by the 2nd axes, that is associated with precipitation-related variables. In spite of the
274 high niche overlap and similarity of both vectors species, the result of the one-tailed
275 niche equivalence test showed a significantly lower niche equivalence between both
276 main dengue vectors (p -value = 0.001).

277 **4. DISCUSSION**

278 Contrary to previous expectations that urban heat islands (UHI) effect might favor
279 dengue transmission, our results suggest that areas under UHI stress have lower risk of
280 the disease spread by its both main vectors. The threat of dengue transmission potential
281 into the southeastern U.S. has been placed decades ago based on mosquito vectors
282 invasion (Monath, 1994). The incorporation of temperature on disease transmission
283 models later reinforced the predictions of *Ae. aegypti* and *Ae. albopictus* potential
284 dengue transmission into the region under current and future global climate (Brady et
285 al., 2014; Messina et al., 2019). However, here we show that the downscaled
286 temperature difference between warmer urban and cooler sub-urban areas– the so
287 called UHI –have a contrasting inverse relation with dengue transmission potential (Fig.
288 2; Table 1). Contrary to the expectation that warmer conditions generally promote
289 mosquito borne disease (Morin et al. 2015; Thomson et al. 2017). Still, UHI effect, wind
290 speed, and precipitation all together were highly congruent with the expectation of
291 dengue transmission suitability on the southeastern U.S., which aligns with the concern
292 of urbanization style shaping the probability of mosquito-borne disease transmission
293 (Gubler, 2011).

294 The starting point for realized dengue transmission depends primarily on the
295 presence of virus strains, susceptible host population and competent vectors (Gubler,
296 2011). Year-round adequate temperature determining transmission competence of
297 mosquito vectors (Ryan et al., 2019), in combination with precipitation, ultimately zenith
298 seasonal dengue cycles into tropical endemic areas (Van Panhuis et al., 2015). In
299 contrast, cooler subtropics are expected to avoid transmission following an unimodal

300 variation on vector-borne transmission that limits dengue around 18 C° (Ladeau, 2015;
301 Mordecai et al., 2019). Here we outline that on summer the combination of temperature
302 with other environmental features is congruent with dengue transmission potential and
303 vectors accumulation on the subtropical southeastern U.S. (Fig. 2; Table 1). However,
304 contrary to the expected higher dengue probability in warmer urban temperature
305 (Halstead, 2008), transmission potential showed conformity with the sub-urban lower
306 temperature. In fact, previous works highlighted that mosquito transmission increased
307 around lower temperature ranges (Carrington et al., 2013), advocating for a
308 thermoregulation scape from urban to bordering greener sites where environment
309 afford thermal respite (Huey, 2012; Misslin et al. 2016). Still, the dengue potential
310 contrast we found between urban and surrounding areas might also reflect the scale
311 considered to predict the temperature range of dengue transmission potential, which
312 ignores low scale environment where transmission takes place.

313 In cities where dengue transmission is a seasonal event, human population cluster
314 share space with high density of mosquitoes, usually a strong predictor for arboviral
315 transmission potential (Halstead, 2008; Ladeau et al., 2015). Our results otherwise
316 showed that the density derived from occurrence data was not a good predictor of the
317 dengue potential predicted by the temperature-based transmission model in the
318 southeastern U.S. This result might either represent that the mosquito records within
319 the studied area are not sufficient to predict the emergence of dengue, or that both
320 species aggregation does not overlap the dengue transmission suitability areas.
321 Although previous works have indicated a positive association between vector density
322 and disease incidence (Walk et al., 2009), this association does not occur in all cases
323 (Halstead, 2008). For instance, in Singapore the extreme reduction of *Ae. aegypti* density

324 did not avoid the continued dengue infection (Chan, 1985). Here we found that both
325 mosquito species densities were more related with urban than suburban temperatures
326 (Table S1), congruent with urban microclimates favoring vector population growth-
327 while it has not reached thermal performance peak -(Huey et al., 2012; Mordecai et al.,
328 2019). Additionally, day and nighttime UHI range revealed fully relation with *Ae. aegypti*
329 density (Figs. 2, S1), a primarily urban specie when compared with the *Ae. albopictus*,
330 which dominates in suburban areas (Beaulieu et al., 2019).

331 The southeastern U.S. have a particular precipitation regime with much higher
332 humidity than other U.S. locations. Consequently, the UHI effect- which follows
333 precipitation gradient (Manoli et al., 2019) -is increased in this region, where annual UHI
334 effect is around 3.9 C° higher than dryer U.S. regions (Zhao et al., 2014). Besides the
335 indirect effect on urban temperature higher precipitation is also expected to increase
336 mosquito density by increasing breeding sites and oviposition (Halstead, 2008), and our
337 results showed a positive association between precipitation and both species' densities,
338 supporting this prediction. However, precipitation was not a good support for the
339 dengue suitability range expected by the global temperature model. In this sense, the
340 background effect of higher precipitation on the southeastern U.S. UHI might indirectly
341 impose thermal limitations to dengue transmission range, even where wind speed is
342 expected to facilitate the transmission contact (Cummins et al., 2012). To fully
343 comprehend this complex association between precipitation and UHI on dengue
344 transmission, further works should include the urban differential climate into mosquito-
345 borne disease transmission models.

346 The niche comparison revealed that, in spite of distinct invasion time by dengue
347 vectors into the southeastern U.S.- where there is a niche conservatism evidence for

348 both species (Cunze et al., 2018) -their occupied climatic space markedly overlap (Fig.
349 4). Accordingly, given the observed low prediction of dengue transmission suitability by
350 vector density on the southeastern U.S., the ongoing climatic space occupied by both
351 species may be the main factor avoiding a dengue outbreak into the region, when other
352 important features are favorable (*e.g.*, autochthonous virus, lack of heard immunity).
353 However, our results also highlight that the climatic niche space of both species are not
354 completely fulfilled (solid line Fig. 3), which ultimately indicate future potential for
355 dengue transmission due to range expansion. In fact, Kraemer et al. (2019) showed that
356 there is strong evidence for future *Ae. aegypti* and *Ae. albopictus* range expansion
357 poleward with anthropogenic pressure, ultimately fulfilling the remaining suitable
358 climatic space and increasing the risk of dengue transmission into subtropical areas like
359 the southeastern U.S.

360 5. CONCLUSIONS

361 Here we highlight that the southeastern U.S suburban areas show higher realism
362 with expected dengue transmission thermal bounds. If the expected dengue potential
363 range is accurate, suburban great transmission suitability ultimately represent higher
364 risk of infectious contact between humans and competent vectors once this is a
365 residential zone. However, vectors density pattern did not show correspondence with
366 the suitability range based on global temperature, which might indicate an
367 underestimation of dengue risk on warmer urban areas. In addition, the niche space
368 currently occupied by both vectors are similar but not equivalent, and part of their
369 climatic niche remain unfilled, representing an ahead risk of vectors population grow
370 into areas of dengue transmission competence. In this sense, range expansion of both

371 species under anthropogenic and climatic changes claim that the combat of mosquitoes
372 must be intersected in areas where the contact of hosts and competent vectors
373 represents a risk. Accordingly, here we suggest that considering the UHI effect on further
374 predictive dengue transmission models might be crucial to accurately identify areas of
375 dengue transmission risk. Moreover, further research is still needed to address the heat
376 suitability on mosquito's traits to transmit other concerning viruses such as Zika and
377 chikungunya (Carlson et al., 2018), in the light of virus and vector coevolution and
378 evolutionary adaptation to new environments.

379 **DATA ACCESSIBILITY**

380 This article has no additional data.

381 **AUTHORS' CONTRIBUTIONS**

382 L.M.S. and R.R.D. conceived the project; L.M.S managed the project; L.M.S and J.N.P-L.
383 conducted the analyses; all authors contributed to the project and/or drafting of the
384 manuscript.

385 **COMPETING INTERESTS**

386 The authors declare that the research was conducted in the absence of any
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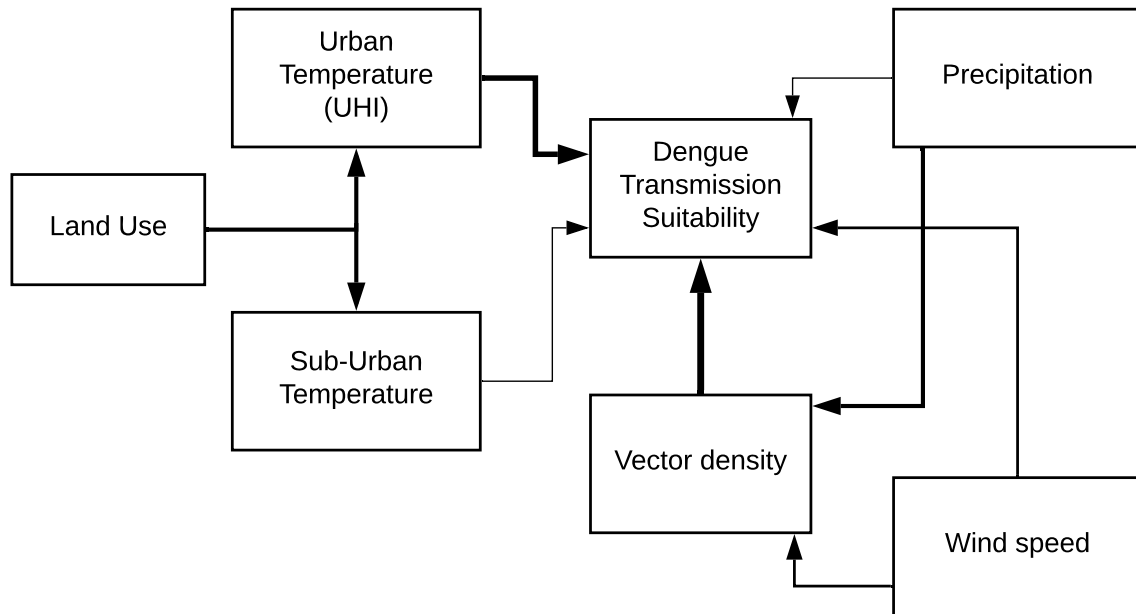
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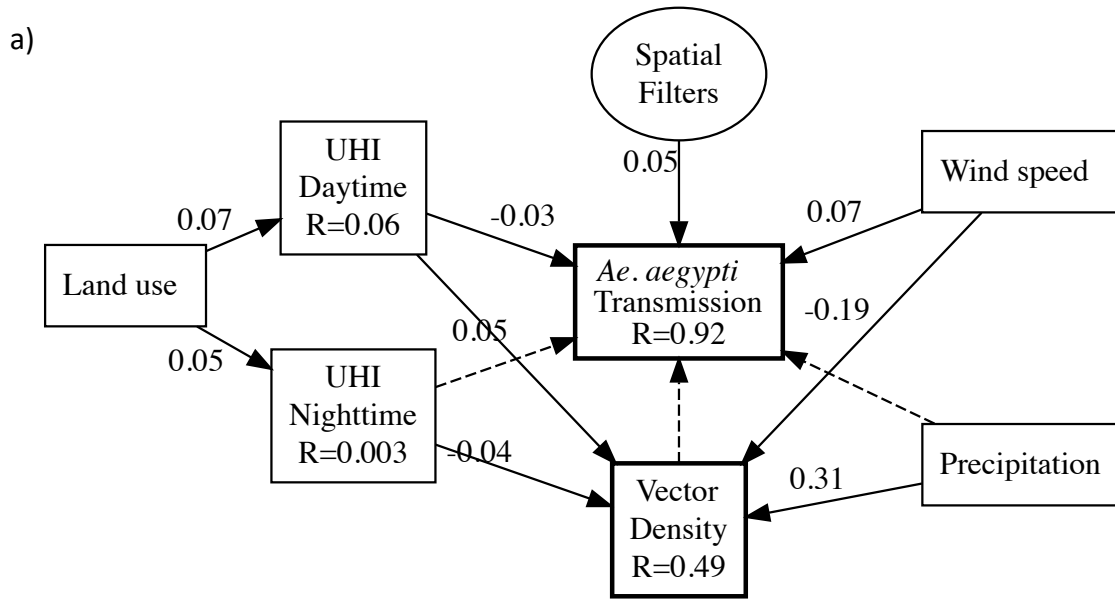
606 **FIGURES AND TABLES**



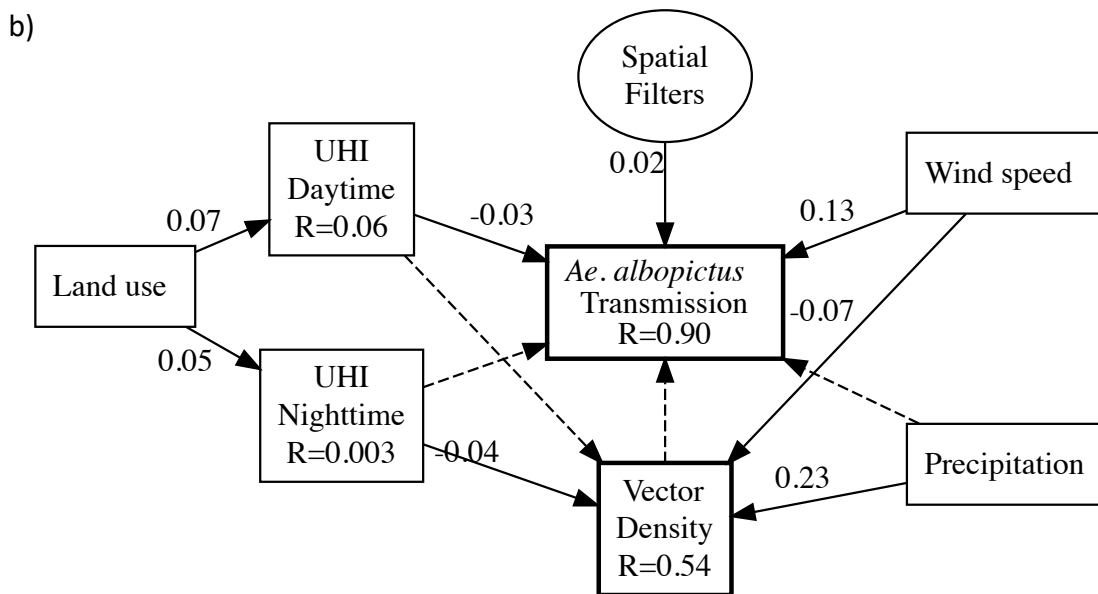
607

608 **Figure 1** Conceptual Path model defining the expected relations between predictors and

609 response.



610



611

612 **Figure 2** Structural equation model outcome for a) *Ae. albopictus* and b) *Ae. aegypti*. R² is shown
613 for the dependent variable. The values associated with arrows are standardized regression
614 coefficients and dashed arrows indicate non-significance path coefficient (P > 0,05).

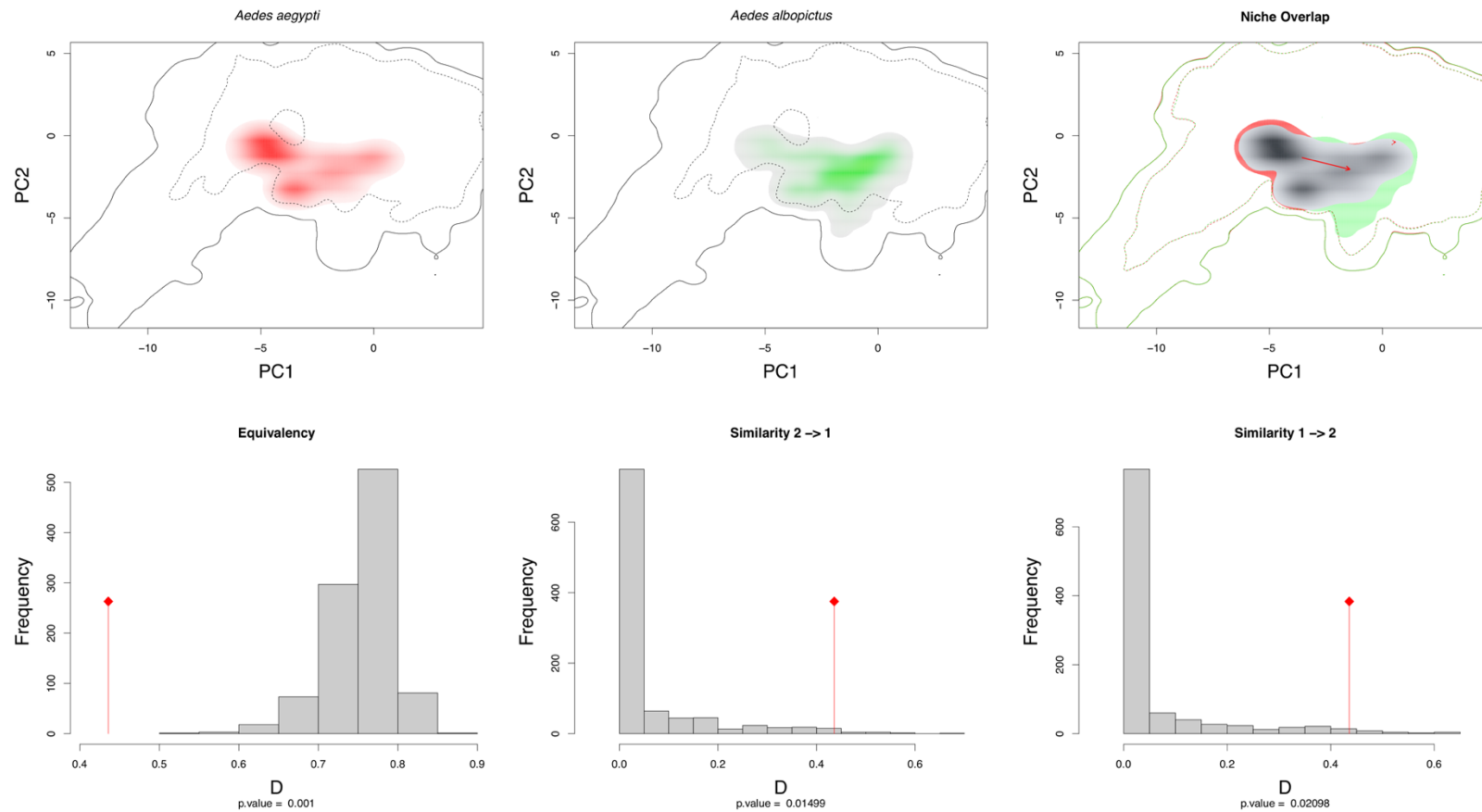
Table 1 Table showing the outcome correlation coefficients of each path resulting from SEM analyses and the respective adjust of each model given the consideration autocorrelation by spatial filters.

	Vector: <i>Ae. Aegypti</i>		Vector: <i>Ae. albopictus</i>	
	Parameter estimate	Standard Error	Parameter estimate	Standard Error
Dengue transmission suitability ~				
Mosquito Density	-0.02*	0.01	-0.01	0.01
UHI Daytime	-0.03***	0.02	-0.03***	0.02
UHI Nighttime	0.001	0.01	0.002	0.02
Wind Speed	0.07***	0.01	0.013***	0.03
Precipitation	-0.03	0.04	-0.08	0.04
Spatial Filters	0.04*	0.01	0.02***	0.01
Mosquito density ~				
UHI Daytime	0.05***	0.03	0.02	0.02
UHI Nighttime	-0.04***	0.02	-0.04*	0.01
Wind Speed	-0.19***	0.03	-0.07***	0.01
Precipitation	0.31***	0.06	0.23***	0.06
Spatial Filters	0.04	0.04	0.03*	0.02
AIC	11631.864		11845.485	
AIC (nf)	15356.419		15655.011	

*p≤0.10.

***p≤0.01.

(nf) No spatial Filter.



616
 617 **Figure 3** Niche overlap and niche equivalence result showing the occupied climatic niches of *Aedes albopictus* and *Aedes aegypti* (Top left) in the niche space
 618 available, and the amount of niche overlap between them (Top right). Both ways intersection (Bottom right) showed higher overlap degree than expected
 619 by the null model (*i.e.*, Schoener's $D > 0.4$). In spite of highly overlapped, their niche spaces are not equal (Bottom left).

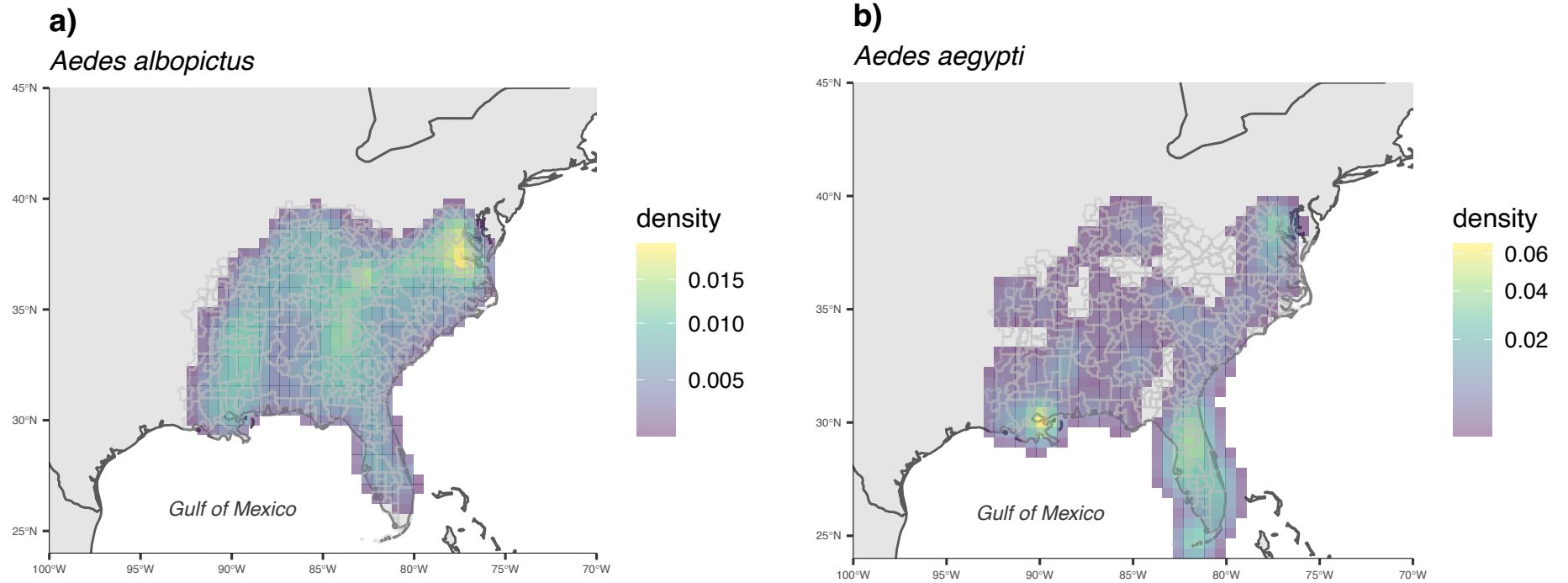


Figure 4 *Aedes albopictus* (a) and *Aedes aegypti* (b) spatial density estimation based on Kernel smooth approach of available occurrence records.